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Felling for Photovoltaics: Remote Sensing for the Detection of Solar Facilities in Maine

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ABSTRACT

Solar power is an area with increasing development in the State of Maine. Photovoltaic solar, which uses large arrays of panels constructed on facilities of several hectares, is an ideal renewable energy source for Maine, because of its low population density and small proportion of conserved lands. Since most of the state of Maine is forested, the development of photovoltaic solar will require increasing amounts of deforestation. Environmental impacts of this deforestation include loss of carbon sequestration, erosion, damage to habitat, and inhibition of other forest benefits. This study uses Landsat data and remote sensing to analyze a large portion of central and western Maine to detect photovoltaic solar facilities. We found a total of 418 sites that had been deforested for photovoltaic solar and 223 sites with photovoltaics built on farmland or grassland. The carbon emissions avoided by the renewable energy benefits outweigh the carbon sequestration benefits from the area deforested, but the ecosystem services lost as a result of the deforestation remain less clear. This is important because of the large number of incentives and limited regulation around photovoltaic construction. For future studies, we recommend a survey of the entire state, more research into the impacts of deforestation for solar photovoltaic on ecosystem services, and monitoring the changing rates of photovoltaic construction over time.

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CHAPTER 1: DEFORESTATION FOR PHOTOVOLTAIC SOLAR IN THE STATE OF MAINE: A REVIEW OF SCIENTIFIC LITERATURE

1.0 Introduction

Solar power is the capture of radiation emitted by the sun, which is then used to generate electricity. Solar photovoltaic, sometimes abbreviated as "PV", is a type of solar power based on the photovoltaic effect, when a photon of light impacts a semiconductor surface (such as silicone), generating the release of an electron. The electron is then captured and used for electricity (Green 2005). Solar power has seen wide scale adoption due to its ability to consistently produce electricity with minimal greenhouse gas emissions (Larson et al. 2021). Photovoltaics come in two main forms: utility solar, which utilizes dedicated power plant facilities, and distributed solar, which comes in the forms of much smaller photovoltaic installations, often in backyards or on rooftops (Hernandez et al. 2014). In the Northeastern United States, utility scale photovoltaics usually take up anywhere from 3.5 to 10 acres of land (Raham et al. 2022), and generally produce public power for the grid, while distributed solar may help power a business or home. Solar photovoltaics have the benefit of being both clean and renewable, creating no atmospheric emissions and generating power from a source that replenishes naturally, the sun.

Several other types of solar power exist in addition to photovoltaics. These include floating photovoltaics (FPVs), which use large rafts moored to lake bottoms to act as platforms for the PV cells (Da Silva and Branco 2018), agrovoltaics, in which crops are planted underneath and around photovoltaic panels (Jain et al. 2021), and concentrated solar power (CSP), which uses large reflector arrays to redirect heat from the sun to boil water, which is then used to spin turbines and generate power (Peuser et al. 2013). In some cases, this technology is still emerging, and has not been implemented on a large scale (FPVs, agrovoltaics), while others are geographically limited to areas with close to year-round sun to be efficient (CSP).

Construction of a PV power plant (also known as a "farm") is a process that takes anywhere from a few months to two years to complete (Balfour et al. 2013). Before installation, PV cells are constructed in factories out of many thin layers of semiconductor material, usually silicon, which absorbs the energy from the sun and allows it to be captured as energy (Vodapally and Ali 2023). Cells are built into large panels for the most effective collection of solar radiation. Once a site is selected, it is then prepared for the installation of the panels. Usually, any vegetation under half a meter in height, as well as all root systems, are removed (Turney and Fthenakis 2011), if they are present on site. During this process, roads and other necessary infrastructure are often constructed, if necessary, to allow access to the site. The area is then graded flat, and concrete pads are sometimes set into the ground to form a foundation (Pimentel Da Silva and Branco 2018). Sometimes, gravel or concrete may be laid down, while other times, the natural soil is left to regrow a limited amount of vegetation. Piles are either bored into the concrete foundations or directly into the ground, and the solar panels are installed on top of them (Pimentel Da Silva and Branco 2018). Finally, the site's wiring is connected to the grid, the area is landscaped, a fence or other barrier is installed, and the site is made operational.

A photovoltaic facility can be constructed on many types of terrain. In relatively open landscapes such as old farm fields, prairies, or deserts, little landscaping is required. In the case of a solar farm being built in a forested area, however, complete deforestation for the preparation of the site is usually required. The process of deforestation for construction is different from that of clearcutting. While clearcutting is the harvest of all marketable timber for commercial sale and can eventually allow for the regeneration of the forest (Schönenberger and Brang 2004), deforestation is the total removal of forest with the end goal of changing the land use type from forest to a different designation, commonly agriculture or industrial. All vegetation, wildlife, and organic matter is removed (Balfour et al. 2013), rocks, boulders, and other debris are hauled away, and the top layer of soil is removed via bulldozer. This is to ensure that construction takes place on a solid, inorganic layer of soil that will not break down and compromise construction (Balfour et al. 2013). In many cases, the site must also be graded, removing any slope and creating a flat surface for construction to occur in order to ensure water drainage and structural integrity (Balfour et al. 2013). This process of deforestation, land clearing, topsoil removal, and grading prepares the site for the installation of a photovoltaic solar facility.

The state of Maine has recently begun to develop its solar infrastructure and capacity. In 2019, Maine passed Public Law 2019, Chapter 477 (Solar, Governor's Energy Office), which requires 80% of Maine's energy generation to come from renewable sources by the year 2030. To facilitate this, in 2023 Maine established the Maine Solar Energy Act, with the goal of "ensuring that solar electricity generation, along with electricity generation from other renewable energy technologies, meaningfully contributes to the generation capacity of the State…" (Solar, Governor's Energy Office). Finally, many homeowners, organizations, and businesses have chosen to install PV solar panels on their own rooftops in what is called distributed energy generation. These solar arrays can be used to provide power directly to a household or business, and the excess power generated can then be sold back to the state in exchange for credits. (Solar, Governor's Energy Office). The results of these policies have been noticeable: as of 2023, Maine has 797 megawatts (MW) of solar installed in the state, up from 600 MW in 2022, with more being added every year (Solar, Governor's Energy Office). Solar energy has shown a consistent trend of growth over the past three years (Figure 1). In terms of solar power, Maine is in the middle when compared to other states in New England. Massachusetts has 3,178 MW of solar power (U.S. Energy Information Administration - EIA), and Connecticut 1,161 MW, significantly more than Maine. Rhode Island, Vermont and New Hampshire, by comparison, lag behind Maine with 600 MW, 288 MW and 165 MWW of solar capacity, respectively (U.S. Energy Information Administration - EIA 2023).

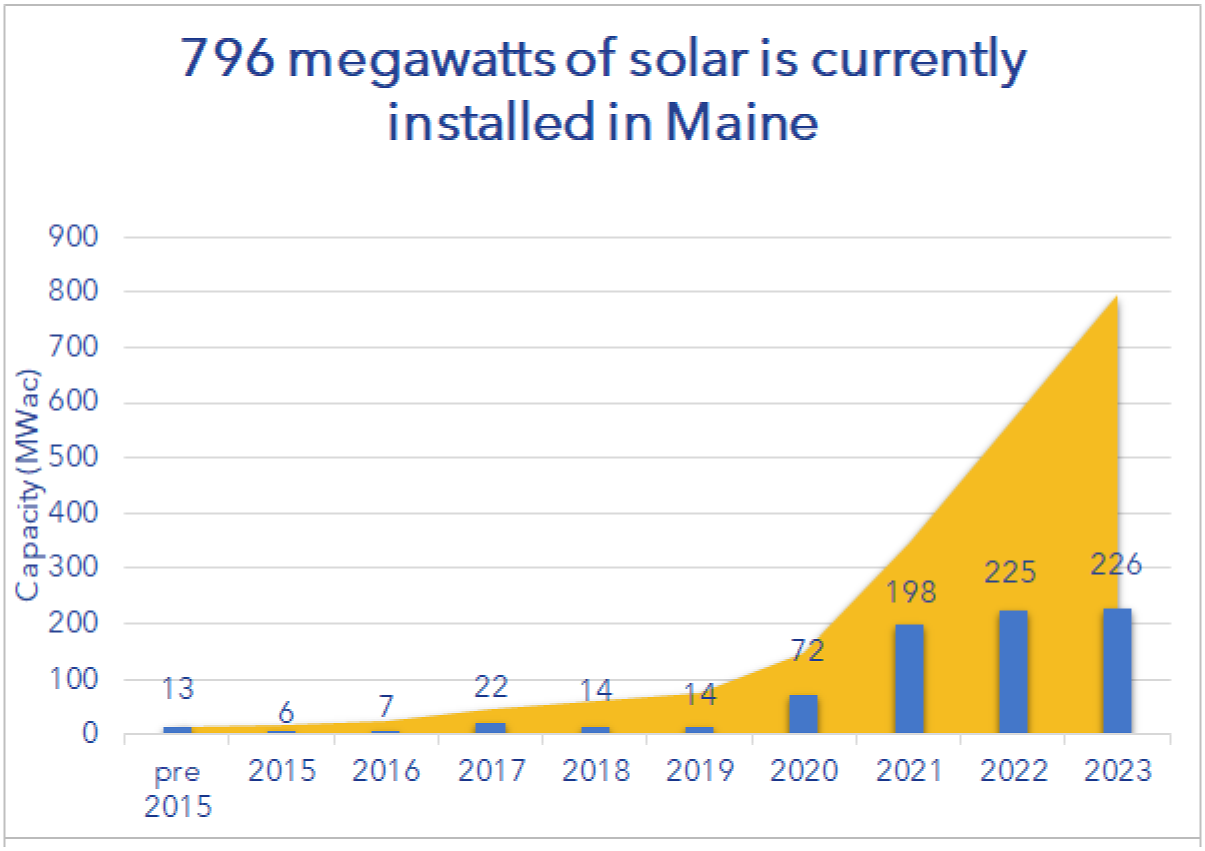

Figure 1: Growth of solar energy capacity in Maine, represented by megawatts per acre (MWac) over time. The yellow fill represents total solar capacity in the state, while the blue bars represent total solar development per year. (Governor's Energy Office).

While photovoltaics are a clean and renewable source of energy, they often require deforestation for their construction. This thesis seeks to understand the effects of deforestation and photovoltaic facility construction on forests in Maine. Geographic information systems and remote sensing can provide an effective tool in the detection and mapping of solar facilities, which may allow scientists and policymakers to understand the scope of PV development in the state.

2.0 Analysis

This section reviews three areas. The first of these is an analysis of renewable energy trends in Maine over the past several years, and an analysis of landowner decisions. The second covers the environmental impacts of deforestation, including carbon, watersheds, habitat, and other effects. The third and final section is a detailed study into different remote sensing methods to be used for the detection and mapping of photovoltaic solar facilities in the state of Maine and the deforestation they have resulted in.

2.1 *Political Feasibility and Landowner Analysis*

Maine is the largest state in New England, the most forested state by percentage of total land area in the country, and the 9th least populous in the nation (Rector 2020). As of 2023, around 21% of Maine's total land area is conserved (Irland 2018). This includes federal and state lands, as well as some locally and privately conserved lands. This means that the remaining 79% of Maine is privately owned and managed. These sections of privately owned forestland are managed for many different goals: recreation, timber production, carbon sequestration, and more. In addition, many of these lands may be protected under conservation status, such as land trusts, conservation easements, or long-term sustainable management plans. Overall, however, most of these lands are managed in some ways for saw and pulp log production (Acheson and McCloskey 2008). What's more, many Maine landowners managing their forests for conservation will often decide to switch to timber production, if the stumpage price increases (Zhao et al. 2020). Privately conserved timberland in Maine is often treated as an investment, and may be harvested if there is a financial incentive to do so.

Several cost-benefit analyses (CBAs) have considered forest ecosystems compared to photovoltaic power facilities. In an analysis done in Tennessee, photovoltaics were valued at $792,219 per acre compared to local forest ecosystems at $14,382 per acre (Novak 2019). While in this CBA forests were only measured on the metrics of carbon sequestration and timber production, the difference is still notable. Another study that considered more parameters, including timber, carbon sinks, biodiversity, and disaster risk, found photovoltaic to be valued at a rate of 1.37 to 1 compared to forest ecosystems (Mori and Tabata 2020). These studies are by no means exhaustive but show a trend of photovoltaic facilities being valued at a higher level than forests. At a time when Maine landowners have been shown to be willing to sell or harvest their timberland if there is enough financial incentive to do so, this may show a similar incentive for the development of photovoltaic solar facilities.

Considering these financial and land use trends, the Maine Department of Agriculture, Conservation, and Forestry (DACF) has put forward a set of guidelines and rules related to both deforestation and the development of solar facilities in the State of Maine. These rules require that developers wishing to construct photovoltaic facilities comply with all land development and resource protection laws and submit notification for timber harvest and land use change. Developers must also complete the construction of the facility within two years of initial deforestation and can have their project halted if it interferes with specific rare plant populations and threatened natural communities. Finally, developers are highly recommended to follow a number of guidelines for land clearing, construction, site maintenance, and decommissioning, to prevent excessive damage to the land and protect surrounding ecosystems (Maine DACF 2021).

Given Maine's private landowner trends, statewide energy goals, and the promise of local power generation, it is likely that Maine will continue to develop more photovoltaic energy facilities. Signs of these trends are already presenting themselves. In 2022 and 2023, construction has begun on at least five new PV facilities in Maine (Hubley 2023, Lund 2022), with more on the way. These solar facilities are being constructed near population centers, but with Maine's population the most rural in the nation (Rector 2020), this is a trend that will likely continue for most or all populated areas of the state. A good example of this is the Three Corners Solar Project, a 931 acre solar facility being constructed in Kennebec County, in a mostly forested area between the towns of Unity, Benton, and Clinton (Maine DEP). While a source of clean and renewable energy, PV facilities still have environmental impacts, on wildlife, carbon storage, soil, water, and more.

2.2 *Effects of Photovoltaic Construction and Operations on Forest Ecosystems*

While solar facilities are often constructed in areas such as deserts or prairies, an option like this is not possible on a large scale for the state of Maine. With 89% of its land area forested, Maine holds the title of the most forested state in the country (Woodall et al. 2022). While oftentimes photovoltaic solar facilities are constructed on former agricultural land or unused industrial areas, due to the lower expenses of reduced land clearing, a large number of PV plants are being constructed in formerly forested areas (Turney and Fthenakis 2011). The deforestation and subsequent construction of solar facilities can eliminate large portions of existing forest.

2.2.1 *Habitat*

The deforestation that the construction of solar facilities requires leads to the eradication of almost all plant and animal habitat in solar facilities. What vegetation does remain after the construction of the facility is either removed with herbicide or mowed regularly, preventing the regrowth of any plant species or the repopulation of any animal species in a significant way (Turney and Fthenakis 2011). The deforestation and subsequent land clearing of a section of forest for the construction of a photovoltaic facility also creates a large scale disturbance event, which can result in the increased spread of invasive species of both plants and animals, which are able to take advantage of the gap left in the local ecosystem to establish themselves (Cochard 2011). In some cases, photovoltaic facilities have even directly resulted in the deaths of animals, with one example being reflected heat from the PV cells melting the wings of the birds in several recorded instances (Rahman et al. 2022).

In addition to the forest ecosystem habitat they directly destroy when constructed, photovoltaic facilities can degrade the habitat that surrounds them. When a photovoltaic facility is constructed, walls or fences are usually erected around the site as a measure for both safety and security (Turney and Fthenakis 2011). This reduces the connectivity of a landscape, which is defined as how much or little a landscape facilitates the movement of organisms through it (Rudnick et al. 2012), and in turn can lead to habitat fragmentation. Animals are forced to travel around the solar facilities, causing them increased stress and forcing them to expend more energy to survive, which can result in increased animal mortality and overall reduced individual fitness (Turney and Fthenakis 2011). Habitat fragmentation also has a negative effect on biodiversity, and affects large animals, such as moose and black bear in Maine, which need large amounts of connected habitat to roam and inhabit (Conceição and de Oliveira 2010). As a result of their construction, photovoltaic facilities cause habitat fragmentation and reduce the overall ecological richness and biodiversity of the forest land that surrounds them.

2.2.2 *Carbon*

Carbon is another important point to consider when looking at the potential costs of photovoltaics. Forests have the effect of both actively sequestering carbon and storing carbon in vegetation and in the soil. When a site is deforested for a PV facility to be installed, the active sequestration of carbon stops. Usually, around 20% of aboveground biomass (timber) that is sequestering carbon remains intact and sequestered. The carbon in the remaining 80% of timber, as well as all of the carbon sequestered in belowground biomass, is emitted back into the atmosphere within months of deforestation (Turney and Fthenakis 2011). After a site is harvested for timber, carbon sequestration usually occurs for the subsequent 75 years due to growth of trees and soil horizons, at a rate of 500–3000 kg CO_2 ha^{-1} yr^{-1}, before the forest matures and the rate of carbon sequestration drops off to ±20 kg CO_2 ha^{-1} yr^{-1}. (Turney and Fthenakis 2011). This process is well described by the system of carbon stocks and fluxes. As trees grow, there is a flux as atmospheric carbon is sequestered in the carbon biomass stock of the tree. When the site is deforested and cleared for construction, however, the existing biomass carbon stock of the tree is removed. As the belowground biomass of the trees decay, the carbon previously stored there is then respirated back into the stock of the atmosphere in a positive carbon flux, at a rate of 400–2000 g Co2 ha^{-1} yr^{-1} (Turney and Fthenakis 2011) for the first 15 years after PV site construction, not including the additional positive carbon flux that comes from the decomposition of the trunks of the trees, also a significant carbon stock. The potential for future carbon sequestration in the trees is also removed as a result of this. Overall, a PV facility constructed in a temperate forest within the United States results in a maximum of 86.3 g CO_2 ha^{-1} yr^{-1} of emissions per year (Turney and Fthenakis 2011).

2.2.3 *Erosion and Water Resources*

When a site is deforested and cleared for the installation of PV cells, the lack of vegetation on the landscape can pose negative effects. Vegetation, both woody and herbaceous, often has the effect of supporting and structuring the soil on which it lives via root systems. When these root systems are destroyed, the soil can be easily displaced during a disturbance event such as a flood or rainstorm. This soil is then eroded downhill, coming into contact with nearby streams, ponds, and other parts of the local watershed (Sweeney et al. 2004). The erosion of sediments into aquatic ecosystems can have negative effects. Aquatic populations are often directly negatively affected by sedimentation, with studies showing increased mortality in populations of both fish and aquatic macroinvertebrates (Newcombe and Macdonald 1991). As sediments erode into a stream or pond, they may also carry with them industrial pollution, such as herbicides or construction materials, both of which are regularly used in and around PV sites (Chen et al. 2019). When these pollutants reach a watershed, they can cause die offs of aquatic macrophytes, reduce organism fitness by altering water quality, and change algal growth patterns further, damaging aquatic ecosystems (Shuman et al. 2020). On a larger scale, sedimentation can cause stream narrowing, which compromises habitat and pollutant processing (Sweeney et al. 2004). When sedimentation and eroded pollutants enter a stream, the effects can compromise stream ecosystem services, and an effect can ripple outwards, affecting both the surrounding terrestrial ecosystems while also moving downstream to affect larger rivers and watersheds.

2.2.4 *Urban Forests*

In addition to potentially damaging nearby aquatic ecosystems and water sources, the construction of photovoltaic facilities can result in negative effects for those living nearby, and may result in the deforestation of urban forests. These urban forests provide the people who live near them with a large number of positive benefits, in addition to the ecosystem services they already provide, such as carbon sequestration, erosion control, and wildlife habitat. For one, urban forests allow for the amelioration of air quality, by removing pollutants such as nitrous oxides, particulate matter, and aerosols, via both deposition on plant surfaces and through stomatal uptake (Roeland et al. 2019). Urban forests also help provide for soil and water quality, act as windbreaks, and provide sources for outdoor recreation (Roeland et al. 2019). One of the largest services that urban forests provide, however, is the regulation of the urban heat effect. Due to the high heat absorption of buildings and man-made infrastructure, sunlight causes urban areas to become warmer than similarly located rural areas. Urban forests relive this effect, via evapotranspiration of water on plant surfaces, and shading from forest foliage (Roeland et al. 2019). When a photovoltaic facility is built on top of an urban forest, all of these benefits are lost. In addition, due to their design, solar panels have high reflectivity, which often contributes to the effect of urban heat islands (Turney and Fthenakis 2011). Finally, while hard to quantify, forests also provide value beyond their immediate use or their ecosystem services, including for recreation, religion, a source of food, and a classroom for learning about natural sciences.

2.2.5 *Environmental Benefit Analysis*

More than a third of Maine's electricity comes from natural gas power plants, with petroleum power plants also being present in the state, according to the Energy Information Administration (EIA 2024). Natural gas is a fossil fuel that directly emits around 0.97 lbs of CO_2 per Kwh, excluding any concerns for deforestation that results from the construction of the power plant (EIA 2024). In terms of carbon, petroleum power plants have even more pronounced outcomes, emitting 2.44 lbs of CO_2/ per kwh (EIA 2024). Natural gas and petroleum power plants also contribute to local air pollution via the emissions of nitrous oxide, sulfur, mercury, and particulates (Hannun and Razzaq 2022), and have similar outcomes related to habitat, soil, and water, due to the land for the power plants having to be completely deforested, in the same manner that it is for the construction of photovoltaic facilities.

In comparison, solar photovoltaic facilities emit 0.192 lbs CO_2 per kwh at the absolute maximum, a number is one fifth of the emissions from natural gas and one twelfth of those from petroleum, and also includes carbon emitted from the ground after deforestation, and the loss of carbon sequestration from the potential future life of the trees that were cleared (Turney and Fthenakis 2011). Natural gas and petroleum also require drilling and extraction operations to obtain them, which can cause negative environmental impacts, including damage to soil, wildlife, and water, and the clearing of large areas of land for storage sites and pipelines, while also using large quantities of resources to accomplish (EIA). While photovoltaic solar is not without its downsides, on an environmental and ecological scale it has fewer negative impacts when compared to the other non-renewable fossil fuels that also contribute to Maine's electricity generation.

2.3 Remote Sensing and Analysis of Photovoltaic Solar in Maine

Even with a good understanding of the effects of deforestation for photovoltaics, it is difficult to understand the full impact of PVs in Maine due to the size of the state. With a land area of 33,215 square miles (Woodall et al. 2022) and a population of 1.385 million people (Rector 2020), many solar facilities exist in Maine dispersed over a wide area. What's more, there is no publicly available list of these facilities, their total acreage, or the total amount of forest they have disturbed in their construction.

Remote sensing can be used to fill this gap in knowledge. Remote sensing is the science of the acquisition of information about the surface of the earth without direct contact with the target of interest. Remote sensing data is widely available and provides an effective way to analyze landscapes to understand their features. Remote sensing can also provide information on a large scale, making it a good candidate for a tool to use for cataloging all of the photovoltaic sites in Maine.

There are different sources of remote sensing data. A commonly used remote sensing platform is satellite imagery (Congalton 2010). Satellites used for remote sensing, such as the USGS LandSat program, work by detecting solar radiation reflecting off the earth's surface. Using a suite of different bands, remote sensing satellites can detect different frequencies of solar radiation reflected off the earth's surface to gather data for different uses (Congalton 2010). While effective at covering large areas, satellite imagery often has a low spatial resolution when compared to other remote sensing methods, which sometimes causes problems when attempting to remotely sense objects on large scales. Aerial imagery can also be used to capture remote sensing data, which has the benefit of being of a higher spatial resolution than most satellite imagery but is usually only available for smaller areas, such as cities (Malof et al. 2016). As such, remote sensing data collected from satellites is the most promising data source for PV detection on a statewide scale.

There are several publicly available sources of satellite imagery that are potential sources of remote sensing data for this project, with two of the largest being the European Space Agency's (ESA) Copernicus program, and the National Aeronautics and Space Administration's (NASA) Landsat program. The most modern satellite of the ESA's Copernicus program is the Sentinel 2. Tao et al. (2023) used data from Sentinel 2 satellites for their survey of photovoltaic facilities across the state of Massachusetts, specifically using the visible and near-infrared bands to view bottom of atmosphere reflectance images, ideal for identifying solar facilities. The Sentinel 2 has a spatial resolution of 10 m per pixel over a 290 km scene size, a 10-day temporal period (how often the satellite comes back to the same point), and a 12-bit resolution for clear imaging (Phiri et al. 2020).

The second source of satellite data available is the National Aeronautics and Space Administration's (NASA) Landsat program, specifically in the form of the Landsat 8 and Landsat 9 satellites. Both Zhang et al. (2022) and Wang et al. (2023) used imagery from Landsat 9 for their remote sensing of photovoltaic facilities across China, both using the surface reflectance (SR) product generated from a combination of several sensor bands. Landsat 8 and 9 have a spatial resolution of 30 m pixels over a 185 km scene size, a temporal resolution of 16 days, and a 12-bit radiometric resolution (Roy et al. 2014).

Once the satellite data has been collected, it must be cleaned for defects and discrepancies, such as air pollution and clouds. Zhang et al. (2022) and Wang. et al. (2023) both used the Landsat pixel quality control band to clean their data, and Tao et al. (2023) made use of the Sentinel 2 cloud mask band to the same effect. Tao also performed image segmentation via a simple non-iterative clustering (SNIC) algorithm to ensure PV panel homogeneity.

Once the spatial data has been collected and cleaned, several methods can be used to process it. The first decision that must be made is between automated and manual classification. Automated classification uses a machine learning algorithm to detect and sort the spatial data, and manual classification involves visually inspecting the data by hand to survey for desired points (Congalton 2010). Due to the large land area of Maine, automatic classification provides a more effective option in this case. The second decision is between supervised and unsupervised classification. Supervised classification uses training areas to represent different land area brightness and reflectiveness, and an algorithm uses the training to identify pixels with similar spectral characteristics (Rozenstein and Karnieli 2011). Unsupervised classification uses cluster analysis to group similar pixels together over large scale landscapes (Rozenstein and Karnieli 2011). Unsupervised classification is excellent for covering and classifying large amounts of land but less effective for the precise classification of specific areas (such as PV facilities). Because of this, supervised classification is the option we chose for the detection and classification of the photovoltaic facilities within Maine.

In addition to standard machine learning algorithms based on supervised classification, at least two studies have been done that use deep learning to identify photovoltaic facilities (Kausika et al. 2021, Li et al. 2020). Deep learning is a relatively new technology that works by teaching computers to process data in a way similar to that of the human brain. Since uses of deep learning for remote sensing are relatively limited at the current time, it is unlikely that this would be useful in the pressing need for the mapping and documentation of all PV facilities within the State of Maine.

Several methods of supervised automatic classification exist for the analysis of remote sensing data. However, an issue exists for the classification of remotely sensed photovoltaic data. Standard photovoltaic solar panels installed in utility level solar facilities are usually around 1.75 meters wide, and are often installed in rows of two, with a total width of around 3.5m, of a length of around 100m or more. At the same time, satellite remote sensing pixels come in a variety of sizes. In the case of Sentinel, the pixels are 10m square, while Landsat pixels (from most of its bands) are 30m square. In each pixel of a PV facility, the surface material that the solar panels are mounted on, usually soil or concrete, is visible between the rows of solar panels. This means that a more advanced system of supervised automatic classification will need to be applied.

Random forest algorithms potentially provide a solution. Random Forest (RF) algorithms are widely accessible and available and work by using multiple decision trees to assign a probability or confidence to each pixel processed relative to the training sample (Sruthi 2021). This creates a map of pixels with various likelihoods of where PV facilities are located. Pixels are then grouped together and sorted into objects with corresponding percent likelihoods of being solar facilities. Zhang and Wang both applied 350 tree RF classification within Google Earth Engine, a cloud based geospatial computing platform that supports remote sensing data and machine learning algorithms (Zhang 2022). For algorithm training, Zhang used training samples from Dunnett's dataset, a global solar plants dataset annotated by volunteers, and used nine variables for detection criteria: the original six bands (B2-B7), and three indices (NDVI; Tucker, 1979, NDBI; Zha et al., 2003, and MNDWI; Xu, 2006). Wang, with a study similar to Zhang's, applied a similar method, also using Dunnett's dataset and applying many of the same detection variables. Wang also used the six original bands as well as the NDVI index and MNDWI index (2023). Instead of the NDBI index, however, Wang used the EVI LSWI indices, and additionally applied four texture indices, homogeneity, correlation, contrast, and entropy, as variables (Wang 2023). Tao also applied a random forest classification model, trained from the Harvard Experimental Forest, and using 500 trees (2023). Based on the work done by Zhang, Wang, and Tao, there is precedent for using random forest classification for the detection and classification of utility level photovoltaic solar facilities.

Once a photovoltaic solar site has been identified, its total land area can be calculated by digitizing its outline in ArcGIS Pro or another piece of GIS software. From there, Google Earth can be used to view historical remote sensing imagery of the land area, which can be used to know if the land was deforested for the installation of the facility. The same polygon can then be used to calculate the total acreage of forest lost for that facility, which can in turn be used to calculate the total loss of carbon sequestration as well as the total loss of other ecosystem services such as habitat, erosion control, and air pollution remediation.

3.0 Discussion and Synthesis

Currently, Maine has both the political incentive and the landowner cooperation to continue with the construction of photovoltaic solar facilities across the state. The state goal of 100% clean energy by the year 2040 (Governor's Energy Office) shows that, by and large, the state government is on board with future renewable energy development. In addition, solar facilities provide incentives to local landowners in terms of local power generation and energy independence, and landowners are likely to be willing to clear their land if the financial incentive is large enough, which may be added to via the sale of the deforested timber. Due to these factors, it is likely that solar facility construction will continue on a statewide scale.

There are several documented negative effects of photovoltaic solar facility construction and operation. Solar facilities destroy the carbon sink of trees and result in a flux of carbon into the atmosphere, where it contributes to climate change. PV site construction also eliminates, degrades, and fragments plant and animal habitat, and has negative effects on watershed health and biodiversity. Solar facilities may also result in the destruction of urban forests, which provide several benefits, including improved air quality and heat island reduction, and also cause forests to be lost as a source of recreation and education.

Several remote sensing options exist for the detection of PV facilities. For the state of Maine, the most effective choice is the combination of satellite imagery with a random forest machine learning algorithm, which will allow a user to quickly and efficiently identify and map all photovoltaic facilities in the state. Once mapped, sites can be further analyzed, and the extent of deforestation and loss of resulting ecosystem services can be uncovered, if they are present.

Through a thorough analysis of photovoltaic solar development in Maine, we can fully understand its damage to the state's forest, which will allow informed decisions to be made in the future regarding Maine's conservation and renewable energy development goals, as well as for the general public to understand the complete extent of PV facilities in the state.

SECTION 2: CLEARCUTTING MAINE FOREST FOR SOLAR POWER: A REMOTE SENSING ANALYSIS

1.0 Introduction

The development of solar energy in Maine is increasing: from 2019 to 2023, Maine's solar energy capacity increased from 76 megawatts to 796 megawatts, an increase of more than 900% (Governor's Energy Office, 2024). The development of renewable energy systems as a whole has been rapidly increasing over the past several years, most recently due to the passage of the Inflation Reduction Act and more broadly in order to reduce carbon emissions in the face of climate change. In 2019, Maine signed into effect Public Law 477, which set forward the goals of 80% statewide renewable energy by 2030, and 100% renewable energy by 2050 (Maine Legislature). In 2023, Maine passed the Maine Solar Energy Act, which provides government investment, tax credits, and infrastructure development in order to reach this target (Maine Legislature).

Photovoltaic solar provides a cost effective and land efficient source of renewable energy. Maine provides an excellent location for solar development, due to its low population density and low amounts of conserved land (Larson et al., 2021; Rector 2020; Irland 2018). Maine also ranks as the most forested state in the nation by percentage of total land area, at 89% (Woodall et al. 2022). As a consequence, solar development in Maine is more likely to require deforestation compared to regions with less forest cover area.

Currently, no list of photovoltaic solar facilities and their locations is publicly available. The Governor's Energy Office, the state energy planning office of Maine, does not maintain a publicly available comprehensive list of all facilities within the state. Individual solar companies maintain lists of facilities they own and operate, but these lists are not often comprehensive, are often out of date, and are limited to the facilities the developer owns.

Remote sensing, the process of the acquisition of information regarding the surface of the earth without direct contact with the target of interest, provides a way to detect and understand the extent and environmental impacts of this development. Via the use of different sensor bands, satellite programs such as NASA's Landsat and the ESA's Copernicus provide an effective way to gather large scale data regarding the surface of the earth and is also publicly available and free to use.

The goal of this study is to quantify the extent of deforestation for solar development occurring in the state of Maine, and to calculate the associated environmental impacts. To do so, we used data from the Landsat 8 and 9 satellites combined with machine learning classification algorithms to detect solar photovoltaic facilities over a large portion of Maine. We calculated the total amount of deforestation occurring for solar development and estimated the associated environmental impacts and benefits from these solar facilities.

2.0 Methods

The state of Maine is mostly forested, with a mix of other land use types including agricultural and urban (Woodall et al. 2022). Maine's forests are mainly made up of post-agricultural secondary forests (Woodall et al. 2022). Maine has a Warm Summer Humid Continental climate type under the Köppen climate classification scheme, and has warm, humid summers, and cold winters (PRISM 2024). We looked at data from the fall of 2023, in order to have the most up to date spatial data without winter snowfall potentially covering PV facilities and making them difficult to detect.

We used the data from NASA's Landsat 8 and 9 satellites based on their effectiveness in other studies with similar purposes. Several studies (Zhang et al. 2022; Wang et al. 2023) have used Landsat data for the purpose of detecting photovoltaic solar facilities, based on its availability and large spatial and temporal scale. Multispectral data from Landsat 8 and 9 are made available in a 30m square spatial resolution over an 185 km wide scene, with a temporal resolution of data collected every 16 days (Roy et al. 2014). We used data from the Landsat 8-9 Operational Land Imager (OLI) and Thermal Infrared (TIRS) Collection 2 Level-2 Science Products (USGS), abbreviated as Landsat 8-9 OLI/TIRS C2 L2, because of its wide range of bands and large quality of available spatial data. We acquired the data through the USGS EarthExplorer, using the predefined area tool to search for scenes in the state of Maine and filter out data that had cloud cover greater than 5%. For our initial analysis and classification, we selected a scene at row 12, path 029, taken on September 7th, 2023. This scene covers a large selection of central and western Maine, as well as parts of northeastern New Hampshire (Figure 2). We used UTM Zone 19 N NAD83 as our coordinate system for this project.

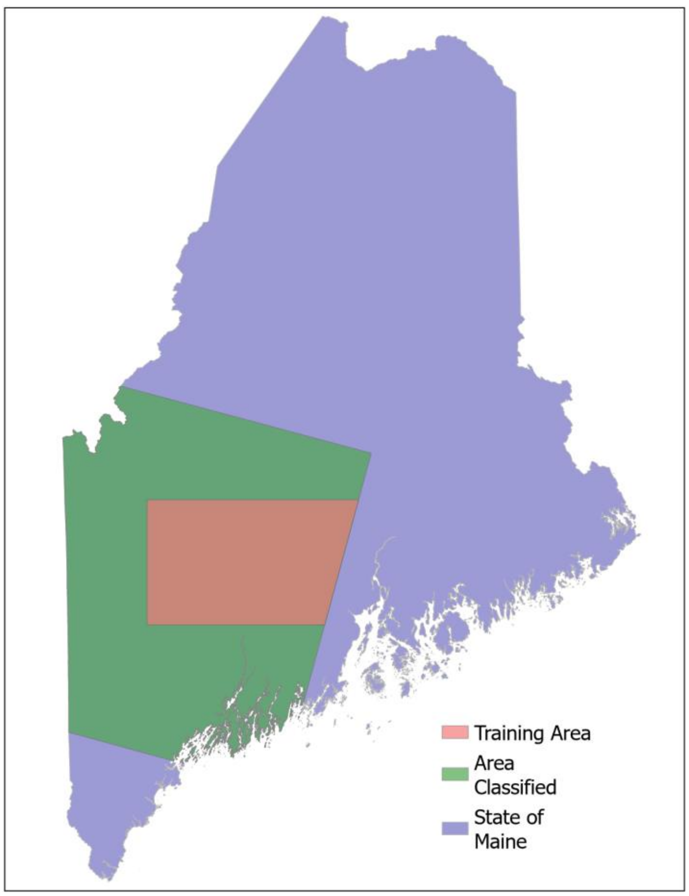

Figure 2: Training area and area classified within the State of Maine

Of the 11 available bands, we selected data from bands 2-7 for our detection of photovoltaics: bands 2, 3, and 4 (blue, green, and red), band 5 (near infrared), and bands 6 and 7 (shortwave infrared 1 and 2). We selected bands 2-4 because of their general relevance and ability to visually confirm potential PV facility locations, and the infrared bands because of their documented effectiveness in the detection of PV facilities (Zhang et al. 2022). From there, we used the program ArcGIS Pro to classify and analyze the scene. We used ArcGIS' training sample manager to create a new classification schema with two categories: PV and non-PV. For training samples, we used a combination of news sources and Google Earth imagery to find recently constructed PV facilities and digitized the areas that these facilities covered in the training sample manager. For the training and refining of the classifier, we decided to use a smaller subset of our larger scene ("Training Area" in Figure 2) and found 11 confirmed PV sites within that area to use as initial training samples, also selecting and inputting three or more non-pv training samples from areas such as farm fields, urban development, and water, per confirmed site.

The next step of the process was the refining and training of the classifier. For classification, we used the ArcGIS Pro classification wizard tool (ESRI 2024), which provides an easy-to-use graphical interface for different classification settings and techniques. We chose to use supervised classification, which classifies all imagery within the chosen scene based on the characteristics of the training samples provided (ESRI 2024). Additionally, we chose to use object-based classification, which uses a process called segmentation to group similar pixels in close proximity to each other together, something that would apply well to the detection of PV facilities with similar spatial and spectral properties (ESRI 2024). After we had chosen our initial classification types and provided training samples of both PV and non-PV areas, we then adjusted the more specific classification settings of the classifier. These fell into two categories: the segmentation settings and the classification method settings. The segmentation settings were:

1. Spectral detail, the importance of spectral differences in the imagery, values ranging from 1 to 20.
2. Spatial detail, the importance of proximity between features in the imagery, values ranging from 1 to 20.
3. Minimum segment size in pixels, defining the minimum size of each segmented area.

Several classification methods were available, including maximum likelihood, support vector machine, and random trees. Each of these methods uses a different classification strategy and are useful for different tasks. Based on suggestions from other projects that used remote sensing to detect PV facilities Zhang et al. 2022; Wang et al. 2023) we eventually decided on using random trees, also known as random forest (RF) classification. RF classification is a machine learning algorithm, and works by using multiple decision trees to assign a probability or confidence to each pixel processed relative to the training sample (Sruthi 2021). The random trees classifier had an additional three settings, max number of trees, max tree depth, and max number of samples per class.

After running the classifier with the default settings, we then began the process of refining the settings. Each time, we would modify one of the classifier settings, beginning with the segmentation settings and then moving on to the random trees, and then run the classifier to determine if the results had improved. Once we had found the optimal settings for our classifier, the next step in the process was the refining and addition of training samples.

After running the classifier, we used Google Earth and Google Maps street view to confirm if the areas detected were actual PV facilities. Once the identify of a sensed location was confirmed, we then digitized them and added the areas to our collection of training samples: if the site was a PV facility, its area would be digitized and added to the list of PV facilities, and if the site was not a PV facility, its area would be digitized and added to the list of non-PV areas (Figure 3). We would then run the classifier again with the newly added training areas and repeat the process, adding more examples of PV facilities and non-PV areas to our training samples. Through this process we were continually able to refine our classifier and provide training samples of PV and non-PV areas.

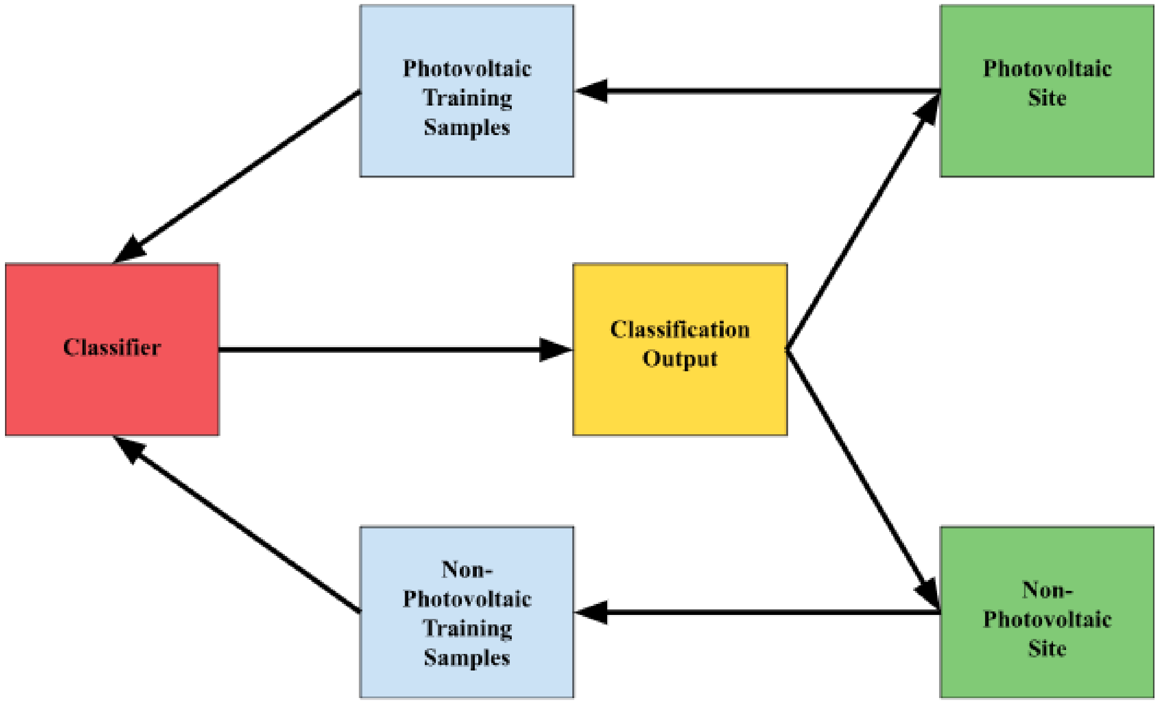

Figure 3: Diagram of training samples in the classification process. After the initial training samples had been inputted, we used a process of continuous refinement to improve our classifier.

After eight rounds of refinement, 12 sites remained in the classification training area that could not be confirmed as PV or non-PV. Sites were then visited for ground truthing. After these were added to the list of training samples, the classification had been refined to the point that the classifier was able to correctly identify 22 of the 25 confirmed PV facilities, including the initial 11 facilities included as training samples. An 88% accuracy rate of classification was the highest we were able to achieve. If we further increased or decreased any settings, confirmed PV facilities would begin to appear in the classifier as false negatives. Considering the goal of this project was to understand the effects of deforestation, we decided that it would be better to potentially underestimate, rather than potentially overestimate, the number of PV facilities we detected. Our final classification used object-based classification with a spectral detail of 20, a spatial detail of 15, and a minimum segment size in pixels of 15, with a random trees classifier with a maximum trees of 500, a maximum tree depth of 30, and a maximum number of samples per class of 1000.

After the classifier had reached maximum functionality, we extracted and classified the area of Maine within the Landsat scene with the same classifier settings and training samples from our initial training area. We initially attempted to classify the entirety of the state of Maine, using several Landsat scenes together, but after initial results, we abandoned this idea. With our classified area of Maine, we transformed the data from raster to feature class, creating a polygon feature class for all PV facilities. Using aerial imagery, we then further sorted the detected PVs by hand into four types: Type 1, PV facilities built on deforested areas (Figure 4), type 2, PV facilities built on agricultural fields or meadows (Figure 5), type 3, other types of PV facilities, mainly rooftop mounted arrays, and type 4, non-pv locations (false positives). While we were able to make use of high-resolution aerial imagery from Google Earth to confirm the land type beneath sensed PV locations, we were unable to find recent spatial data for the same areas. As a result of this, aside from the facilities we had used as training samples, we were unable to confirm the accuracy of the classifier in the scene classified, only in the area used for training. After we had sorted the data, we used Google Sheets for basic statistical calculations and data organization, and R for graphing (R Core Team 2023).

3.0 Results

In our study area, we detected 418 type 1 photovoltaic facilities (sites that were a result of deforestation, Figure 4), and 233 type 2 photovoltaic facilities (sites that were built on grassland and cropland, Figure 5). For the 418 type 1 facilities, a total of 1,859 hectares (18.59 km^2) of forest was cleared, in total 0.1% of the total forest in the scene. For the 233 type 2 facilities, 1,000 hectares (10 km^2) of land was used, in total 0.45% of the total grassland and cropland in the scene. A higher concentration of type 1 photovoltaic facilities was observed in the less densely populated Western Mountains region of Maine, and a higher concentration of type 2 facilities was observed in the more densely populated eastern part of the scene.

The Landsat scene was 27,002 square kilometers (km^2), approximately 29% of the state (U.S. Census). With large bodies of water in the scene, such as Flagstaff Lake and Great Pond, subtracted, the area totaled 25,653 km². Of this area without water, 18,867 km² (73%) was forested, and 2,273 km² (9%) was grassland and cropland (USGS).

Figure 4: Type 1 photovoltaic facilities. The top row shows before the deforestation has occurred, and the bottom row afterwards, once the facility has been constructed. From left to right: facilities in Augusta, Otisfield, and Farmington. Imagery from Google Earth.

Figure 5: Type 2 photovoltaic facilities. Top row shows before construction, bottom row shows after construction. From left to right: facilities in Winslow, Lewiston, and Gardiner. Imagery from Google Earth.

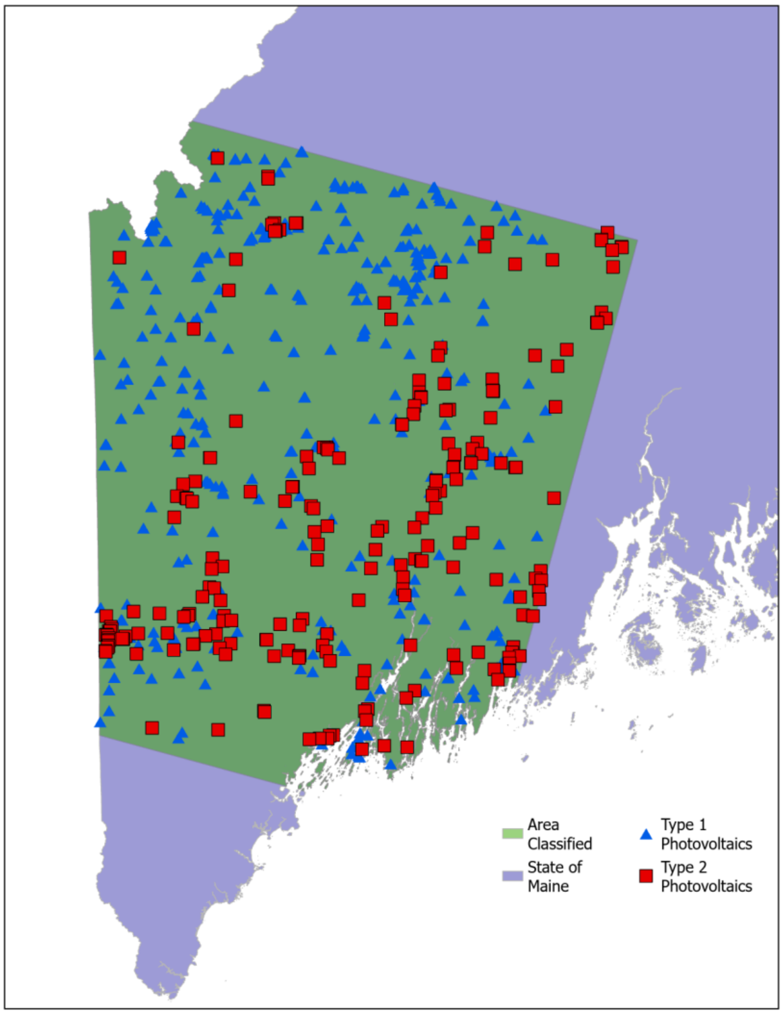

Figure 6: Type 1 and 2 photovoltaic facilities detected across the area classified.

Five federally identified metro areas were included in the scene we analyzed: the entirety of the cities of Brunswick, Lewiston-Auburn, Augusta, and Waterville, and some of the northern parts of Portland. 17% of photovoltaic sites, a total of 109 sites (46 type 1, 63 type 2) were identified across these areas, at a total of roughly 1 photovoltaic facility per four square kilometers, compared to the roughly 1 photovoltaic facility per 39 square kilometers for the entire scene.

While the mean photovoltaic facility was 4.41 hectares, the median was substantially smaller, at 2.97 hectares. This was because the majority of photovoltaic facilities, a total of 625 sites (Figure 7), were less than 15 hectares in area. Only 16 facilities were larger than 15 hectares: 12 of these were smaller than 30 hectares, and 4 were larger. The largest current PV facility we found was located in Farmington, Maine, and was a total of 52.6 hectares. Type 1 facilities and type 2 facilities showed only minor variation between types in size and showed similar overall size distributions.

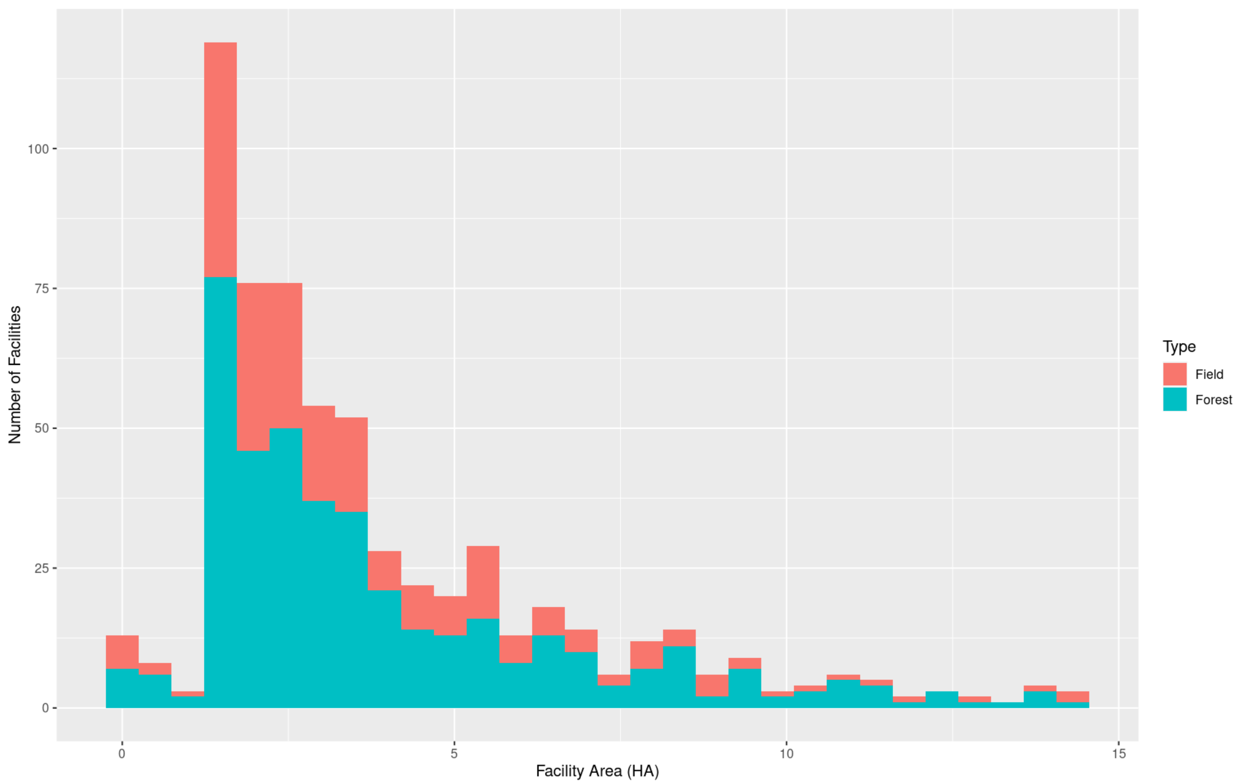

Figure 7: Facilities less than 15 hectares. The blue represents Type 1 photovoltaics, where deforestation has occurred, and the orange represents Type 2 photovoltaics, where deforestation has not occurred.

4.0 Discussion

4.1 *Overall Findings*

In our study area, we found a total of 652 photovoltaic solar facilities, over an area of 2859 hectares. Of these facilities, a total of 418 (termed type 1 PVs) required deforestation to be constructed, while 233 of them did not (termed type 2 PVs). A total of 1,859 hectares of mainly secondary growth forest was clear cut for the construction of the type 1 facilities. By total land area, type 1 PVs made up 65% of detected facilities. By number of facilities, they made up 64% of detected facilities.

These results are not unexpected. The majority of the scene we analyzed, 73%, was forested, while only 9% was farmland, grassland, or other already cleared areas. Because of this, it makes sense that we found more type 1 than type 2 PV facilities. Considering the increasing buildup of renewable energy systems and specifically solar power in the state of Maine, and the fact that the majority of the state is forested, we expected to see most sites being constructed on deforested areas. Additionally, forest landowners have the added financial incentive of selling the timber harvested from the clearcutting required to construct a type 1 facility, making them more financially attractive to construct. Based on a conservative estimate of 3 hectares per MWac (megawatt hour alternating current) for solar facilities (Ong et al. 2013), we found that the facilities we detected produce an estimated 953 MWac of electricity, more than 150 MWac more than the Maine Governor's Energy Office lists as Maine’s total solar capacity as of 2023.

The 1,859 hectares of forest that was clear cut to construct the 419 type 1 PV facilities in our scene made up a total of 0.1% of the forest in the scene we analyzed. In 2021, clearcutting for timber harvest in Maine totaled 9,465 hectares, a total of 8% of the total timber harvested in the state that year (Maine Forest Service 2024). Comparing these two statistics, the deforestation required for the construction of type 1 PV facilities in this scene is approximately 29% of the state, and the ratio of clearcutting for PV development to overall clearcutting is 1:5, or 20%.

4.2 *Development Regulations*

The Maine Department of Agriculture, Conservation, and Forestry (DACF), the state agency responsible for the majority of Maine's land-based natural resources, has published substantial regulations on how the development of photovoltaic solar power is to occur. Depending on the site criteria, environmental permitting is required for categories such as stormwater management, large-scale disturbance (>20 acres), construction near or on water resources such as streams and wetlands, and threatened fish and wildlife species (Maine DACF 2021). Permits may be necessary through several federal and state agencies, including the U.S. Army Corps of Engineers, Maine Department of Environmental Protection, and Department of Inland Fisheries and Wildlife, as well as local municipalities (Maine DACF 2021).

In addition to the required environmental permitting, the Maine DACF requires state notification, planning, and other regulations regarding the active development of a solar facility (Maine DACF 2021). If forested land is being cleared for a solar development project type 1 PV facility) the developer is required to notify the state, the land must be developed within two calendar years of clearing, and all rules required for traditional timber harvests must also be followed (Maine DACF 2021). When a facility is to be decommissioned, a decommissioning plan is required for sites larger than 20 acres, with plans required for the removal of all equipment, above and below ground, the removal of access roads, regrading of the landscape, and revegetation (Maine DACF 2021).

While the Maine DACF requires significant environmental permitting for the initial establishment of a solar facility, as well as practices for the land clearing and eventual decommissioning of a solar facility, the agency requires few practices for site management. The agency provides a detailed list of recommendations to landowners and developers, including soil sampling, minimization of soil compaction, regrading, and water division, among other topics, but none of these are required regulations (Maine DACF 2021). In many cases, the only site management practices that are required fall under other categories of land management, such as deforestation for land clearing, or changes in land use (Maine DACF 2021).

While the development of photovoltaic solar in Maine requires significant permitting and supervised management from federal and state agencies and local municipalities, there are also many ways that the state of Maine makes the development of solar installations easier. In addition to the recently passed state policies encouraging solar development, Maine has introduced incentives for utility scale solar projects in the form of tax credits for both residential and commercial solar facilities (Maine Public Utilities Commission). These come on top of the additional federal level tax credit and write-off programs for the development of utility level solar (Office of Energy Efficiency and Renewable Energy 2024). Maine has also limited the ability of local municipalities to regulate photovoltaic solar facilities. All municipal regulations on solar adopted after September 30th, 2009, must comply with the requirements of Maine Legislature Title 33, Chapter 28-A, which regulates solar development (Maine Legislature). In April of 2023, Governor Janet Mills signed into law a proposal that gives state preference for solar contracts to photovoltaic facilities developed on PFAS-contaminated farmlands, lands that are otherwise unusable for agricultural purposes (Maine Legislature). While the state of Maine continues to regulate and control its process of solar development, it has also made significant progress towards its continued development.

4.3 *Environmental Impacts*

4.3.1 *Carbon*

On average, one hectare (ha) of forest in Maine stores 70.9 megagrams (Mg, also known as metric tons) of carbon (Hoover and Smith 2021). The same hectare of forest takes in, on average, 2-4 Mg of carbon from the atmosphere each year (Gough et al. 2016). When a site is cleared for the construction of a photovoltaic facility, around 20% of the aboveground biomass (timber) is harvested and remains intact, continuing to keep the carbon it contains sequestered. The carbon in the remaining 80% of timber, as well as all of the carbon sequestered in belowground biomass, is emitted back into the atmosphere within months of deforestation (Turney and Fthenakis 2011). Thus, for each hectare of forest, 57 Mg of carbon is emitted back into the atmosphere, and sequestration ceases on a large scale until the photovoltaic facility is removed and the forest is allowed to re-grow. With 1,859 hectares of forest in the scene being lost from deforestation due to photovoltaics, Maine lost roughly 105,963 Mg of sequestered carbon and between 3,718 and 7,436 Mg of active carbon sequestration capacity a year.

A 0.4 hectare solar array in Methuen, Massachusetts, only 40 miles from the Maine border, produces around 245,000 kWh of electricity a year. By using this photovoltaic facility as a baseline, the 1,859 hectares of type 1 solar photovoltaic facilities constructed in the scene produce around 1.12 billion kWh, or 1.12 terawatt hours (tWh), of electricity per year, around 8% of Maine's yearly energy production (Department of Energy). While Maine generates most of its electricity from renewable sources, such as hydroelectric and wind power (Energy Information Administration), 6 tWh of the state's electricity is generated through natural gas (Department of Energy). On average, natural gas power plants produce 0.41 Mg Co2 per megawatt-hour. To produce the estimated same amount of electricity as the type 1 photovoltaic facilities in the scene with natural gas power, 127,320 Mg C would be emitted per year (Greenhouse Gas Reporting Program, 2019). Considering that photovoltaic solar facilities themselves emit a negligible amount of carbon (Turney and Fthenakis 2011), this quantity of emissions avoided overtakes the total carbon dioxide sequestered by the areas deforested in less than a year and is well above the yearly amount of carbon sequestered if the forest was still in place (Figure 8).

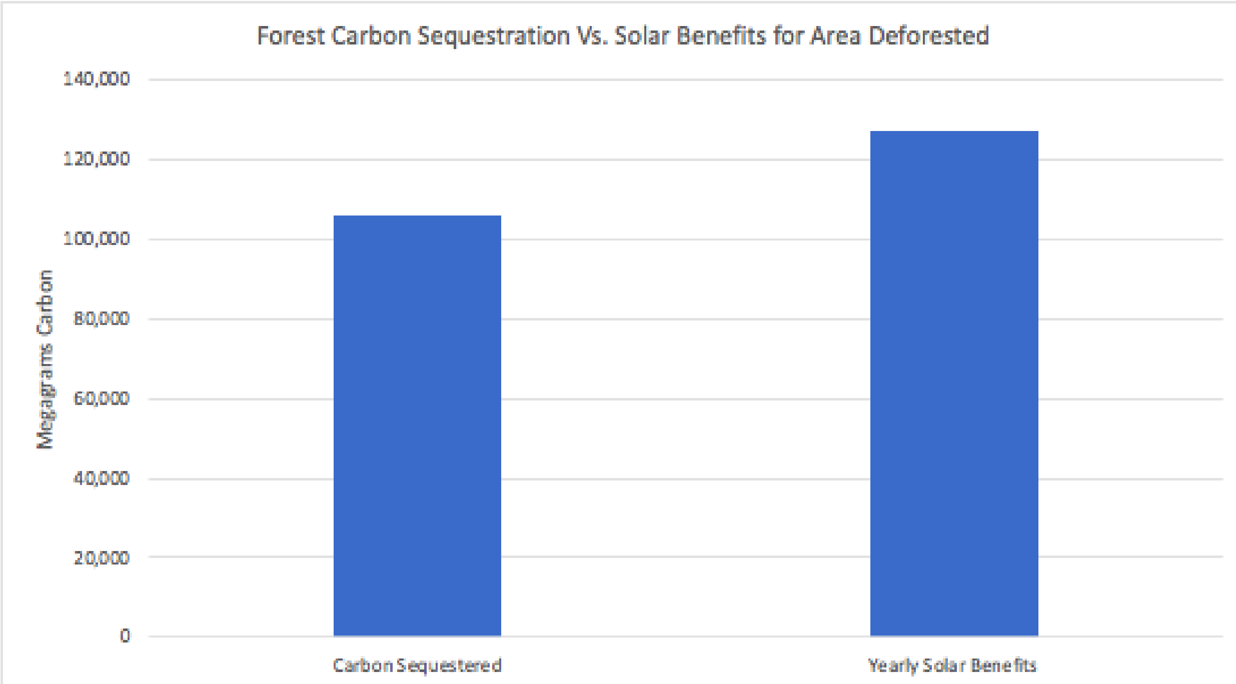

Figure 8: Total carbon sequestration over 1,859 hectares deforested compared to avoided natural gas emissions from photovoltaic solar facilities constructed on the same land area.

4.3.2 *Habitat, Erosion, and Other Forest Benefits*

Construction of a photovoltaic facility can lead to significant damage to natural ecosystems. The complete deforestation and land clearing of the space for the facility removes habitat for most plants and animals (Turney and Fthenakis 2011), reduces the connectivity of the surrounding landscape (Cochard 2011), and contributes to habitat fragmentation (Conceição and de Oliveira 2010), overall reducing the richness and diversity of whatever section of forest they occupy. If a facility is constructed on a steep slope, erosion as a result of photovoltaic facility construction can lead to sediments, pesticides, and industrial chemicals coming into contact with aquatic ecosystems, damaging fish and macroinvertebrate populations (Newcombe and Macdonald 1991), causing algal blooms (Shuman et al. 2020), and shifting the entire course of streams (Sweeney et al. 2004). Deforestation for urban photovoltaic construction can lead to reductions in urban cooling, increased air pollution, and a lack of communal greenspaces (Roeland et al. 2019).

4.3.3 *Land Renewal*

Modern solar facilities have an expected lifetime of around 30 years (Turney and Fthenakis 2011). When this timeframe is up, facilities are usually deconstructed. In their place, a new facility may be constructed, or the land may be left to return to its original state. The Maine Department of Environmental Protection requires a decommissioning plan to be created for each solar facility larger than 20 acres to ensure deconstruction and cleanup of facilities occur in the correct way. Facility owners are required to remove and dispose of all above and belowground structures, remove access roads, regrade the site to its natural grade, and perform any necessary restorative work on adjacent lands (Maine DACF, 2021). If this process is completed correctly, forests are able to re-grow without significant interference, and farmland can be restored to its original purpose.

4.3.4 *Spatial Analysis*

The spatial distribution of the development of type 1 and type 2 photovoltaic facilities show an interesting pattern. While the photovoltaic facilities in the western counties of the scene, such as Oxford, Franklin, and Somerset, have mostly Type 1 facilities, the eastern counties of the scene, including Androscoggin, Kennebec, and Cumberland, all have more Type 2 facilities. When compared to elevation and population maps of Maine, a corresponding pattern can be seen: The western regions are at a generally higher elevation, with a lower population, and the eastern regions are more highly populated and lower in elevation (Figure 9). In addition, none of the five urban areas in the scene are found in the eastern counties of the scene. This corresponds to historical trends of settlement in Maine. During Maine's initial settlement by white settlers in the 1700s, the southwestern region of the state was the first area settled. Once these regions had been mostly logged, they transitioned into agricultural production and were then reforested as farms subsequently closed down (Fobes, 1944). The patterns from this can be seen today. In the more densely populated and flat eastern region of the scene, fields and agricultural land are more readily available for the development of solar facilities. Conversely, the more sparsely populated western and mountainous part of the scene has less cleared land, so forestland is more often cleared for the construction of photovoltaic facilities.

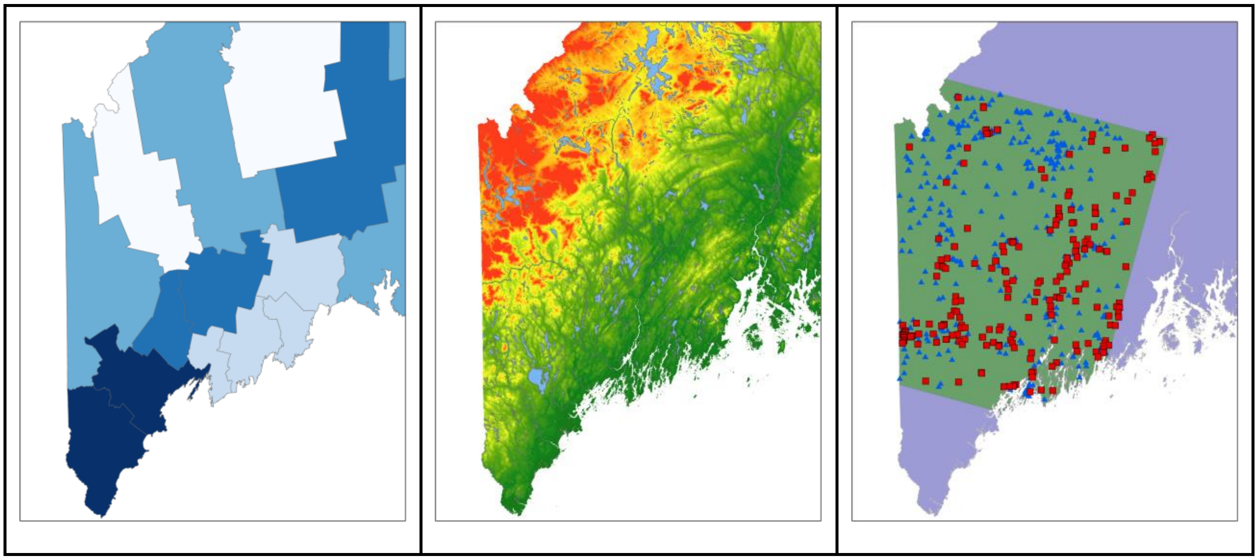

Figure 9: From left to right: population of Maine counties (darker colors indicate a higher population), Maine elevation (Reds indicate a higher elevation), type 1 and 2 PV facilities.

4.4 *Study Limitations*

The largest limitation of this study was time. All of the remote sensing analysis occurred in January of 2024 as independent thesis research. At the end of January, we had refined the classification system to be functional for one Landsat scene. The initial plan had been to expand this classification to the entirety of Maine using a mosaic of Landsat scenes, but when we tried doing so, we learned that the classifier was only effective for the scene we had trained it on because of a lack of training samples for the other scenes and small cases of spatial distortion between scenes. If time was not a factor, we could have repeated our process, refining the classifier and finding training samples, until the classification was functional for the entire state. Unfortunately, by the end of January, we were forced to move into the data analysis for the project, and did not have time to do this.

We conducted limited ground truthing of our classification. For our remote sensing, ground truthing was limited to Google Earth imagery and street view, and one ground truthing trip via car to several photovoltaic facilities identified around our initial training area. Because of this, we were unable to verify the existence of the majority of photovoltaic facilities we identified, including most in our larger Landsat scene. While we had access to aerial imagery via Google Earth to confirm land cover types (e.g. field vs. forest), this imagery was often too old to be used to confirm the presence of recently built photovoltaic facilities. As a result of this, the majority of sites within the scene are unconfirmed.

An additional limitation was our classifier. The highest functionality we achieved was the detection of 22/25 confirmed photovoltaic sites within our training area. Further modifications of classification settings consistently led to the classifier detecting a large number of false positives. Due to the goal of this project, to understand the impacts of deforestation related to photovoltaic solar development, we made the decision to have our classifier detect false negatives, for a potential underestimate of the total effects, versus having our classifier detect false positives, for a potential overestimate of total effects. Overall, however, we would have liked to have been able to have brought our classifier to a higher level of overall functionality instead of having to choose between different inconsistencies in the data.

4.5 Conclusion

In this study, we found that deforestation for photovoltaic solar is occurring in Maine, and that photovoltaic solar facilities are being built more frequently on forestland than farmland or grassland. Considering Maine's trend of continuing renewable energy buildup and its mostly forested land area, this result did not surprise us. We found that the carbon benefits from the renewable energy generated outweighed the loss of the carbon sequestered in the forest and the future carbon sequestration potential. Other impacts were less clear, and we did not attempt to quantify the impacts of deforestation for photovoltaic solar on habitat, erosion, and other forest ecosystem services beyond basic trends. We recommend that future research focus on quantifying these impacts, not just of deforestation but also of the construction of photovoltaic solar facilities on the deforested land. In addition, we recommend future studies focus on the analysis of photovoltaic facilities for the remainder of the state we did not classify to understand the scale of photovoltaic development there. Finally, considering the increasing rates of photovoltaic solar development in Maine, we recommend future studies conduct research into the changing rates of solar development and land use change in the state.

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APPENDIX

Spatial and classification data from this project can be found in Professor Justin Becknell's folder, in the "Research" folder of the Colby filer. The folder with the data from this project is labeled "Lane_2024_DefoPV_Thesis". Within this folder, there is all of the imagery, spatial data, and classification data used on this project. The training samples can be found in the file "PV Schema 242.ecs", and both the direct result of the classification and the subsequent shapefiles created based on it can be found within the geodatabase, "Deforphotovol_Thesis.gdb". Please do not hesitate to contact any of the authors if questions arise regarding this data. James Lane can be reached at Jamesaldenlane77@gmail.com.