Solar Radiation Big Data Analysis for Strategic Positioning of Residential Solar Panels

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INTRODUCTION

This project explores how optimizing the tilt of the solar panel improves residential energy output in South Texas. Effectiveness of SOLPOS data is also investigated by comparing with the experimental data. The findings connect real-world solar engineering with STEM education.

OBJECTIVES

- Validate SOLPOS data accuracy with real-world irradiance measurements.
- Using SOLPOS data, identify optimal tilt angles for maximum daily, monthly, and annual solar energy output.
- Develop educational tools and modules for classroom integration.

BACKGROUND

How Solar Panels Work

- Photons from sunlight strike photovoltaic (PV) cells, exciting electrons and generating direct current (DC).
- An inverter converts DC into alternating current (AC) for home use.
- Electricity powers household appliances directly from the sun.

SOLPOS Calculator

The Solar Position and Intensity (SOLPOS) model, developed by the National Renewable Energy Laboratory (NREL), calculates solar elevation and irradiance based on geographic location and time. It's used in research, solar planning, and classroom simulations.

How Irradiance Affects Energy Output

Energy output depends on how much sunlight is absorbed. Factors like tilt, panel type, time of day, and weather influence this. Reflective losses reduce output unless mitigated by panel texture or coatings. The higher the irradiance, the more energy generated.

Power Equation: $Energy = A \times r \times H \times PR$

A = Panel area (m^2)
r = Panel efficiency
H = Irradiance (W/m^2)
PR = Performance ratio (~0.75)

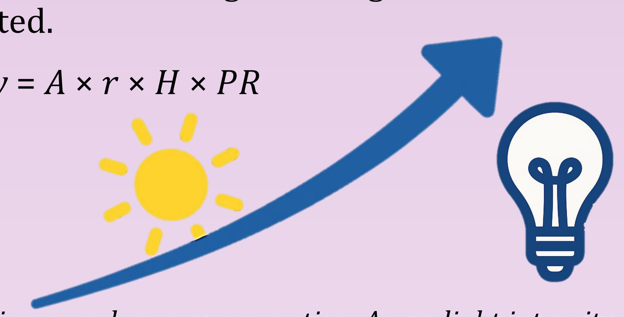

FIGURE 2: Relationship between solar irradiance and energy generation. As sunlight intensity increases, so does the electrical power output, highlighting the direct link between solar input and system efficiency.

LITERATURE REVIEW

- Solar panels work best when perpendicular to sunlight, maximizing energy absorption.
- Fixed-tilt systems are low-cost but less efficient than tracking systems.
- Single-axis tracking boosts output up to 25% by rotating east to west.
- Dual-axis can raise efficiency by 30–45% by adjusting tilt and direction.
- SOLPOS models sun angles and irradiance for optimal tilt choices.
- Automated systems adjust tilt by hour or season.

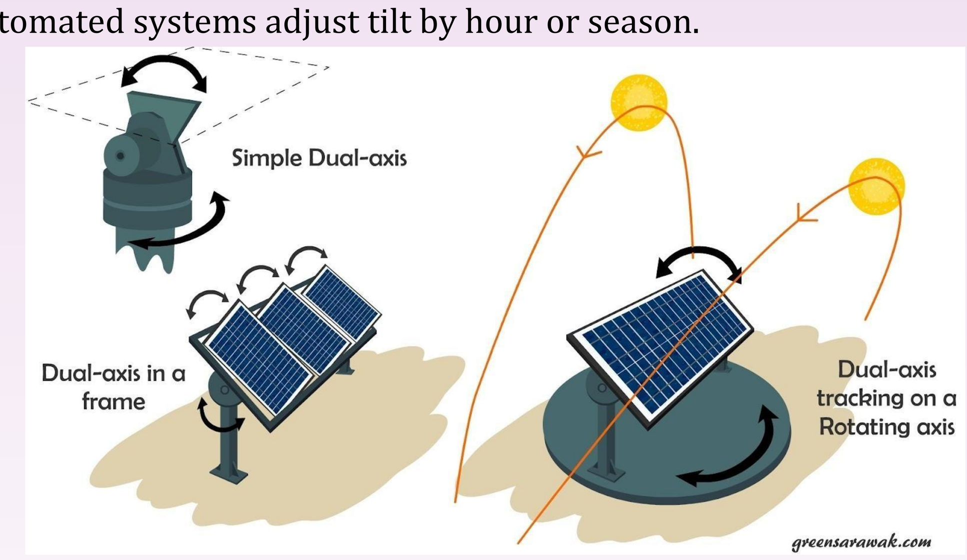

FIGURE 1: Tracking system types. Illustration of solar panel tracking technologies: simple dual-axis, dual-axis in a frame, and dual-axis on a rotating base.

System Type	Description	Output Boost	Common Use
Fixed-Tilt	Panels at a fixed angle	Baseline	Rooftops, low-cost installs
Single-Axis	Rotates east to west throughout the day	+15–25%	Utility-scale solar farms
Dual-Axis	Tracks both sun angle and direction	+30–45%	High-output or space-limited systems

TABLE 1: Summary of how each system type affects energy output, with dual-axis systems offering the highest performance gains.

METHODS & RESULTS

Experimental Data: Recorded irradiance (W/m^2) and surface temperature (°F) at 30-minute intervals between 8:00 AM and 7:00 PM in July 2025 using a Fluke IRR1-SOL meter. Panels were set at tilt angles of 0°, 35°, 40°, and 50°, all fixed at an azimuth of 180° (due south).

Experimental Validation: Side-by-side comparisons between experimental and SOLPOS irradiance curves show strong alignment. Minor differences are attributed to cloud cover and local weather. This confirms SOLPOS as a reliable tool for field modeling and classroom applications.

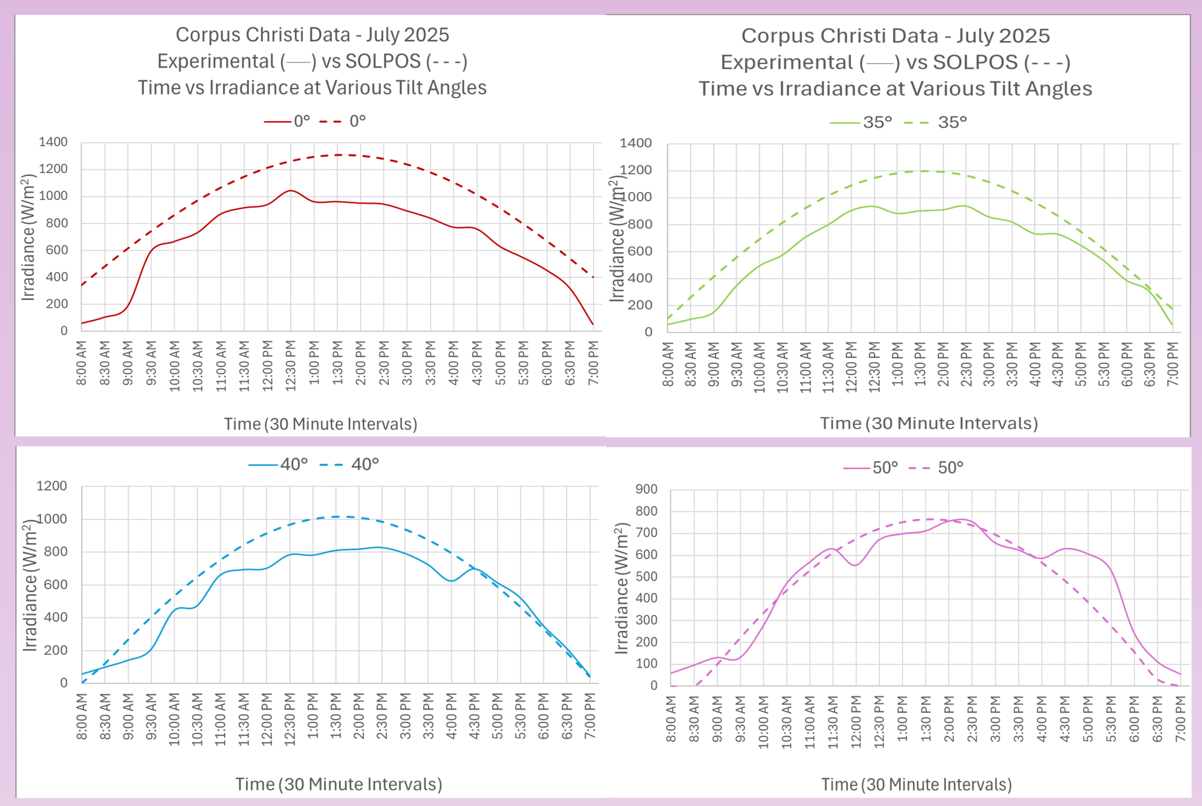

FIGURE 3: Experimental irradiance trends across tilt angles (0°, 35°, 40°, 50°) on clear July days. Real-world data closely matches SOLPOS simulations, validating model accuracy.

Modeled Data Collection: Collected hourly solar irradiance values for Corpus Christi, TX (27.8°N, 97.4°W) using NREL's SOLPOS calculator for tilt angles from 0° to 90°, covering a full calendar year. Created comparative visualizations and 3D surface plots showing irradiance trends across time, tilt, and day of year.

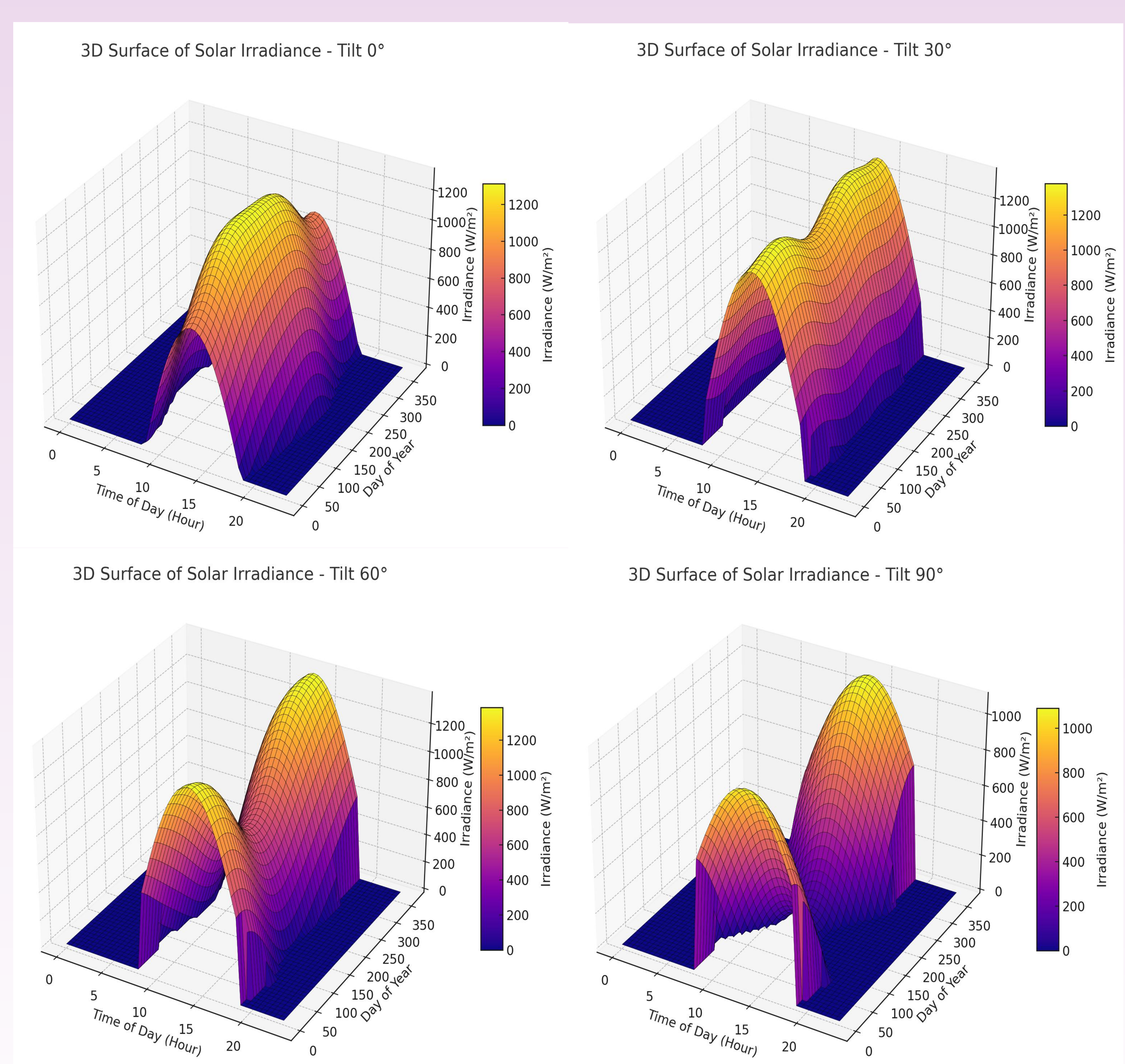

FIGURE 4: 3D surface plots by tilt visualizes irradiance as a function of hour and day across tilt angles 0°-90°. Reveals seasonal intensity peaks.

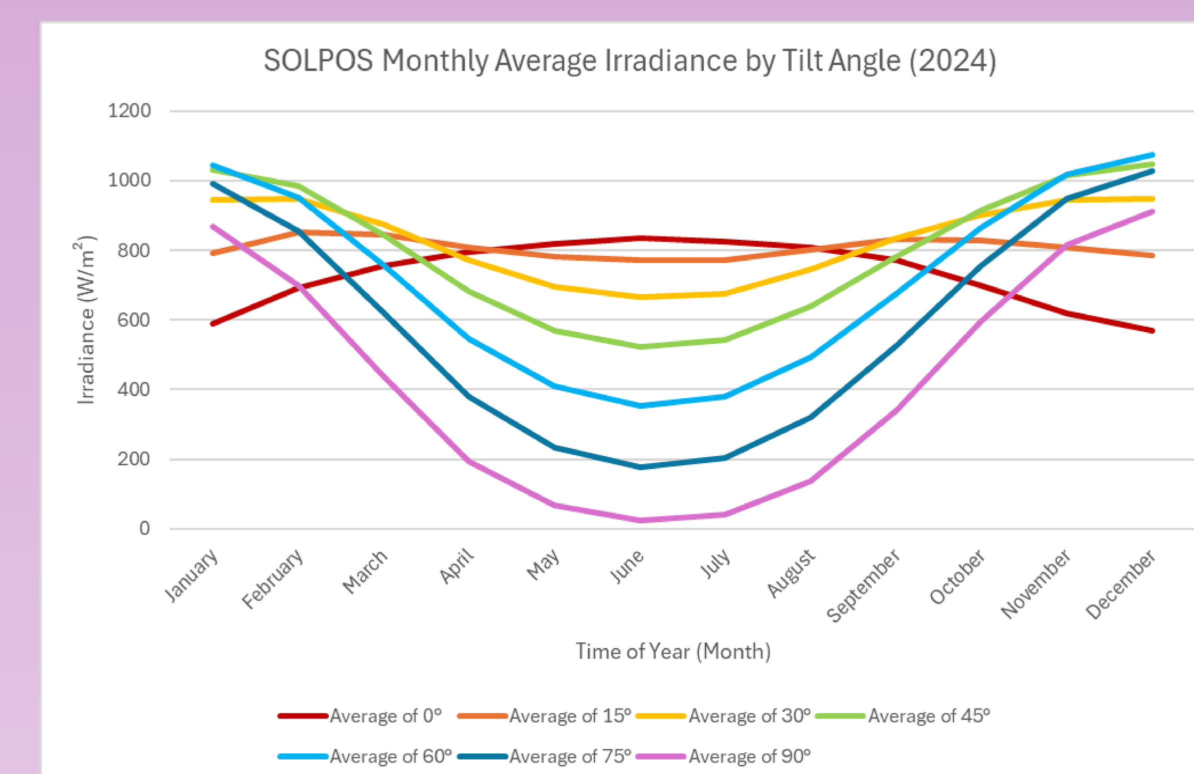

FIGURE 5: Annual performance of solar panels at different fixed tilt angles: 0° excels in summer, 60°–90° peak in winter, 15°–30° perform steady all year.

CONCLUSIONS

SOLPOS modeling and experimental data confirm that optimal tilt angles vary by month in South Texas, supporting the value of seasonal adjustment.

- **May–August**: Best performance at **0°** due to high solar elevation.
- **October–February**: Steep tilts (**60°–90°**) yield the highest irradiance.
- **15°–30°**: Consistently strong output year-round, ideal for fixed residential panels.

These trends emphasize the advantages of adjustable or tracking systems for maximizing energy production.

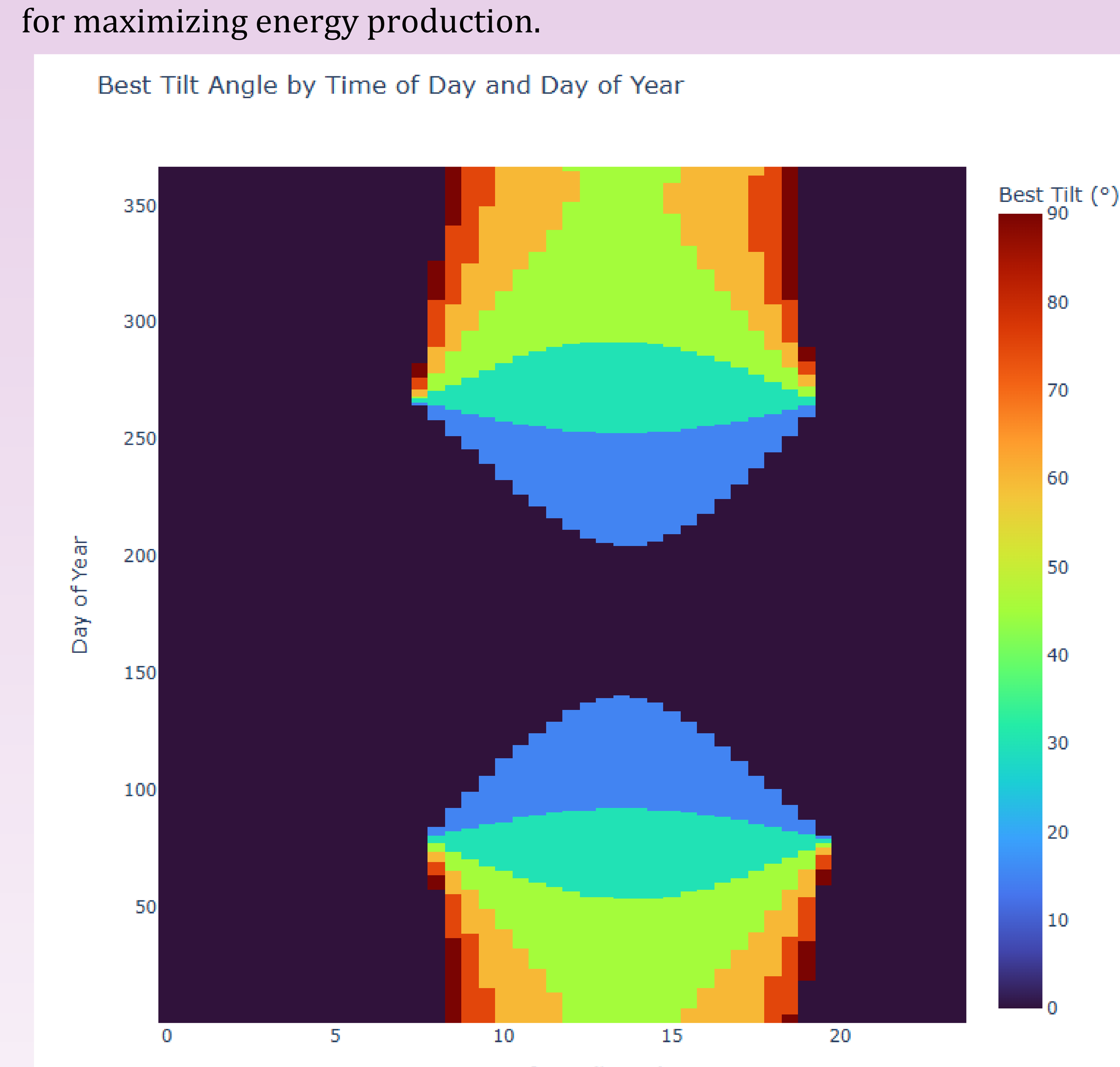

FIGURE 6: Best tilt heatmap shows the ideal tilt angle by time of day and day of year based on modeled irradiance. Helps users choose seasonal panel settings for maximum energy collection.

ACKNOWLEDGEMENTS

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CURRICULUM MODULES

Algebra 2: Collect irradiance data every 5 minutes using panels at 0°, 35°, 40°, and 50° tilt angles. After graphing results, analyze trends and apply linear or quadratic regression to model how tilt affects solar output.

TEKS: 111.39(c)(2)(A)(D), (4)(A), (6)(B)

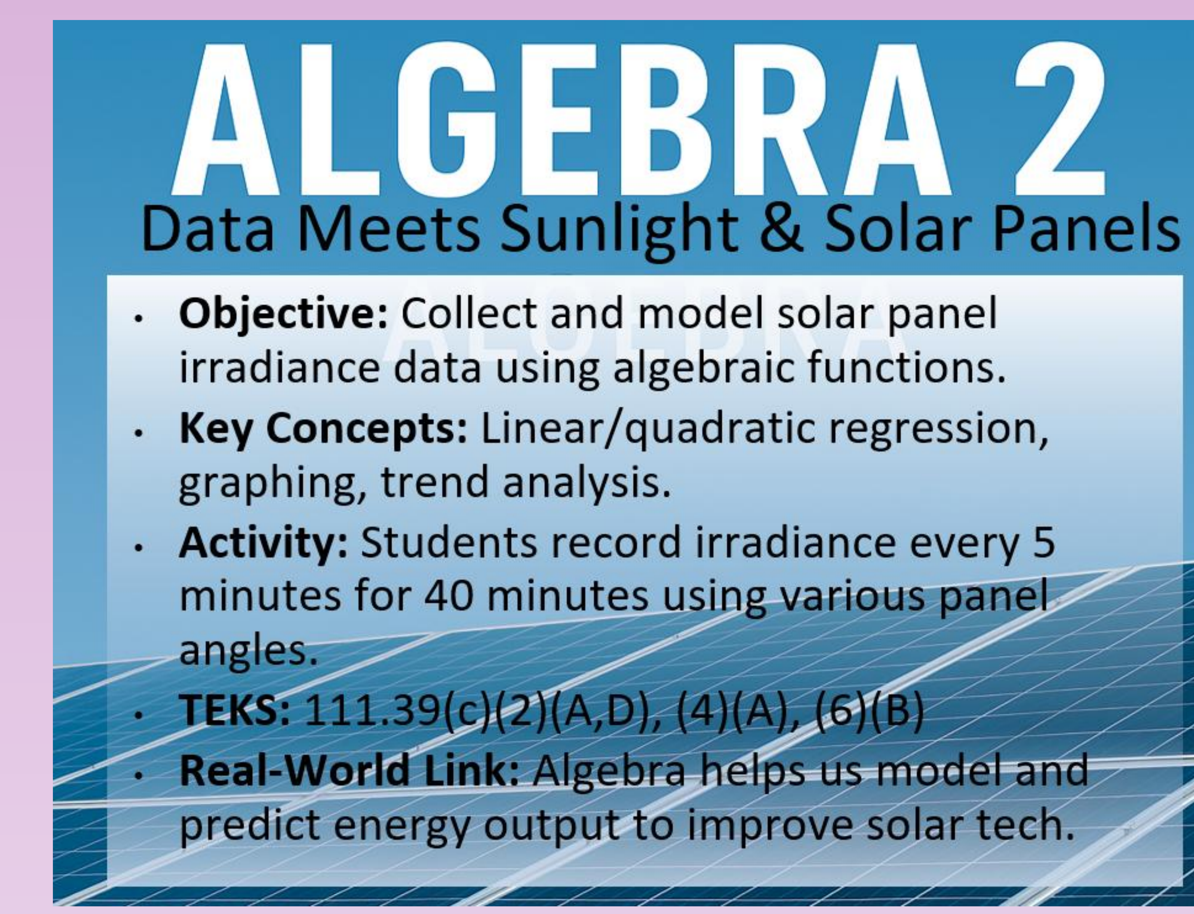

FIGURE 7: Algebra 2 module overview

Geometry: Use trigonometric reasoning to explore how tilt angles affect irradiance. After recording and graphing results, they identify the optimal angle and connect findings to real-world solar applications.

TEKS: 111.41(c)(9)(B), (10), (13)

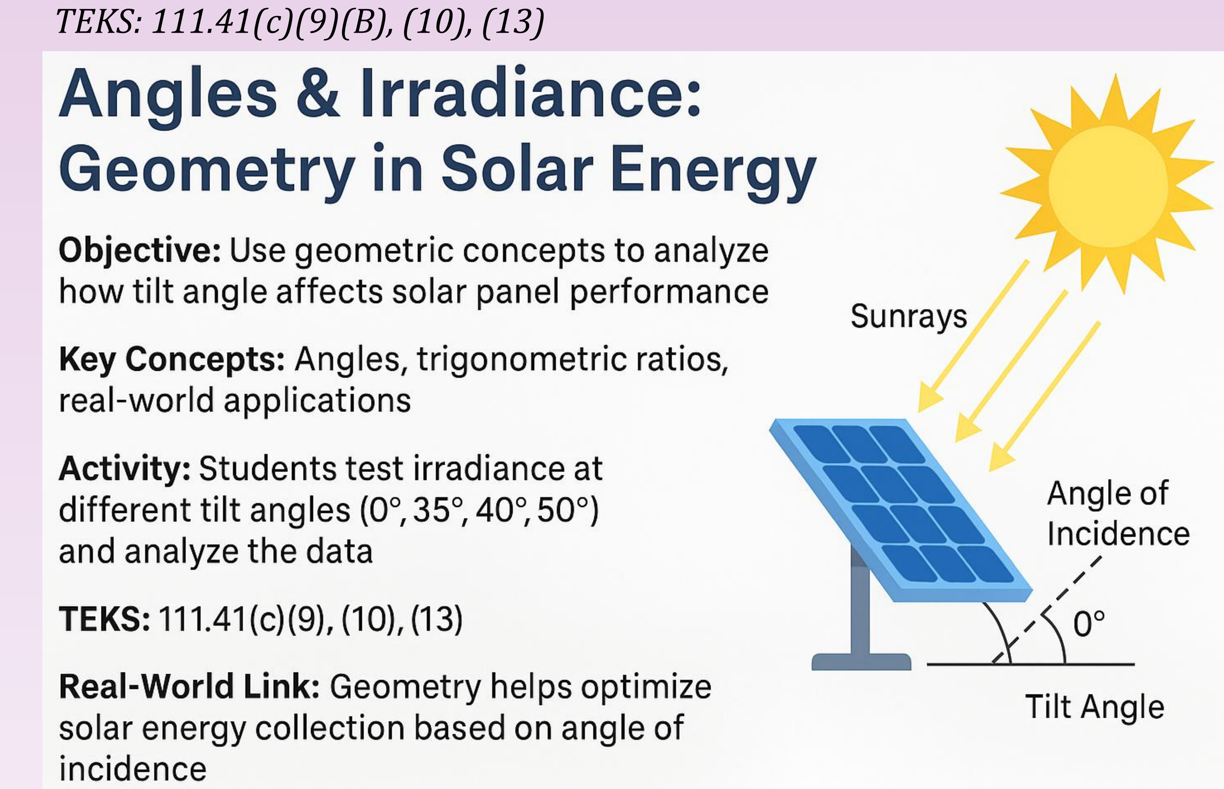

FIGURE 8: Geometry module overview

Pre Calculus: Model solar elevation using sine functions and real irradiance data. They analyzed how tilt angle affects energy collection by comparing graphs of sinusoidal solar paths. *Honors Extension:* Explore amplitude and phase shifts to simulate different latitudes and seasons.

TEKS 111.42(2)(B),(4)(A), (5)(A), (9)(A)

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Wind Condition Prediction Using Different Machine Learning Algorithms

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Abstract

This project explores the use of machine learning methods to predict wind speeds in coastal and inland regions of Texas, using historical data from the National Solar Radiation Database (NSRDB) from 2017 to 2023. Three models were used: Random Forest (RF), Long Short-Term Memory (LSTM), and Support Vector Regression (SVR). These models were trained using full-year datasets in three phases: 1) data from a non-hurricane year, 2) data from a hurricane year, and 3) data from combined both years. Initial predictions focused on forecasting the next-hour wind speed for randomized dates to evaluate model performance. After this comparison, the project focused exclusively on the LSTM model to predict the next 24 hours of wind speeds. For these predictions, input sequences of the previous 24, 168, and 720 hours were tested to determine the optimal historical window for accurate forecasting. The results provide insight into model performance under different weather conditions and time horizons, contributing to more reliable wind forecasting for renewable energy applications.

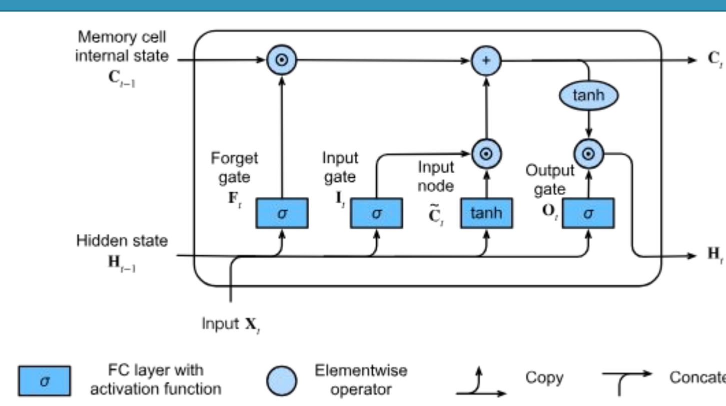
Key Definitions & Concepts

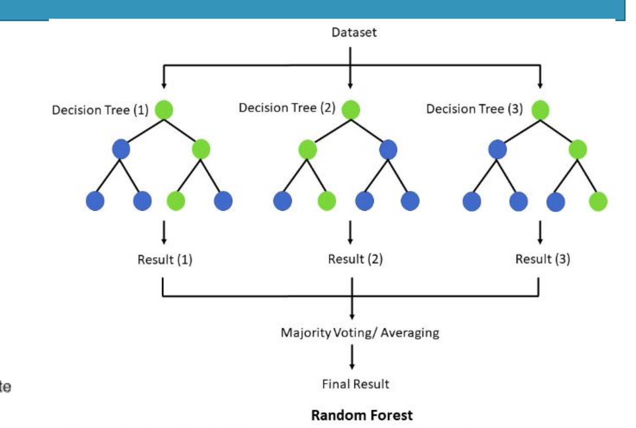
- **Wind Speed Forecasting-** Predicting future wind speeds based on historical data.
- **Machine Learning (ML)-** A type of artificial intelligence that learns patterns from data to make predictions.
- **Random Forest (RF)-** A model that uses many decision trees to make predictions. [2]
- **Support Vector Regression (SVR)-** A model that fits data with a best-fit line. [3]
- **Long Short-Term Memory (LSTM) -** A neural network designed to learn from time-series data. [4]
- **Historical Window -** The amount of past data used to predict future wind speeds (24 hours , 1 week (168 hour), 1 month (720 hours)).
- **Hurricane Year vs. Non-Hurricane Year -** Hurricane years include major storms; non-hurricane years have calmer weather. Training models on both types tests performance in different conditions.
- **Mixed-Years -** Combining hurricane and non-hurricane year.
- **Root Mean Squared Error (RMSE)-** A metric for prediction accuracy. Lower RMSE means better predictions.
- **Training-** Teaching the model using historical data.
- **Prediction-** Using the trained model to forecast future wind speeds.
- **Day-Ahead Wind Market-** An energy market where wind power producers submit bids based on wind forecasts for the next day. [5]
- **Data Preprocessing-** The process of cleaning and transforming raw data to make it suitable for modeling.

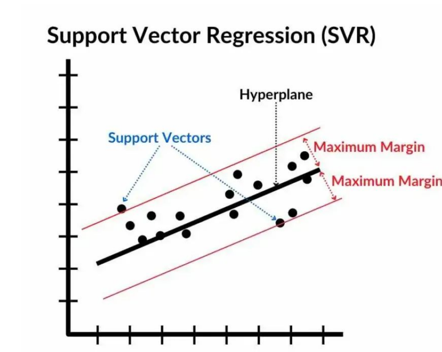
Methodology

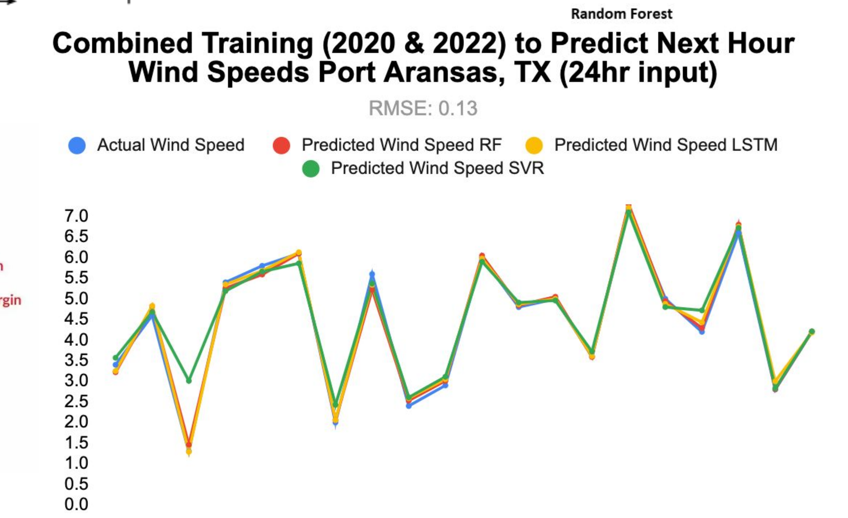
1. Data Collection: National Solar Radiation Database (NSRDB) Wind Speed Data (2017–2023) from National Renewable Energy Laboratory [1]
2. Data Preprocessing and Preparation
3. Model Selection: Random Forest (RF), Support Vector Regression (SVR), Long Short-Term Memory (LSTM)
4. Model Training Phases:
   - Phase 1: Non-Hurricane Year (2022)
   - Phase 2: Hurricane Year (2020)
   - Phase 3: Mixed-Year Data (2020 & 2022)
5. Input Windows: 24 hrs, 168 hrs (1 week), 720 hrs (1 month)
6. Prediction:
   - Stage 1: Next-Hour Wind Speed (All Models)
   - Stage 2: Next-24-Hour Wind Speed (LSTM only)
7. Evaluation: RMSE (Root Mean Squared Error)

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$









Results

Port A---MODELS TRAINED USING HURRICANE YEAR 2020 (HANNA)	PREDICTING HURRICANE AND NON-HURRICANE YEARS			PREDICTING NON-HURRICANE YEARS			PREDICTING HURRICANE YEARS		
Input Size	RF	LSTM	SVR	RF	LSTM	SVR	RF	LSTM	SVR
24 hours	0.13	0.12	0.42	0.15	0.14	0.52	0.11	0.10	0.29
168 hours (1 week)	0.13	0.13	1.77	0.16	0.15	2.09	0.09	0.10	1.38
720 hours (1 month)	0.15	0.11	2.34	0.16	0.13	2.09	0.13	0.10	2.56

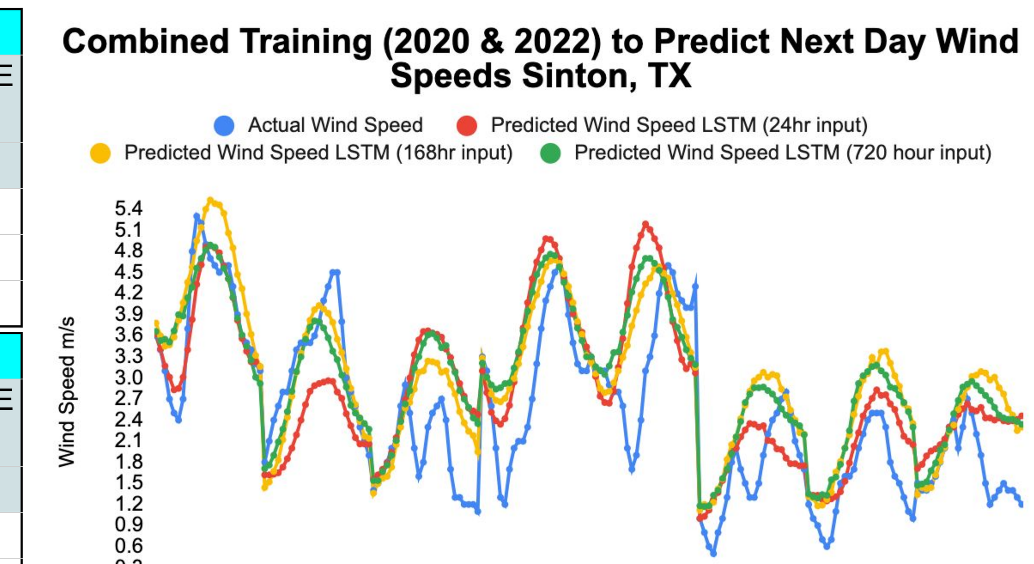
Port A---MODELS TRAINED USING NON-HURRICANE YEAR (2022)	PREDICTING HURRICANE AND NON-HURRICANE YEARS			PREDICTING NON-HURRICANE YEARS			PREDICTING HURRICANE YEARS		
Input Size	RF	LSTM	SVR	RF	LSTM	SVR	RF	LSTM	SVR
24 hours	0.21	0.15	0.72	0.17	0.14	0.96	0.24	0.16	0.33
168 hours (1 week)	0.24	0.16	1.49	0.21	0.16	1.75	0.27	0.17	1.18
720 hours (1 month)	0.21	0.66	1.49	0.18	0.73	1.75	0.25	0.59	1.17

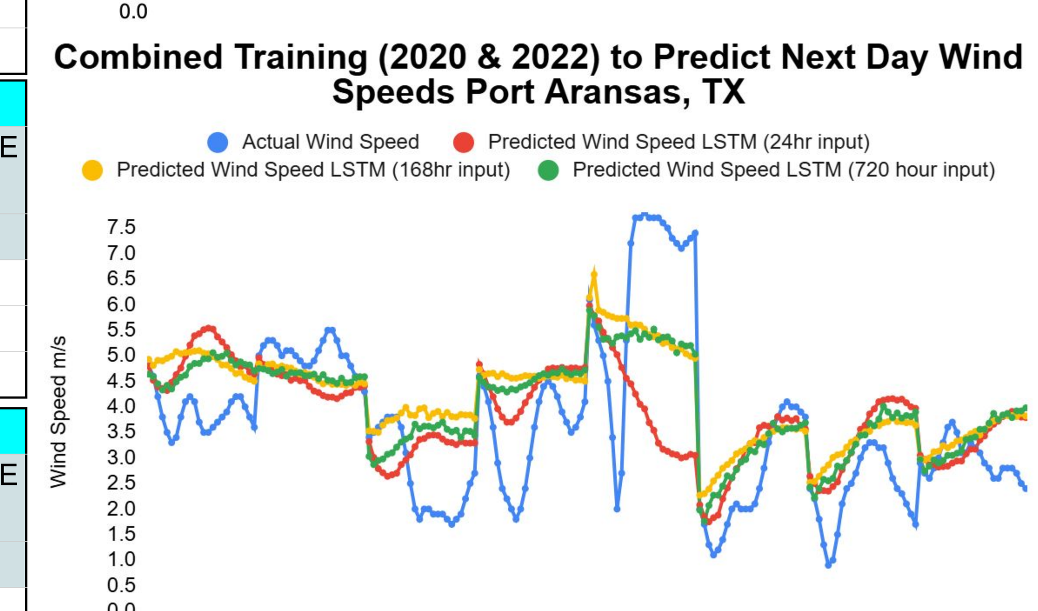
Port A---MODELS TRAINED USING COMBINED YEARS (HURRICANE 2020 AND NON-HURRICANE 2022)	PREDICTING HURRICANE AND NON-HURRICANE YEARS			PREDICTING NON-HURRICANE YEARS			PREDICTING HURRICANE YEARS		
Input Size	RF	LSTM	SVR	RF	LSTM	SVR	RF	LSTM	SVR
24 hours	0.14	0.13	0.43	0.19	0.15	0.58	0.08	0.12	0.19
168 hours (1 week)	0.15	0.13	1.57	0.20	0.15	1.75	0.09	0.10	1.36
720 hours (1 month)	0.23	0.43	1.57	0.30	0.53	1.75	0.09	0.30	1.36

Sinton---MODELS TRAINED USING HURRICANE YEAR 2020 (HANNA)	PREDICTING HURRICANE AND NON-HURRICANE YEARS			PREDICTING NON-HURRICANE YEARS			PREDICTING HURRICANE YEAR		
Input Size	RF	LSTM	SVR	RF	LSTM	SVR	RF	LSTM	SVR
24 hours	0.13	0.17	0.46	0.12	0.19	0.59	0.13	0.13	0.27
168 hours (1 week)	0.24	0.48	1.43	0.25	0.48	1.59	0.23	0.47	1.33
720 hours (1 month)	0.25	0.73	1.46	0.25	0.70	1.58	0.25	0.77	1.32

Sinton---MODELS TRAINED USING NON-HURRICANE YEAR (2022)	PREDICTING HURRICANE AND NON-HURRICANE YEARS			PREDICTING NON-HURRICANE YEARS			PREDICTING HURRICANE YEAR		
Input Size	RF	LSTM	SVR	RF	LSTM	SVR	RF	LSTM	SVR
24 hours	0.20	0.17	0.34	0.18	0.18	0.27	0.22	0.16	0.39
168 hours (1 week)	0.18	0.16	1.45	0.17	0.16	1.44	0.19	0.16	1.46
720 hours (1 month)	0.21	0.71	1.44	0.18	0.58	1.43	0.24	0.82	1.45

Sinton--MODELS TRAINED USING COMBINED YEARS (HURRICANE 2020 AND NON-HURRICANE 2022)	PREDICTING HURRICANE AND NON-HURRICANE YEARS			PREDICTING NON-HURRICANE YEARS			PREDICTING HURRICANE YEAR		
Input Size	RF	LSTM	SVR	RF	LSTM	SVR	RF	LSTM	SVR
24 hours	0.15	0.17	0.19	0.14	0.19	0.19	0.15	0.14	0.19
168 hours (1 week)	0.19	0.21	1.38	0.15	0.20	1.41	0.22	0.21	1.35
720 hours (1 month)	0.19	0.40	1.37	0.12	0.41	1.39	0.25	0.38	1.34





	LSTM Model Combined Year Training (2020 & 2022) Port Aransas,TX		
Input Size	Hurricane and Non-Hurricane Year Predictions	Non-Hurricane Year Predictions	Hurricane Year Predictions
24 hours	1.49	1.63	0.97
168 hours (1 week)	1.26	1.37	0.85
720 hours (1 month)	1.16	1.27	0.76

	LSTM Model Combined Year Training (2020 & 2022) Sinton, TX		
Input Size	Hurricane and Non-Hurricane Year Predictions	Non-Hurricane Year Predictions	Hurricane Year Predictions
24 hours	0.88	0.93	0.70
168 hours (1 week)	0.80	0.86	0.57
720 hours (1 month)	0.85	0.94	0.52

Curriculum Modules

Algebra 1

In this real-world STEM project, students will collect hourly wind speed data using a weather machine, graph and model the data using linear regression **(A.4C)**, and later use machine learning to compare predictive models. Students will evaluate which method—linear regression or Machine Learning—produces more accurate next-day wind speed predictions.

Algebra 1 Full Lesson Plan

6th grade Math

Students analyze wind speed data by calculating the average wind speed, creating graphs, and using data to describe patterns in nature.

6.12(A) represent numeric data graphically, including dot plots, stem & leaf plots, histograms, and box plots. **6.12(C)** Summarize numeric data with numerical summaries, including the mean and median, the range, and the interquartile range.

6th grade Math Full Lesson Plan

Conclusions

- Predicting next hour will have much better accuracy compared to predicting next day wind speed.
- RF and LSTM have better performance than SVR in all the scenarios.
- RF has better performance overall in Sinton, while LSTM has better performance overall in Port A.
- When predicting next hour wind speed, 24-hour window has better performance.
- When predicting next day wind speed, 1-month window has better performance.
- The models have better performance when predicting hurricane year compared to predicting non-hurricane year or combined years.
- The models have better performance when predicting wind speeds in the normal range compared to high or low wind speed ranges.

References

1.https://nsrdb.nrel.gov/
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3.https://www.ibm.com/think/topics/support-vector-machine
4.https://www.sciencedirect.com/topics/computer-science/long-short-term-memory-network
5.https://www.wind-energy-the-facts.org/power-markets.html

Acknowledgements

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Daylighting Performance and Energy Consumption in Classrooms

Teacher Participants: Margie Carrales and Jasmine Espinoza

Faculty Mentors: Dr. Hui Shen and Dr. Marsha Sowell

Lovekesh Singh (Student Mentor), Ralph Pitzer, P.E. (Industrial Advisor)

Abstract

Lighting has always played a role in how successful a person is in completing a task. This is especially important in all classrooms regardless of the educational level. Daylighting has always been utilized in classrooms as a source of light but in the mid 1960's there was shift in the designing of schools. Schools were now being built with air conditioners, promotion of open classrooms and cost saving construction.

As of recently, there has been another mindset shift in how schools should be designed based on multiple factors. Some main factors include reducing energy cost for schools and improving students' performance and overall health.

In this experiment we were able to determine the optimal distance a student can be from a day light source to ensure comfortability. This also allowed us to determine with how much artificial light is needed to supplement the missing daylight. This will help determine how much energy can be saved and essentially how much cost we can cut.

Key Definitions and Concepts

Light- is a form of energy that travels as electromagnetic waves and is detectable by the human eye, allowing us to see the world around us

Artificial Light- is light that is produced by human-made sources, rather than naturally occurring sources like the sun.

Daylighting- the illumination of buildings by natural light

Light Sensor Multiplier-is a numerical factor used to convert the raw output signal of a light sensor (usually current or voltage) into meaningful units of light measurement, such as lux

Lux-a unit of illuminance, which measures the amount of light falling on a surface

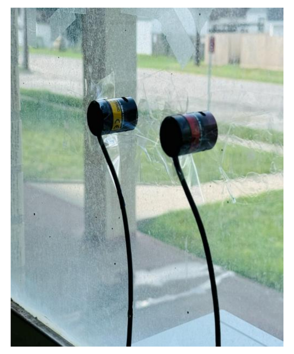
Lumens- are a unit of measurement for luminous flux, which represents the total amount of visible light emitted by a source

Acknowledgements

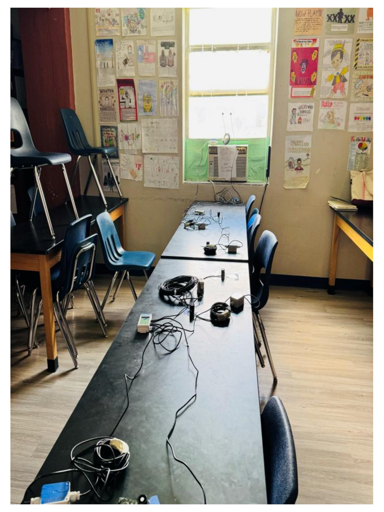
Methodology

Experiment Overview

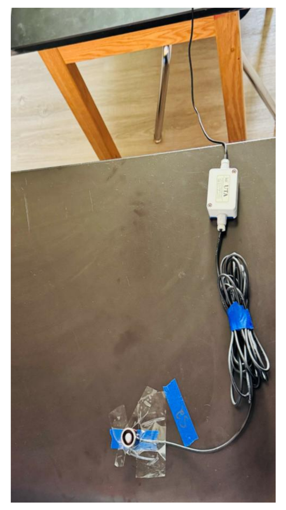
1. Four rooms where selected at Academy High School based on specific requirements which where that each need to have windows facing a different direction. (North, South, East and West)
2. In each room, 5 sensors for light and 3 sensors for solar were placed perpendicular to the window. Each room was set up the same. (For reference, look at the South room setup pictures and layout to the right)
3. Data was collected for 2 full days but only data that was in between business hours (8am-4pm) was considered.
4. Things to mention: Data was collected on different days for each room; weather was relatively the same. West room was removed from experiment due to the window size being drastically different from others.



A solar and light sensor attached directly to the window.

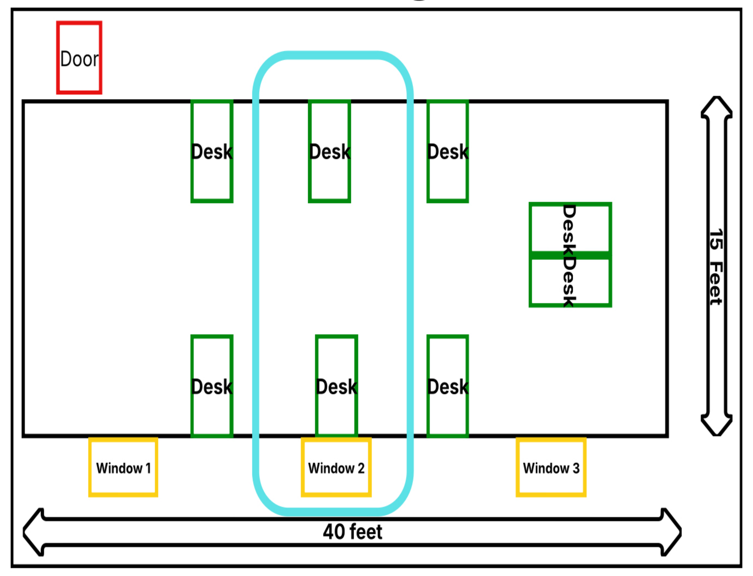


A light sensor is placed 3ft, 6ft and 9ft from the window.



The last sensor, solar, 15 ft away from the window, first one is 7.5ft away.

South Facing Room



Room S9

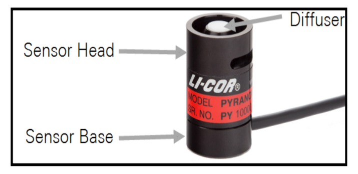
Window Dimensions

Window 1: 5ft X 3ft

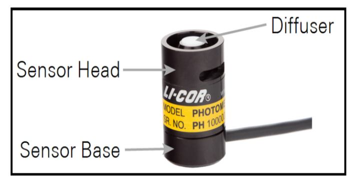
Window 2: 3ft 10in X 3ft 5in

Window 3: 3ft 10 in X 3ft 5 in

DATA LOGGER UX90-006
12 METER RANGE
HOBO DATA LOGGER
MEASUREMENTS ARE IN KLUX
REQUIRES:HOBOWARE SOFTWARE



PYRANOMETER-SOLAR
LI-200R
MEASURES GLOBAL SOLARE RADIATION
MEASURES ARE IN W/M^2



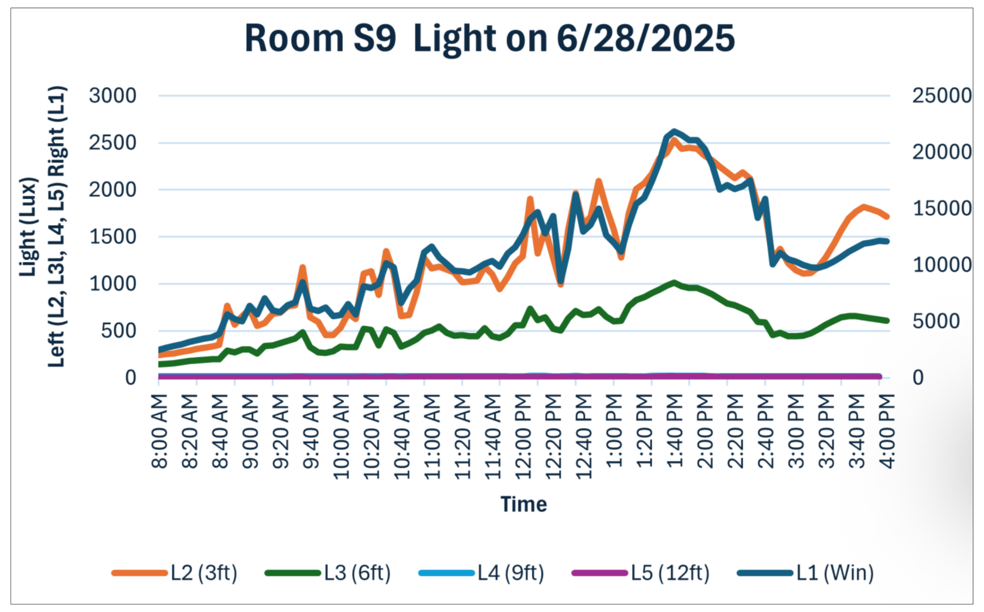
PYRANOMETER-LIGHT
LI-210R
MEASURES LIGHT MEASUREMENTS ARE IN LUX OR KLUX

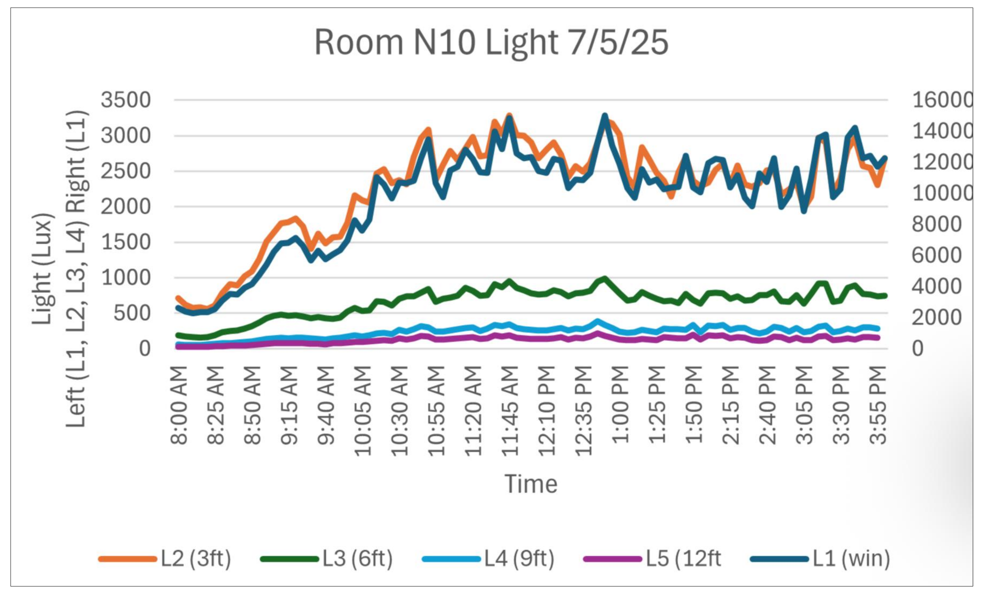
Software

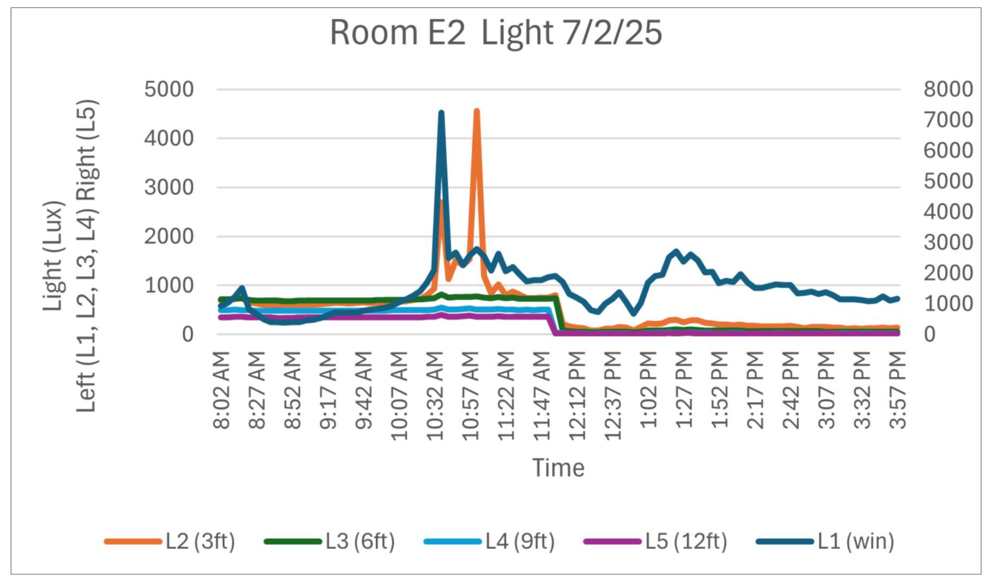
HOBOware was used to collect the data from the data loggers that had the light and solar sensors connected to it.

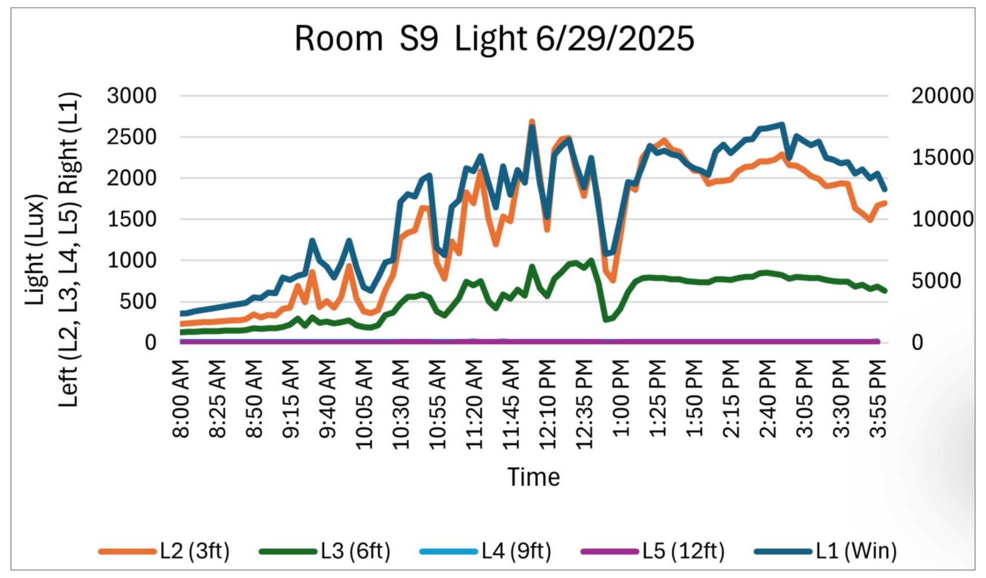
Excel was used to analysis the output data from the sensors along with using the program to convert data when necessary.

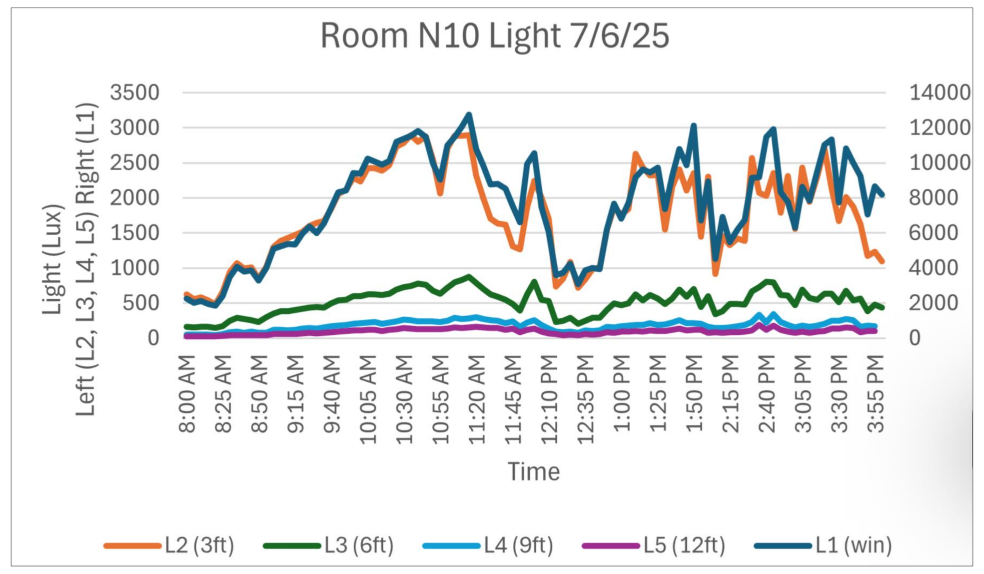
Results

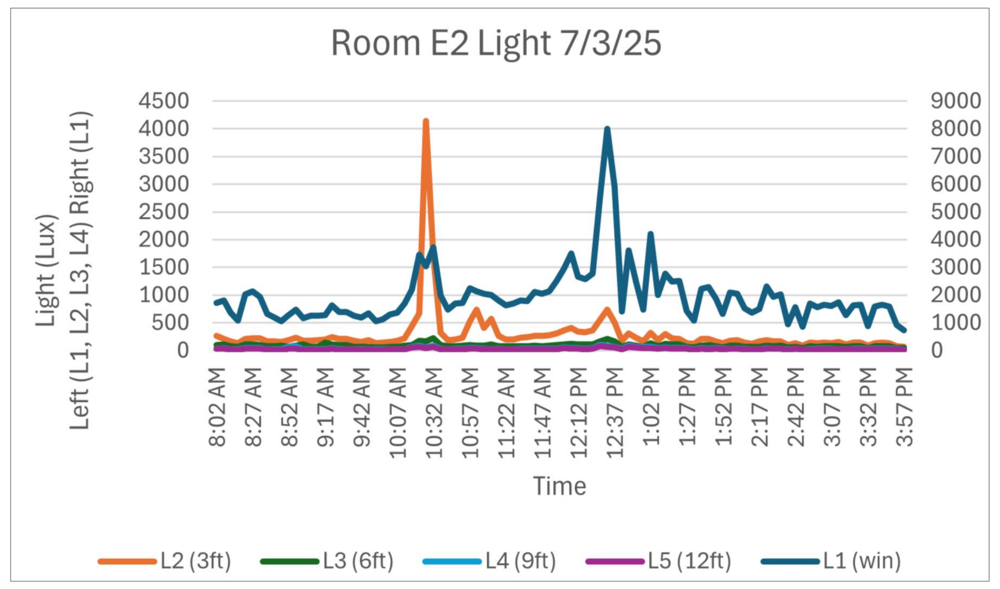


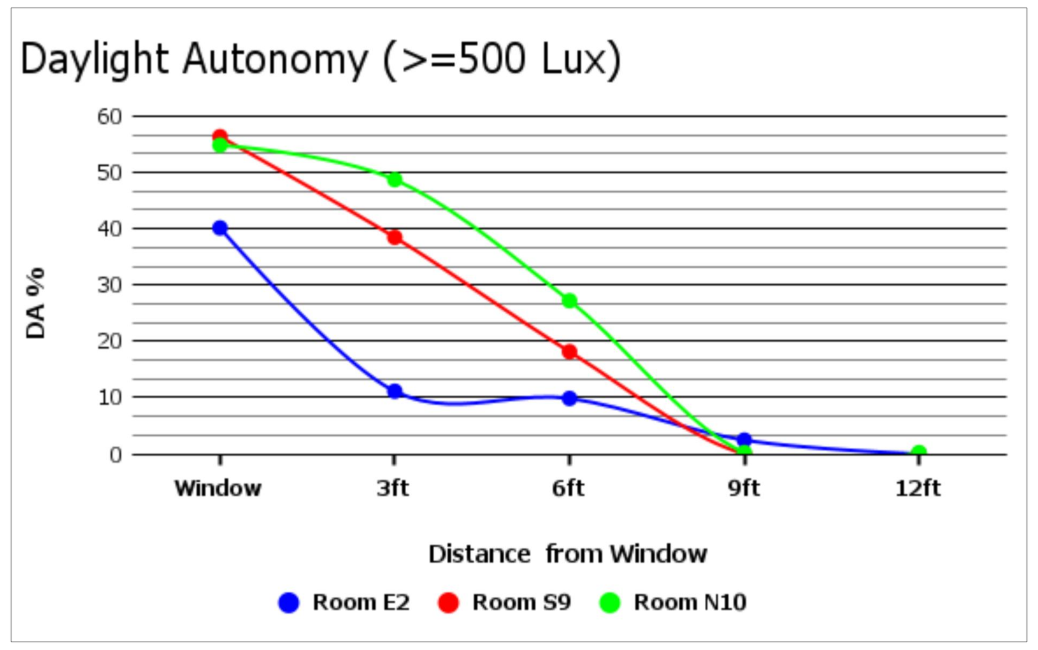












Room	# of Light Bulbs	Watts per Bulb	KWh Used Daily (lights ALL on)	Cost per KWh	Total Cost /Day (Lights ALL on)	Artificial Light Consumption (KWh) needed if Daylighting is Used	Total Cost of Artificial Light needed (KWh) with Daylighting	Savings / Day Estimate
S9	12	32	6.72	$ 0.0494	$ 0.33	1.183288	$ 0.06	$ 0.27
E2	12	32	7.04	$ 0.0494	$ 0.35	4.78094825	$ 0.24	$ 0.11
N10	12	32	7.104	$ 0.0494	$ 0.35	2.541737	$ 0.13	$ 0.23

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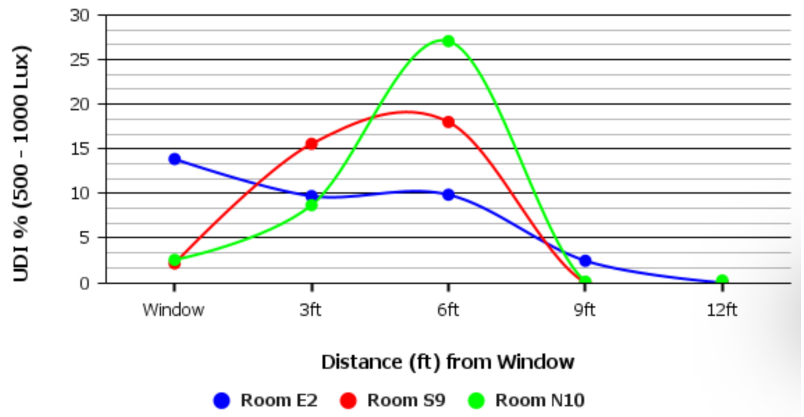
Conclusion

Useful Daylight Illuminance



For a classroom to be within a working UDI (Useful Daily Illuminance) within the largest percentage of business hours (8am-4pm) the optimal workspace distance from daylight would be between 3-6pm.

This would be useful to know because at this distance students can work in a comfortable working environment, and it will be at these times energy can be conserved the most.

Curriculum Modules

Student Objective:

Students will investigate how natural daylight and artificial room lighting affect productivity and focus within a learning environment. Using their findings, they will design and present their own ideal classroom space that promotes effective learning and conservation of energy.

Scan to access full Lesson Plans

8th Grade Math & Algebra 1

11th & 12th Grade Physics

Gordana Barrera
Alice High School, Alice ISD

Faculty Advisors - Dr. Xiaoyu Liu & Dr. Marsha Sowell
Industrial Advisor: Enrique Molina
NSF RET I-READ Texas A&M University Kingsville
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POTENTIAL OF CONVERTING FOOD WASTE INTO RENEWABLE ENERGY IN THE BACKYARD

Introduction

The possibility of converting food waste into renewable energy is an exacting, interesting, and "smart" way of developing technologies that will produce efficient and cost-effective power for our daily life needs. It's like turning trash into treasure!

Instead of throwing out food leftovers, imagine if we could convert that food into energy to power our homes, our cars, or even our cities.
We would also be able to reduce waste and create energy at the same time!

Objective

A key goal of this research is to find out HOW MUCH THERMAL ENERGY could be generated during composting and its potential of converting everyday food waste into renewable energy in our own backyards. This would maximize energy recovery from organic waste while minimizing negative impacts on the environment.

Methodology

01 A composting bin was divided into two compartments:
a) Compartment A, left side 2.4"
b) Compartment B, right side 3.72"

02 Thermometer was placed inside the composting bin to monitor temperature changes, which indicated microbial activity and energy release during composting.

03 Temperature data was recorded automatically every 5 minutes from July 5th to July 11th.

04 The collected temperature data was analyzed to compare the thermal energy generated by the different depth on each side of the bin.

05 Results were visualized using a graph to show temperature variations over time and to compare the energy output from the left side versus the right side regarding different depth

Key Sources & Acknowledgements

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Learning Module

Converting Food Waste into Renewable Energy: Transforming Trash into Treasure

LEARNING OBJECTIVE:

I will analyze the impact of human activities on the environment, describe the interdependence of organisms in an ecosystem, and explain the process of composting and its role in converting food waste into renewable energy.

TEKS 10.11 (B) - describe the flow of energy through food webs and the roles of producers, consumers, and decomposers in an ecosystem.
TEKS 10.12 (B) - analyze how human activities impact ecosystems, including pollution and resource consumption.
TEKS 10.13 (C) - explain the significance of biodiversity in maintaining the health of ecosystems.

KEY POINTS:

-The process of composting involves the breakdown of organic matter by microorganisms, producing nutrient-rich soil.
-Food waste significantly contributes to landfill mass and greenhouse gas emissions.
-Ecosystems rely on the recycling of nutrients, and composting facilitates this process.
-The interdependence of organisms plays a crucial role in maintaining a balanced ecosystem

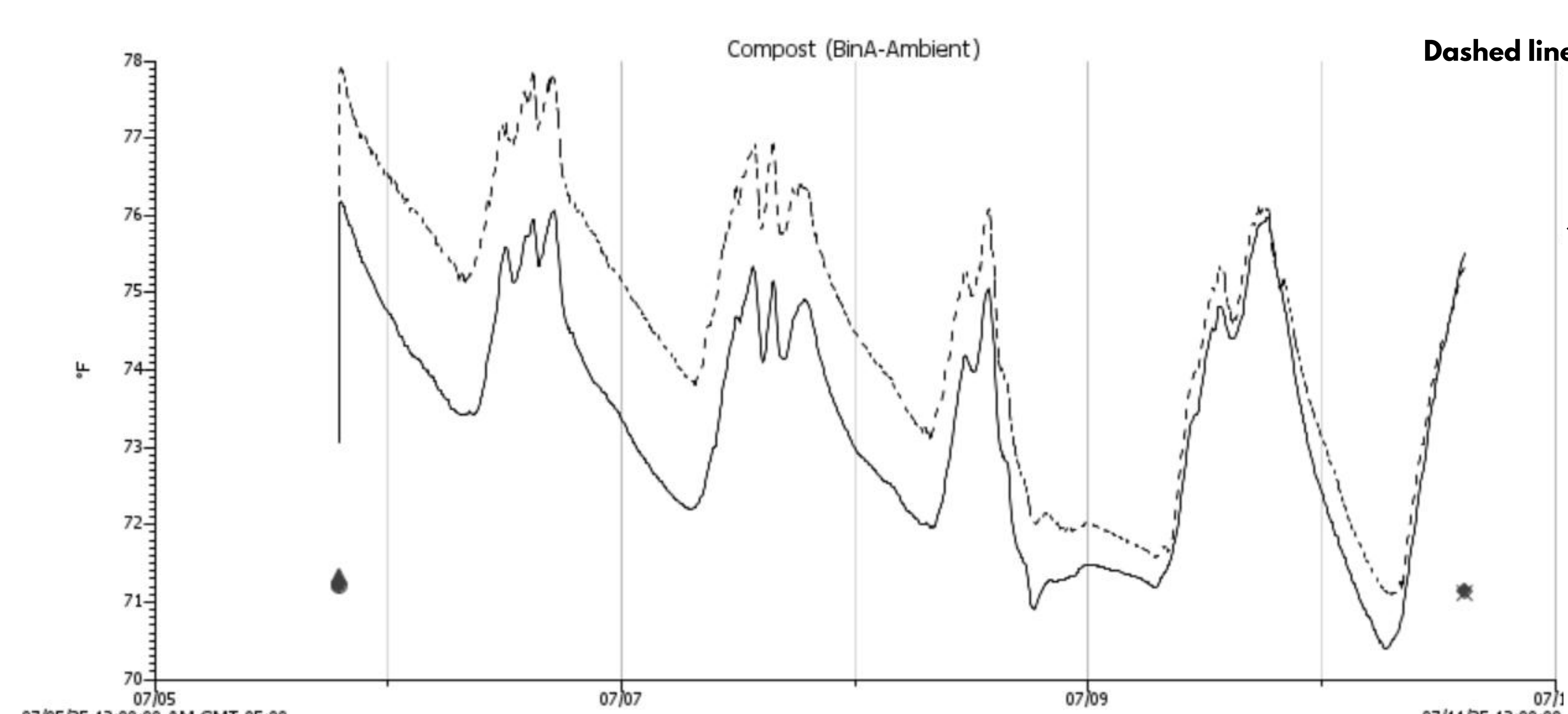
STUDENT ACTIVITY:

Students will complete a project where they set up a composting bin and create a presentation based on the composting processes and its benefits, demonstrating their understanding of the interdependence of organisms and the impact of food waste on the environment.

Compartment A Compartment B

Time Range: July 5 to July 11, 2025
Graph Title: Compost (BinA - Ambient)

Solid line: Temperature at 2.4"depth (Compartment A)
Dashed line: Temperature at 3.72" depth (Compartment B)
Symbols:
▯ = Start
▲ = Button Up
◆ = Host Connected
✕ = End of File



Analysis

The temperature was fluctuating between ~70˚F and ~78˚F over the course of 6 days due to day/night changes and different microbial activity within the compost . We can conclude that the compost is not creating a discernable heat difference from the ambient temperature.
Compartment A had a depth of 2.4" and recorded a lower temperatures than Compartment B with a depht of 3.72", indicating that deeper compost retains more heat, higher temperature trends and is more stable.

Key Findings

-Stable but low composting activity:
The temperature remains relatively cool (low 70s ˚F), which suggests compost is in a stagnant phase rather than an active thermophilic phase.

-Depth matters: Deeper areas maintain slightly higher and more stable temperatures which is important for microbial breakdown efficiency.

-Lack of microbial heat spike and activity. The composting process must be active in order to generate heat.

Conclusion

-This six-week research project aimed to explain how much thermal energy can be generated and evaluate composting efficiency in our backyard composting bins by monitoring temperature fluctuations in a single compost bin with compartments A and B from July 5 to July 11, 2025.

-Data collected showed that temperatures ranged between 71˚F and 78˚F, with the deeper compartment B (3.72") maintaining slightly higher and more stable temperatures than compartment A (2.4"). These readings were below the optimal temperature range, which should be between 130˚F and 160˚F, required for rapid microbial activity, the start of decomposition, and heat release.

-Given the six-week limited time window, the compost has not reached its full decomposing potential. This study showed some biological activity, but the conditions were not sufficient for active composting that would generate the heat needed for energy conversion. However, further long-term studies are needed and recommended to explore the feasibility of converting food waste into energy in our backyards.

Mitigating the Loss of Potential Energy Production in Wind Farms Due to Wake Effect

Teachers: Mrs. Katie Doyle - Flour Bluff High School (FBISD) / Mr. Gordon Dean Haley - Harold T. Branch Academy High School (CCISD)
Faculty Advisors: Dr. Kai Jin - Research Project Faculty Mentor (TAMUK) / Dr. Marsha Sowell – Curriculum Development Faculty Mentor (TAMUK)
Student Mentor: Theophilus Adu-Azumah (TAMUK)
Industrial Advisor: Richard Martinez

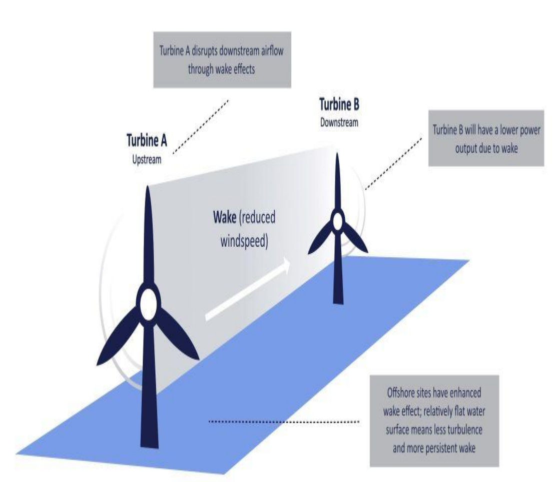
RET Site: Integrating Data-driven research in Renewable Energy Across Disciplines (I-READ)

ABSTRACT

As wind energy continues to expand as a major source of renewable electricity, optimizing turbine layout to mitigate wake effects has become a critical engineering challenge. This study investigates the impact of hub height variation and lateral turbine staggering on wind speed recovery and voltage output in small-scale wind turbine arrays. Using cost-effective educational materials, three experimental configurations were tested: a baseline linear layout with uniform hub height, a vertically staggered linear layout, and a vertically staggered layout with lateral offsets. Wind speed and voltage were measured across all configurations using anemometers and multimeters, and results were analyzed using a simplified Jensen wake model. Findings reveal that increasing turbine hub heights significantly reduces downstream wake losses, with the tallest turbines achieving the highest voltage output due to improved wind access. While the staggered layout enhanced recovery for the final turbine, it intensified wake effects on the middle unit, suggesting a need for careful balance in nonlinear designs. These results support hub height variation as an effective passive strategy for wake mitigation and provide a foundation for future research into combined spatial optimization methods for wind farm efficiency.

INTRODUCTION

- In the US, wind energy accounts for 10% of all energy, making it the largest renewable energy source. Texas is the current leader in wind energy, at approximately 22% of the Texas grid.[1]
- The wake effect causes turbulence and wind speed loss in different areas of a wind farm, resulting in an overall reduction in power production. Power production can be diminished due to turbulence between turbines. [2]
- Wake effect can be mitigated by improved spatial optimization of turbine placement. [3]

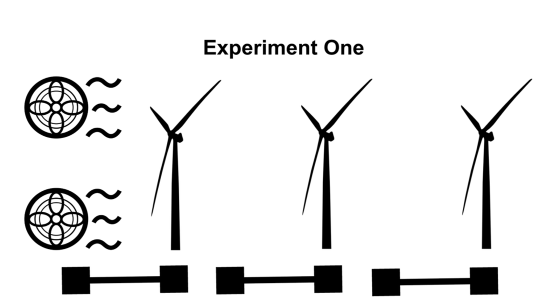


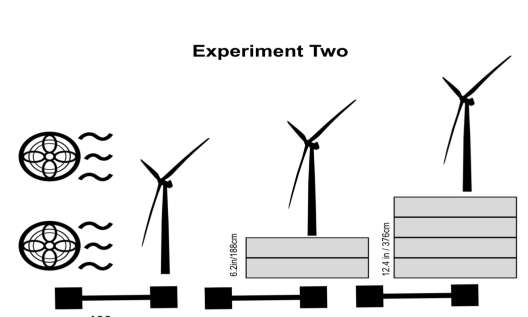
RESEARCH OBJECTIVES

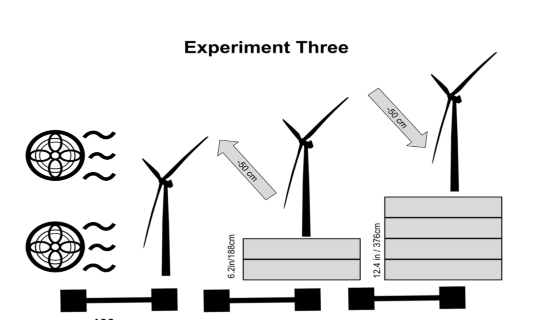
- Investigate the effectiveness of turbine height variations to optimize power production and reduce wake effect.
- Investigate how the use of turbine coordination techniques may enhance overall performance.
- Investigate how the use of height and layout coordination may enhance overall performance by reducing wake effect

METHODOLOGY

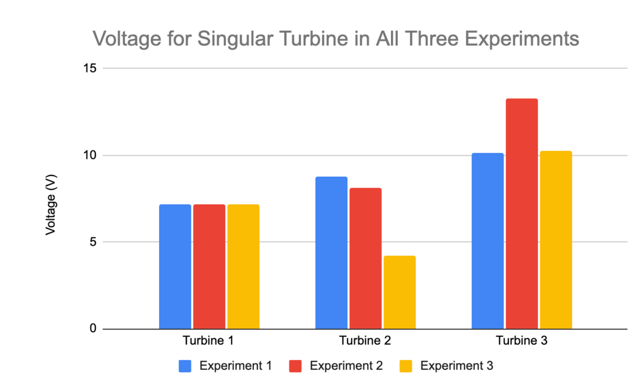
- Create models mitigating energy loss due to the wake effect of wind turbines. We used three methods:
  - Baseline of linear and stagnant heights to demonstrate the wake effect
  - Increased vertical height while turbines are in a linear row
  - Increased vertical height in a staggered lateral formation
- Create a scaled model to show the physical effects of the wake on a wind turbine.
- Create curriculum modules that will teach students across various age ranges about wind turbines and wake effect.

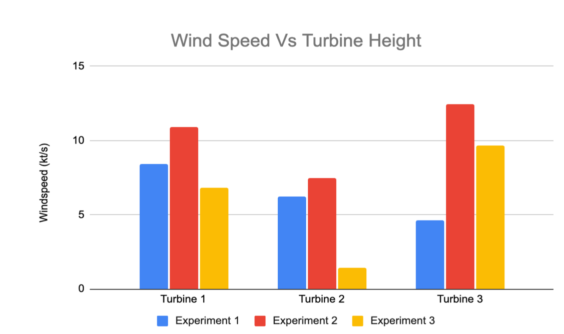


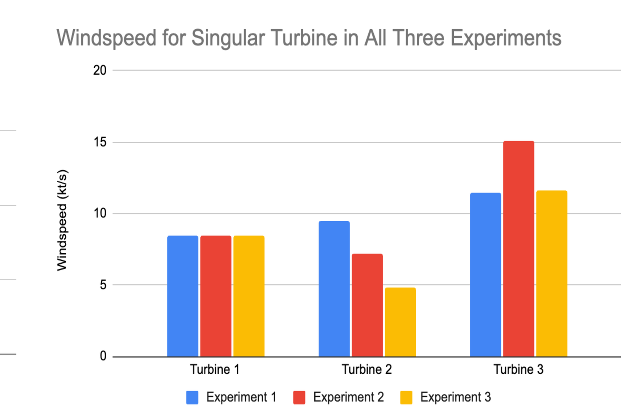


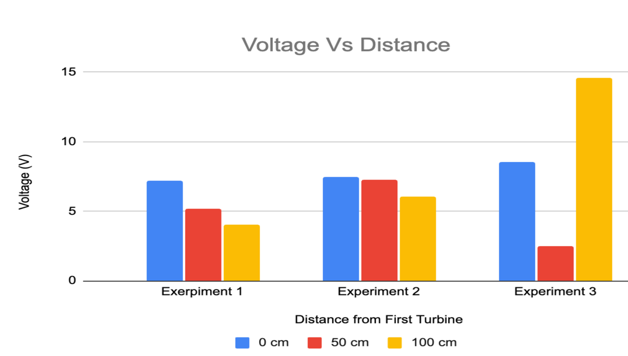


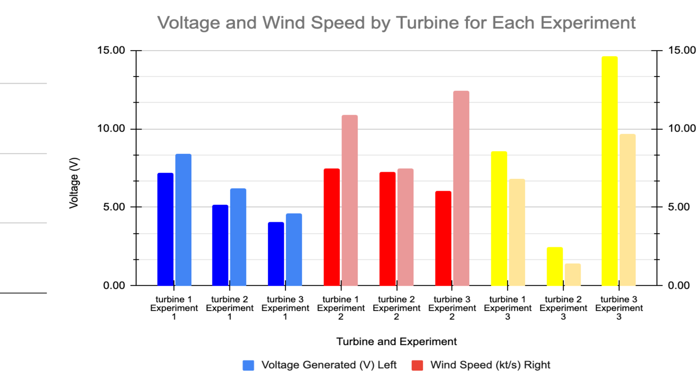
RESULTS

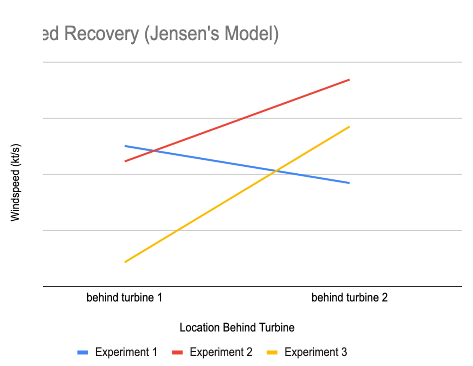






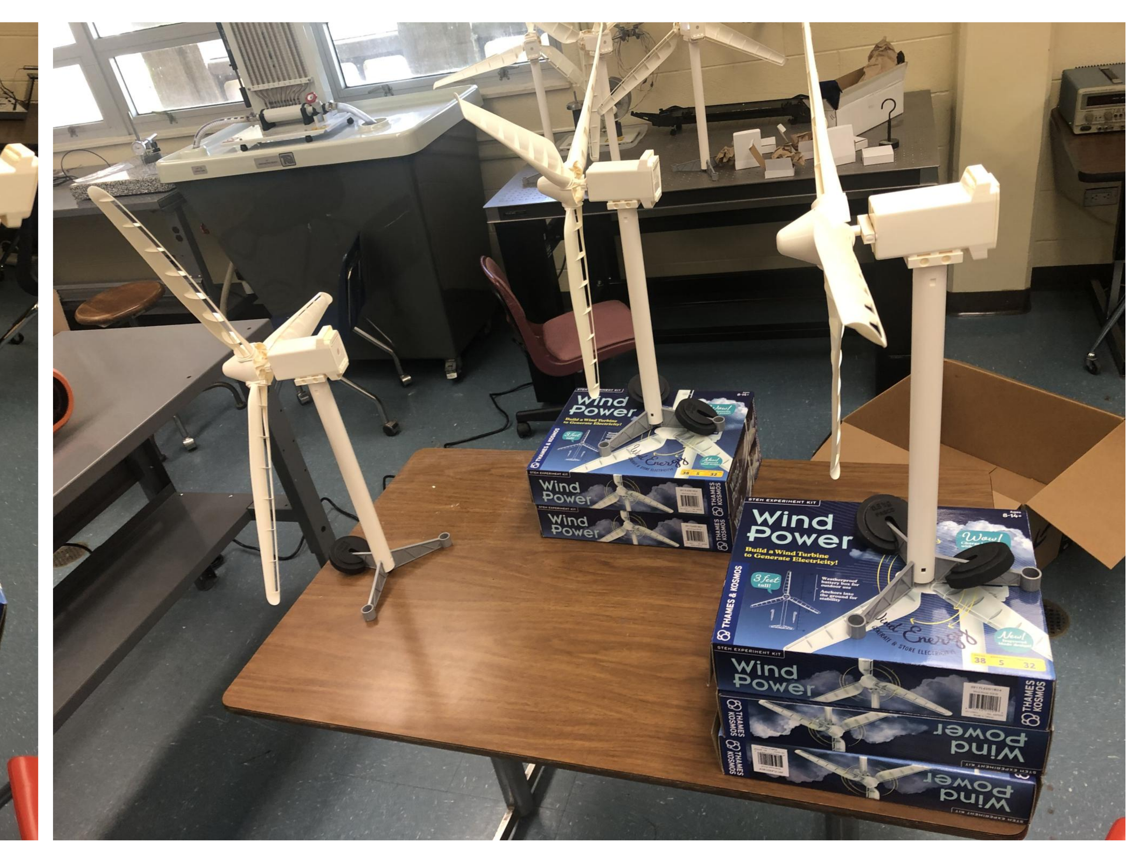






Experiment 1 with all three turbines straight aligned with same height.

Experiment 2 with all three turbines straight aligned with varied height.



Experiment 3 with all three turbines varied horizontally and, also with varied height.

LEARNING MODULES

- Modules will aid in student understanding of the following science and environmental biology principles:
  - Engineering design process
  - Renewable Energy
  - Energy Generation using wind power
- Lesson Objectives
  - Wind Turbine Investigation #1: Energy card sort
    - Students will be able to begin to understand that devices we use everyday require electrical power.
  - Wind Turbine Investigation #2: Circuit Building Using Wind Turbines
    - Students will be able to build basic circuits using energy generated by wind turbines and understand that wind energy can be used in place of traditional electricity such as batteries.
  - Wind Turbine Investigation #3: Measuring Power Generation From Placing Turbines at Various Locations
    - Students will measure wind output at different locations around their school and determine the best location using data collected.
  - Wind Turbine Investigation #4: Create Cars, Boats, and Other Items Using Wind Turbines
    - Students will create different boats and cars using the engineering process.
  - Wind Turbine Investigation #5: Create a model of an offshore wind Turbine
    - Students will design and test out a floating wind turbine
- Student Assessments
  - Lab Based (Report, Excel Data Sheets with Graphical analysis)
  - Project Based (Create a Physical Turbine, Engineering Report)

CONCLUSION

The introduction of variable hub heights in Experiment 2 demonstrated a measurable improvement in downstream performance, supporting the hypothesis that vertical staggering enhances vertical mixing and mitigates wake losses. Notably, the tallest downstream turbine in this configuration generated higher voltage than the upstream unit, indicating successful wake avoidance and increased airflow access. Experiment 3, which added lateral staggering to the vertical variation, yielded mixed results: while the final turbine benefited from enhanced wind recovery, the middle turbine experienced elevated wake interference. These findings suggest that while combined vertical and horizontal staggering holds promise, careful spatial optimization is critical to avoid unintended flow disruption, particularly in midstream turbine positions.

Overall, the data underscores the potential of hub height variation as a low-complexity, passive solution for reducing wake effects and improving wind farm energy yield. The results also highlight the need for further investigation into optimized nonlinear layouts, particularly those that balance flow distribution across all turbine positions. Future research should incorporate more complex modeling tools, such as computational fluid dynamics (CFD), and explore additional variables including atmospheric stability, yaw control, and rotor diameter scaling to validate and extend the applicability of these findings to full-scale wind farm environments.

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