Detecting and modeling *Karenia mikimotoi* abundance in the Gulf of Maine

Erica Lei and Nicky Ling

Introduction

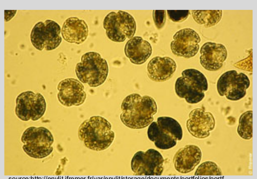
The dinoflagellate *Karenia mikimotoi* is a common phytoplankton found in harmful algal bloom (HAB) events (Brand et al. 2012). Presence of the organism in the nearshore Gulf of Maine was not studied or documented until a bloom took place in 2017, leading to a loss of $250,000 from Maine's economy (McGuire 2017). To mitigate economic loss from harmful algal blooms (HABs), it is necessary to track the presence and abundance of this species in the Gulf of Maine and to model environmental conditions that could contribute to possible HABs of this species.

In this study, we will investigate the presence of *K. mikimotoi* in the Damariscotta River Estuary using an environmental DNA (eDNA) approach and analyze how its abundance is related to two environmental factors: the sea surface temperature (SST) and the photosynthetic available radiation (PAR).

source: https://www.wxrnh.com/thread-781487.htm

Left: a *Karenia mikimotoi* dominated red-tide event.

Right: *Karenia mikimotoi* individual cells.



source:http://envlit.ifremer.fr/var/envlit/storage/documents/portfolios/portfolio20020802/portfolio_album.html

Methods

- Collect water samples around 1:00 pm on Sep 12, 19, 26, Oct 3 and 10 by casting PVC Niskin Type Sampler at two depths, "shallow" (1m) and "deep" (4 - 7m).
- Vacuum-filter the samples using 0.2 µm filter paper.
- Store the filter paper at 4˚C for eDNA extraction.
- Extract eDNA using DNeasy PowerWater Kit protocol (Qiagen, Germantown, MD).
- Run a real-time qPCR based on the methods of Yuan et al. (2012).
- Acquire temperature and radiation data from UMaine LOBO buoys.
- Abundance of *K. mikimotoi* in samples is expressed in gene copies rather than cell counts because the exact number of 28S genes in a single *K. mikimotoi* genome is not known.

Figure 1

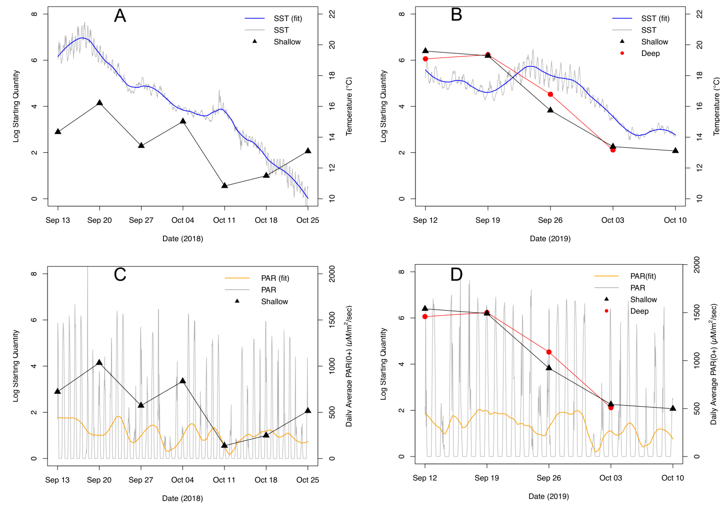


Figure 1. *K. mikimotoi* starting quantity (log10 scale) graphed against (A) temperature changes within 2018 sampling periods, (B) temperature changes within 2019 sampling periods, (C) radiation changes within 2018 sampling periods, and (D) radiation changes within 2019 sampling periods. A loess fitted curve for SST or PAR is shown as guidance for trend on each graph.

Figure 2

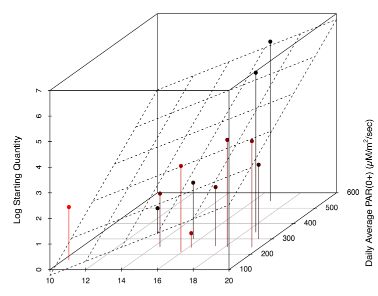


Figure 2. Model (dashed plane) of temperature and PAR covarying with *K. mikimotoi* concentrations. The data points (n = 12) are shown as red dots, highlighted by shorter distance to (0, 0, 0).

- On a 95% confidence level, there is no significant relationship between the *K. mikimotoi* gene concentration and the linear combination of SST and PAR ($F = 3.958$, df = 2 and 9, $p_{SST} = 0.141$, $p_{PAR} = 0.116$, $R^2 = 0.4651$).
- The coefficient for SST has an 85% confidence interval of (0.00521, 0.545) and the coefficient for PAR has an 85% confidence interval of (0.000943, 0.0160), where 0 is in neither of these.

Results

- *Karenia mikimotoi* was present in both 2018 and 2019, with a noticeable smaller temperature range and higher concentration observed in 2019 samples.
- The model expression is:

$$\log_{10}(Starting\ Quantity) = -3.82 + 0.27 * SST + 0.00849 * PAR$$

- At an 85% confidence level, there is evidence showing positive correlations between abundance and the linear combination of temperature and radiation.

Discussion

- Since *Karenia spp.* is thought to live over winter in low numbers as motile cells awaiting favorable bloom conditions (Gentien 1998), one reasonable explanation for the higher concentration in 2019 samples is that *K. mikimotoi* cumulated at a faster pace this year as there was a large amount from previous years available for reproduction.
- The environmental factor model shows that there is weak evidence of positive linear correlations between gene copy numbers and SST and PAR. Future studies can incorporate other abiotic factors that contributes to the ideal growth environment for *K. mikimotoi*, such as hydrology, low salinity, high nutritions, and low wind speed (Barnes et. al 2015). With more data, we hope to predict HAB events in advance.
- One source of imprecision could result from the data not taken at the sample location nor the exact location of the blooms, but instead from the nearest buoy.
- We recommend to encourage citizen scientists to use portable DNA extraction and qPCR kits to support the monitoring dataset in the future.

Acknowledgements

It is not possible to finish this project without the help from Dr. Pete Countway and the guidance from Prof. Ben Neal. Many thanks to Dr. Nick Records for directing us to the LOBO Buoy data source. Last but not least, we are grateful for the opportunity offered by the Environmental Studies Program in Colby College and the Bigelow Laboratory for Ocean Sciences.

Wood vs. Corn

Which Carbon Footprint Better Supports Renewable Chemistry?

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Background

Environmental, economic, and renewable energy policy incentives have prompted an increase in biomaterials and biofuels in recent years. Today, the primary bio-based raw materials or so-called 1st generation feedstocks consist mostly of starchy crops such as American corn, Brazilian sugarcane, and Thai cassava (Noblet et al., 2012). Efforts to commercialize conversion of 2nd generation feedstocks such as woody biomass and agricultural waste are just beginning.

Woody feedstocks are favorable in that trees are not a food source, and the land does not need to be tilled or fertilized, thus are considered more sustainable at the beginning of its life cycle. The ample wood supply for biobased materials in Maine also makes this industry possible, for there are annually 9.6 to 10.3 million green tons of wood feedstock available for the next 40 years, excluding recovery from spruce budworm (Innovative Natural Resource Solutions LLC, 2017). However, the wet milling technology of corns has a relatively high maturity and low cost compared to the conversions of lignocellulosic biomass. In addition, the co-products such as corn gluten feed and corn germ are ready for other uses (Whitney, 2016).

Given the complexity of the emission trade-offs in each manufacturing step, Life Cycle Assessment (LCA) is the main method for this research. If wood offers stronger life cycle benefits compared to corn, especially related to fossil resource usage and greenhouse gas emissions, this might attract investment in wood-based manufacturing.

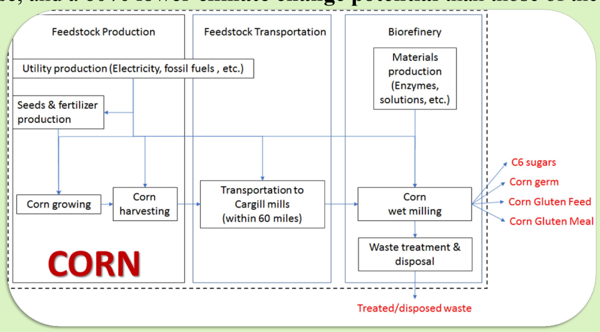
Methods

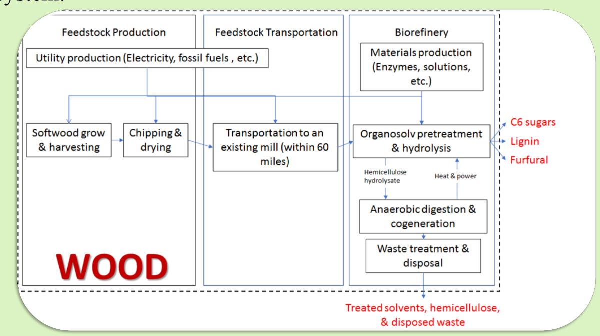
Life Cycle Assessment (LCA) is a technique for assessing the potential environmental aspects and potential aspects associated with a product (or service), by:

- compiling an inventory of relevant inputs and outputs,
- evaluating the potential environmental impacts associated with those inputs and outputs,
- interpreting the results of the inventory and impact phases in relation to the objectives of the study.

- ISO 14040.2: Life Cycle Assessment - Principles and Guidelines

We expect to use the **GREET Model** (the Greenhouse gases, Regulated Emissions, and Energy use in Transportation Model) developed by Argonne National Laboratory to analyze the following life cycles adapted from Moncada et al., 2017. In their study for the Netherlands scenario, when no allocation among co-products is used, the wood system shows a **54% lower non-renewable energy use**, and a **60% lower climate change potential** than those of the corn system.





Corn Life Cycle Assumptions

- Feedstocks include: Yellow dent No.2 corn.
- Typical practices in corn cultivation, harvest, transport and processing at a wet mill.
- Hydrolysis of corn starch to produce industrial sugars.
- Reference to previous LCAs prepared for the production of polylactic acid (PLA), a biobased plastic, by NatureWorks in Blair, Nebraska, from corn sugars.

Wood Life Cycle Assumptions

- Feedstocks include: Low-grade pulpwood (especially softwoods), sawmill residues (mill chips and sawdust).
- Typical practices in forest growth, harvest, transport and processing in Maine.
- Hydrolysis of wood cellulose to produce industrial sugars.
- Co-location of cellulosic sugar production at a current or former pulp & paper mill.

Goals

Do a comparative cradle-to-gate life cycle assessment (LCA) between Maine wood and Midwestern corn as renewable feedstocks for industrial C6 sugars, to determine:

- Which has a more favorable carbon footprint,
- What are other noteworthy differences including land use change, water depletion potential, or human toxicity potential.

Challenges

The biggest difficulty is the life-cycle inventory -- quantifying the energy and raw material inputs and environmental releases associated with each stage of production. Most research about wood as a feedstock uses *ecoinvent* or *GaBi* databases that are expensive to access (Karlsson et al., 2014, Kim & Dale, 2005). The ecoprofiles generated by NatureWorks are useful, but are represented as CO_2 eq./kg of Ingeo product (PLA), yet the energetics of the sub-processes areconfidential (Vink & Davies, 2015). Thus, we need to put together information accessible from open sources, and to validate data credibility. This project is ongoing.

Acknowledgements

- We would like to thank two nonprofit organizations for their previous forest studies: Environmental Health Strategy Center, a public health organization committed to sustainable economic development, and Biobased Maine, a trade association committed to advancing the manufacture of biobased products.
- Forest Bioproducts Research Institute, Umaine.
- Buck Environment and Climate Change Lab, Colby College.
- Reference list attached.

A Scenic Resource Inventory of Quarry Road

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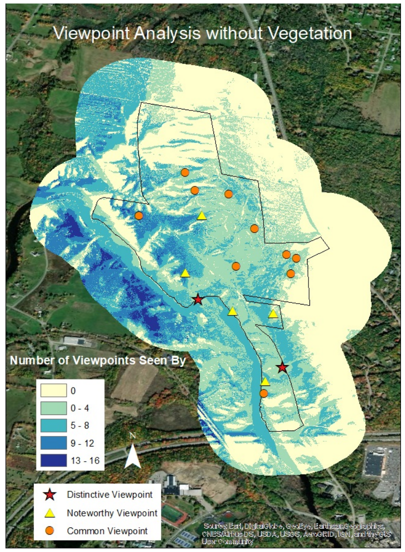
Introduction

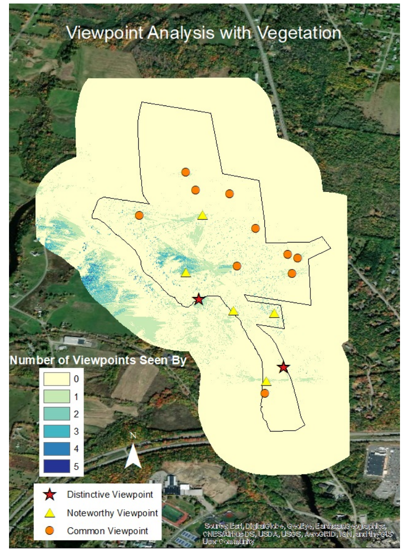
The purpose of a Scenic Resource Inventory is to identify key scenic views from physical features and visual appeal. By identifying areas to be protected and advertised as scenic resources, the inventory provides critical information for the management of scenic areas. We sampled 17 viewpoints from various elevations and trails of Quarry Road on September 29, 2018. Using the criteria defined in our Scenic Viewpoint Evaluation Form, we classified the viewpoints as Distinctive, Noteworthy, or Common. Our GIS analysis allowed us to see important areas in and around Quarry Road that contribute to this scenery.

What's a Viewshed Analysis?

A Viewshed Analysis is a way to understand which places have a high scenic value – in other words, which areas are seen a lot from scenic viewpoints. Using a mapping program called ArcGIS and with the help of Dr. Manuel Gimond, we created Viewshed Analysis maps that analyzed how many times places are seen by our viewpoints.

Viewshed Analysis Maps





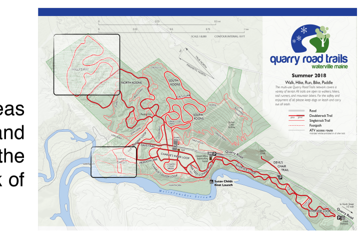
The map without vegetation only takes elevation into account, while the map with vegetation takes other objects such as buildings and vegetation into account when creating the Viewshed Analysis. They include Quarry Road and a 300 meter surrounding buffer.

Seasonality

Seasonality may change views, as shown in these pictures of the waterfall along the entrance road of Quarry Road. Viewable scenery in the summer or early fall may mirror our viewshed analysis with vegetation, while that in the winter or early spring may mirror our viewshed analysis without vegetation. Also, snow covers the bridges and makes certain trails inaccessible to children or seniors.

Limitation

The framed and shaded areas (Wally's Way, Short Circuit, and Hawthorn) were excluded in the inventory due to distance and lack of development.



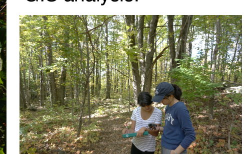
Class A (Distinctive) view at Susan Childs Boat Launch.
Consist of openness, diverse vegetation, water, diverse topography, historic structures, and an accessible path.

Class B (Noteworthy) view at Devil's Chair Trail.
Consist of the same attributes as Distinctive views but in less abundance and with a less accessible path.

Class C (Common) view at the top of old alpine ski.
Consist of natural and cultural features that provide ordinary scenic quality, usually including negative attributes such as power lines and erosion.

Acknowledgement

Special thanks to Ole Amundsen III for his advice throughout the project and to Dr. Manuel Gimond for his guidance and help with our GIS analysis.



Revealing elevational distributions of ants

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edupics.com

Introduction

Ant species are incredibly diverse in morphology and behavior. Their diversity lets them survive in many habitats, and their distribution can be evaluated by sampling regular points on an elevational gradient, along which the environment changes drastically. Evaluating the communities of ants will help us understand how habitat changes affect ants in the future.

Methods

The survey was conducted by placing 4 replicate pitfall traps at 100 ft or 200 ft elevation intervals located at Mt. Blue, Camden Hills, the Perkins arboretum, Frye Mountain, and Kennebec Highlands.

- Pitfall traps were created by hole-punching 23-27 holes along the rims of plastic cups, and they contained about 40 ml of propylene glycol.
- Four pitfall traps with lids were placed in the ground with the holes exposed, at each elevation (2 on each side, placed 10m and 15m away from the trail).
- Pitfall traps were collected once every one to two weeks for 4 times, and separated into vials of bycatch and ants.
- Ants were pinned by using wood glue to attach the ants to small triangular pieces of paper.

Punching holes in cups was difficult

MacGown, Joe. "Aphaenogaster picea". mississippientomologicalmuseum.org.msstate.edu

Data Analysis

A. All traps without ants were marked as 0 ants, and records from spilled traps were discarded.
B. To adjust for uneven sampling, we took averages of abundance per elevation.
C. Species counts were aggregated according to genus.
D. Data was cleaned and graphed in R.

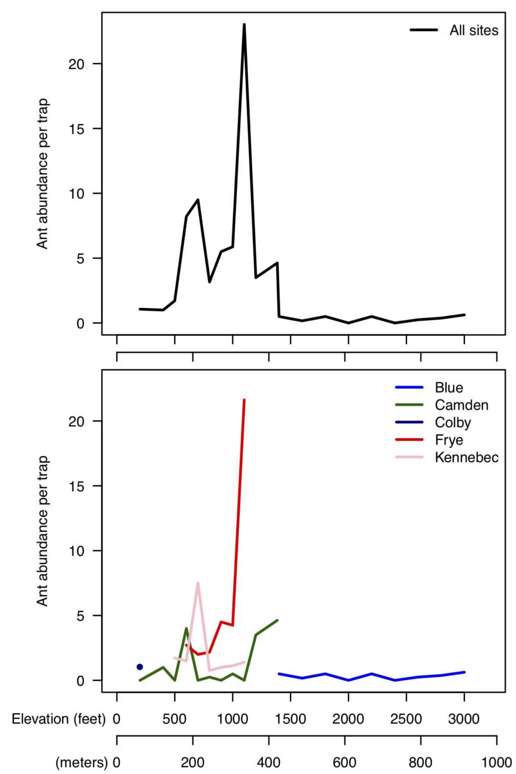


Figure 1: Ant abundance by elevation (upper) and by site (lower)

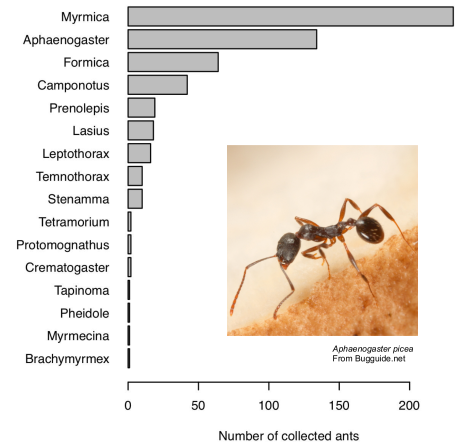
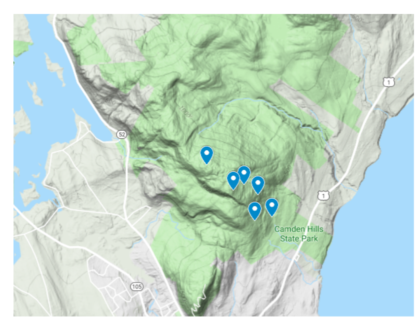


Figure 2: Ant abundance by genus

Results

Ant abundance exhibits a mid-elevational peak, where an average of 23 ants appeared in each cup on the 1100 ft elevation of Frye Mountain (Figure 1). Few ants were observed in high elevations, although only Mt. Blue was sampled in such elevations.

The rank distribution of individuals per genus(Figure 2) displayed a characteristic concave curve. *Myrmica* was the most frequently caught genus, but *Aphaenogaster picea* has the highest count on the species level.



Pitfall sites of Camden Hills (sites on Mt. Blue and Frye Mountain follow the same pattern, not shown due to space limit)

Conclusions

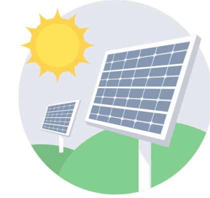
The patterns shown in the data were well-anticipated using ecological experience and knowledge of elevational gradients.

- **Abundance by elevation:** It seems that ants are rarer in high elevations, perhaps due to the changes in temperature and plant composition. As ants are known to be most active in warm environments, we can anticipate that they would be collected most at lower elevations. However, the graphs may be misleading due to the differences between mountain sites. For instance, the largest peak in Figure 1 was an anomaly due to some other biological factor such as proximity to a colony of species that exists in high abundance, or proximity to a major food source. The data can also be interpreted as peaking in intermediate elevations, potentially due to the mid-domain effect.
- **Abundance of species:** As expected, a few genera dominate a region, and there are many rare genera. The data fit a hollow curve well. Further investigations may reveal the strategies of rare species and the reasons that common species are so abundant.

The ant team atop Camden Hills

Is the average household income associated with solar panel installation rates in the US?

Dhruv Joshi ‘21, Zhijun Lei ‘20, Roujia Zhong ‘22



Question:
Is the average household income associated with solar panel installation rates in the US?

Primary explanatory variable:
Average household income in census tract units.
Primary response variable:
Solar panel installation rates in census tract units.

Introduction

Solar energy is an inexhaustible resource that can supply a significant portion of global electricity needs (Barbose et al. 2012). The use of solar energy can decrease the greenhouse gas emission and increase national energy independence, work opportunities, and rural electrification rates (Tsoutous et al. 2005). It is necessary to understand whether the household income is associated with solar panel installation rates so that the government can offer new subsidies for household solar panels based on average household income.

Data

- ❑ Data of solar panel installation rates in each census tract unit was obtained from the DeepSolar dataset from Stanford University.
- ❑ Researchers used machine learning to determine number of solar panels installed in each census tract unit from the satellite images in the 48 contiguous US states (Yu et al. 2018).
- ❑ Average annual household income, number of state-given incentives, and solar radiation data for each census tract are also appended into the DeepSolar dataset.
- ❑ We used random sampling method from the population to select our sample data points (n = 5000).

Category	n	Proportion (of 5000)
Household Solar Panel Installation within Census Tract		
No panels	1231	0.25
Some panels	3769	0.75
Number of State-given Incentives		
Low (8-17)	1499	0.30
Low-Medium (17-21)	1059	0.21
Medium-High (22-41)	1361	0.27
High (42-75)	1081	0.22

Table 1. Frequency table of categorical variables (Installation within census tracts and incentive counts).

Methods

- ❑ The distribution of average household income and solar panel installation rates were skewed to the right. So the data was log-transformed to match the normality assumption.
- ❑ Additional variables include number of incentives and daily solar radiation. We categorized the solar panel installation into 2 categories and the number of incentives into 4 categories (Table1).
- ❑ A two-sample t-test for the difference in means was used to determine if the household income is higher for census tracts with some solar panel installation (Figure 1).
- ❑ A Chi-square test for association was used to see if solar panel installation and number of incentives are associated (Figure 2).
- ❑ An ANOVA test was used on the number of solar systems per household for all levels of incentives. The result showed that at least one mean is different, so pairwise comparisons using t tests with pooled SD and Bonferroni adjustment were conducted between all groups (Figure 3).
- ❑ A linear regression was conducted to determine the association between the solar panel installation rates and average household income (Figure 4).
- ❑ A multivariable linear regression (MLR) was used to determine the influence of the confounder solar radiation on the relationship between two explanatory variables and the response variable (Table 2).

Results

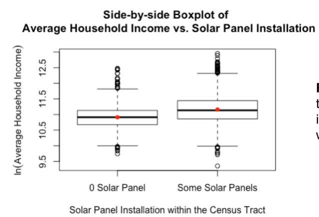


Figure 1 Side-by-side boxplot displaying the distributions of average household income by the solar panel installation within census tract units.

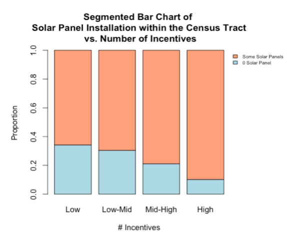


Figure 2 Segmented bar chart displaying the proportion of solar panel installation based on the number of incentives.

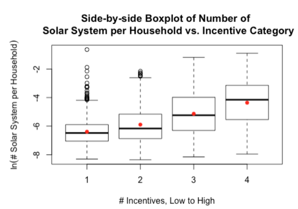


Figure 3 Side-by-side boxplot displaying the distributions of the average number of solar system installed per household by the number of incentives within the census tract (n = 3769).

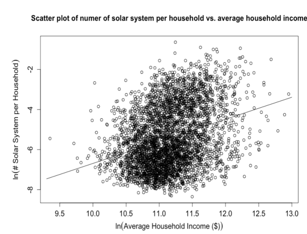


Figure 4. The scatter plot displaying the relationship between the average household income and the number of solar systems per household in census tract units with solar system installations (n = 3769, r = 0.32).
Our model:
ln(solar systems per household) = -17.70 + 1.10 * ln(average household income)

	Coefficient Estimate	Std. Error	t value	Pr(>|t|)
Intercept	13.92001	8.26348	1.685	0.0922
ln(Income)	-2.43592	1.44258	-1.689	0.0914
ln(Income)²	0.15366	0.06424	2.392	0.0168
Daily solar radiation	-6.43560	0.57793	-11.136	< 2e-16
Daily solar radiation²	0.84278	0.06471	13.024	< 2e-16
Low-medium	0.23750	0.05654	4.201	2.72e-05
Medium-high	0.72470	0.05301	13.671	< 2e-16
High	0.81286	0.06505	12.496	< 2e-16

Table 2. A multivariable linear regression is used for the primary explanatory variable ln(income), the secondary explanatory variable level of incentives with the low level as the baseline, and the confounding variable daily solar radiation.

- ❑ Figure 1 shows that the census tracts with Some Solar Panels form a higher boxplot than the census tracts with 0 Solar Panel, suggesting the average household income is higher in the census tracts with some solar panel installations ($p < 0.0001$).
- ❑ Figure 2 shows there is an association between the incentive counts on solar panel installations and solar panel installation in census tract units ($p < 0.0001$).
- ❑ Figure 3 shows that the means of the number of solar panels installed per household are pairwisely different for census tracts with different levels of incentives ($p_i < 0.0001$).
- ❑ Figure 4 shows that there is a weak positive linear relationship between the average household income and solar panel installation rates. ($p < 0.0001$).
- ❑ Table 2 is the output of the MLR. There is strong evidence showing correlations between solar panels installed and all the variables listed except for ln(income). The confounding variable terms (radiation and radiation squared) have a stronger effect among all variables in the model.

Discussion

- ❑ **We found that there is a weak positive linear relationship between household solar panel installation rates (log scale) and the average household income (log scale) after controlling for solar radiation.**
- ❑ **Solar panel installation rates are also weakly positively associated with state-given incentives on solar panels and strongly positively correlated with daily solar radiation received.**
- ❑ **The results indicate that the government can offer monetary subsidies to low-income households to increase the use of solar energy.**

Limitations: The ANOVA and linear regression models only concerned census tracts with solar panel installations because the log-transformation ruled out areas without solar panel installation.

Future research: We would like to examine other variables that might impact the number of solar panel installations, including the average number of years of residents’ education, ratio of votes for Dem to votes for GOP, and electricity price within census tract units.

Recommendations: Since this study utilized a large size of SRS (n=5000), the results of the study are representative of all the census tracts within the 48 contiguous states of the US. Our study indicates the possibility for state governments to incentivize households with lower income to install more solar panels. For example, the government can offer cash rebates and state tax credits and encourage households to sell their carbon offsets to make solar more accessible for today’s homeowners.

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