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

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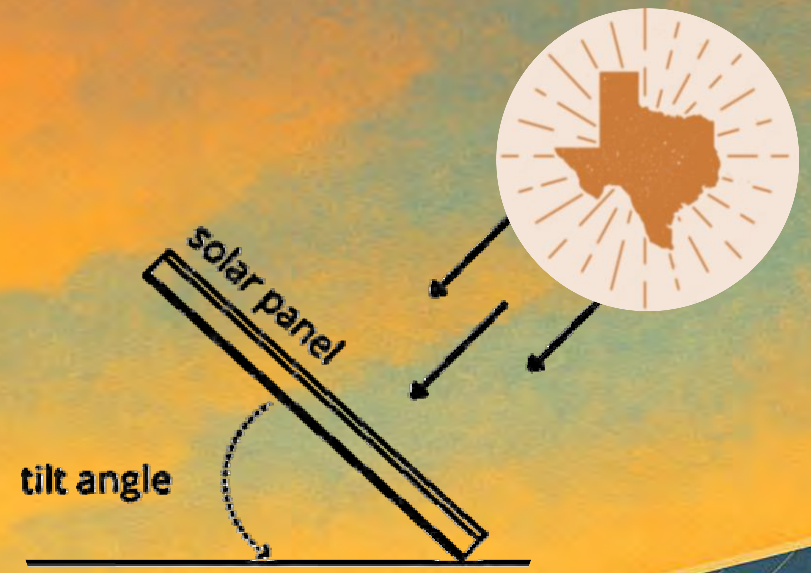
Project Overview

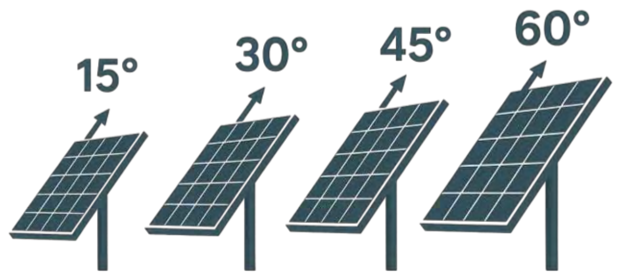
- Explores how different solar panel tilt angles improves energy output in South Texas.

- Investigates how SOLPOS model predictions align with real conditions.

- Bridges real-world applications to high school STEM education.

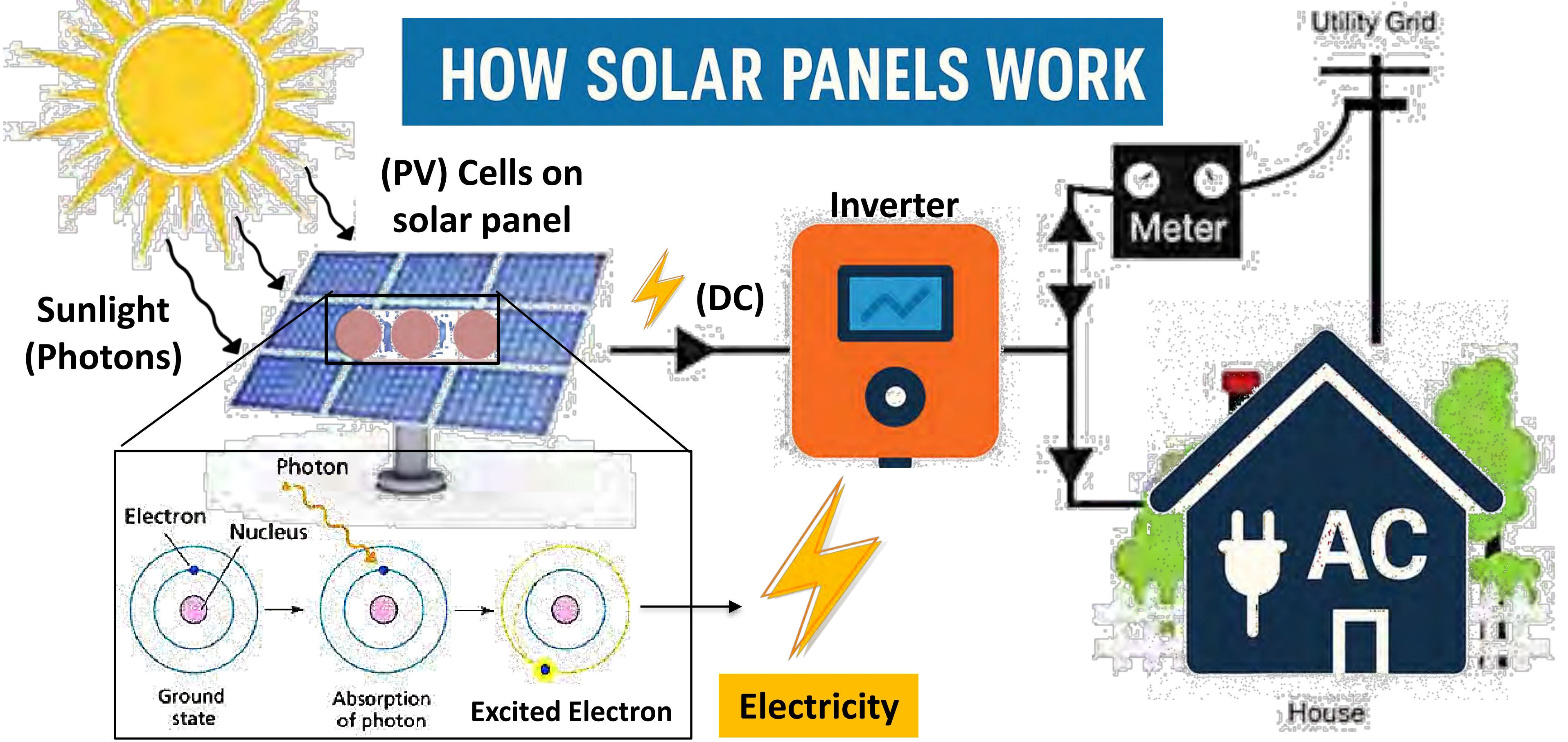


Objective Goals



- Collect real-world solar irradiance data at multiple tilt angles using a FLUKE IRR1-SOL meter
- Validate SOLPOS model accuracy by comparing predicted vs measured irradiance data.
- Identify optimal tilt angles for maximum daily, monthly, and annual energy output.
- Develop TEKS-aligned Algebra 2, Geometry, and Precalculus curriculum modules.

Background



- Sunlight sends photons that hit PV cells and excite electrons, generating DC power.
- Inverter converts DC to AC, the type of electricity homes use.
- Excess power goes to the grid via the meter

Background

Linking Irradiance to Energy

- **Energy output depends on sunlight absorption.**
- **Reflective losses reduce efficiency**
- **Influencing factors:**

Tilt angle • Panel type • Time of day • Weather

- **As sunlight intensity increases, so does electrical power output**

Power Equation: $Energy = P \times A \times I \times r$

- **P = Performance ratio (~0.75)**
- **A = Panel area (m^2)**
- **I = Irradiance (W/m^2)**
- **r = rate of conversion (sunlight to electricity)**

Background

National Renewable Energy Laboratory (NREL)

Position (Azimuth & Elevation)

Intensity (Irradiance W/m²)

Enter Start/End Dates:

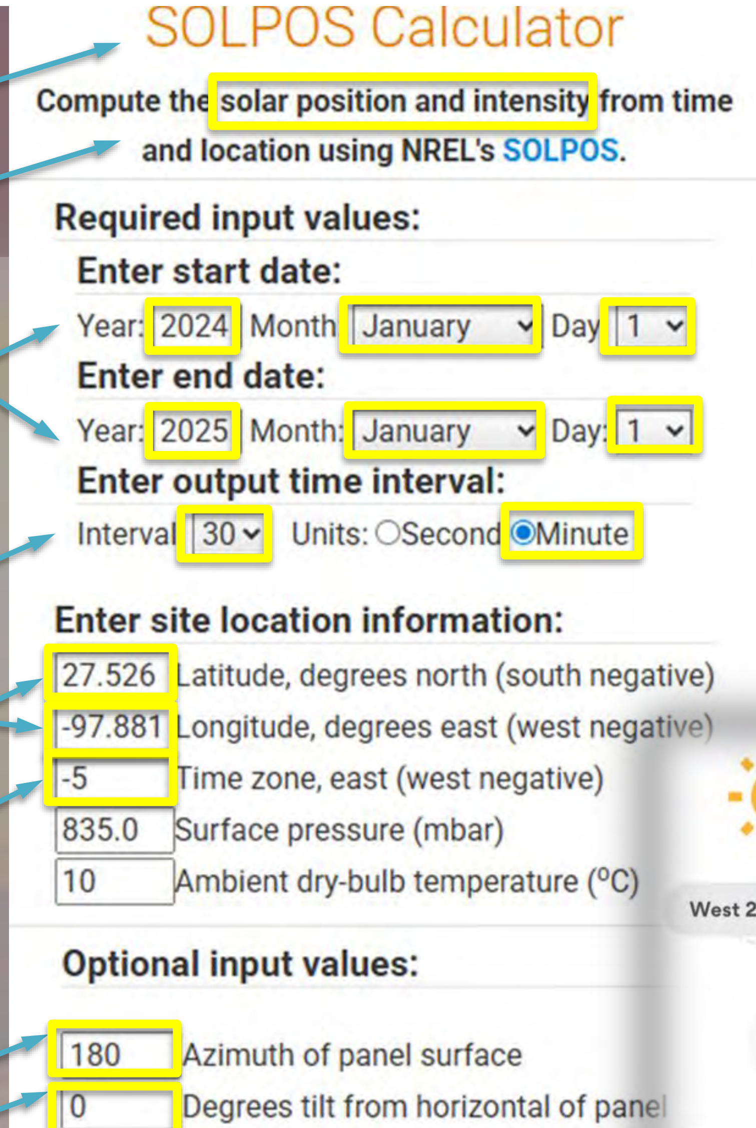
Select Interval Time:

Site Location (Lat/Long):

Time Zone:

Azimuth (South 180°)

Tilt Angles (0° to 90°)


SOLPOS Calculator

Compute the solar position and intensity from time and location using NREL's SOLPOS.

Required input values:

Enter start date:

Year: 2024 Month: January Day: 1

Enter end date:

Year: 2025 Month: January Day: 1

Enter output time interval:

Interval: 30 Units: Second Minute

Enter site location information:

27.526 Latitude, degrees north (south negative)

-97.881 Longitude, degrees east (west negative)

-5 Time zone, east (west negative)

835.0 Surface pressure (mbar)

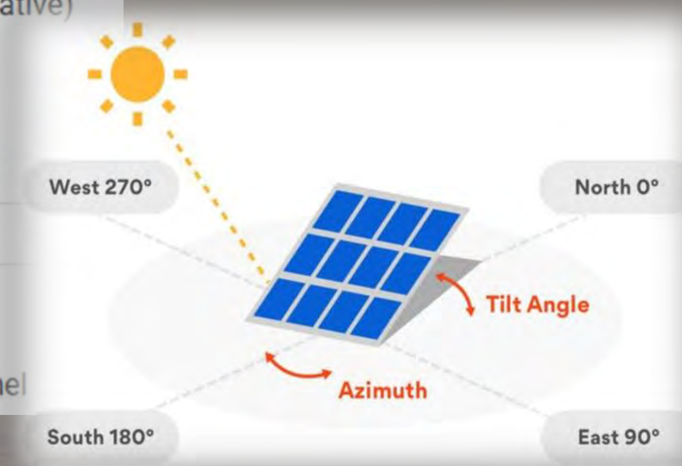
10 Ambient dry-bulb temperature (°C)

Optional input values:

180 Azimuth of panel surface

0 Degrees tilt from horizontal of panel

- **The SOLPOS tool predicts sun position and irradiance based on location and time.**
- **This project pairs SOLPOS with field data to test its accuracy.**
- **Tilt angles affect how much sunlight a solar panel receives throughout the year.**

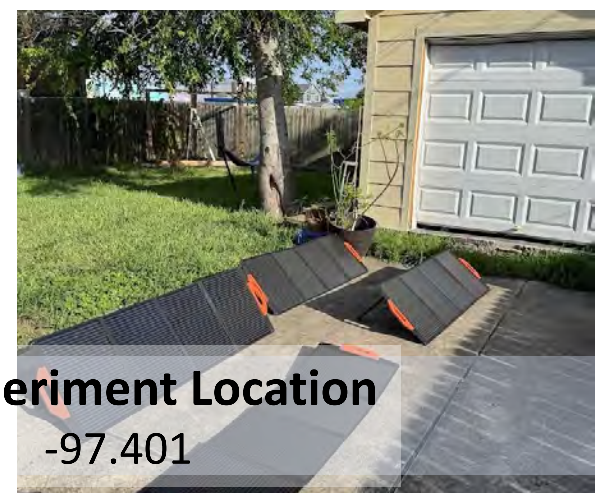


Methods - Experimental Parameters

- Recorded irradiance (W/m^2) & surface temperature (°F) in two locations using FLUKE meter.

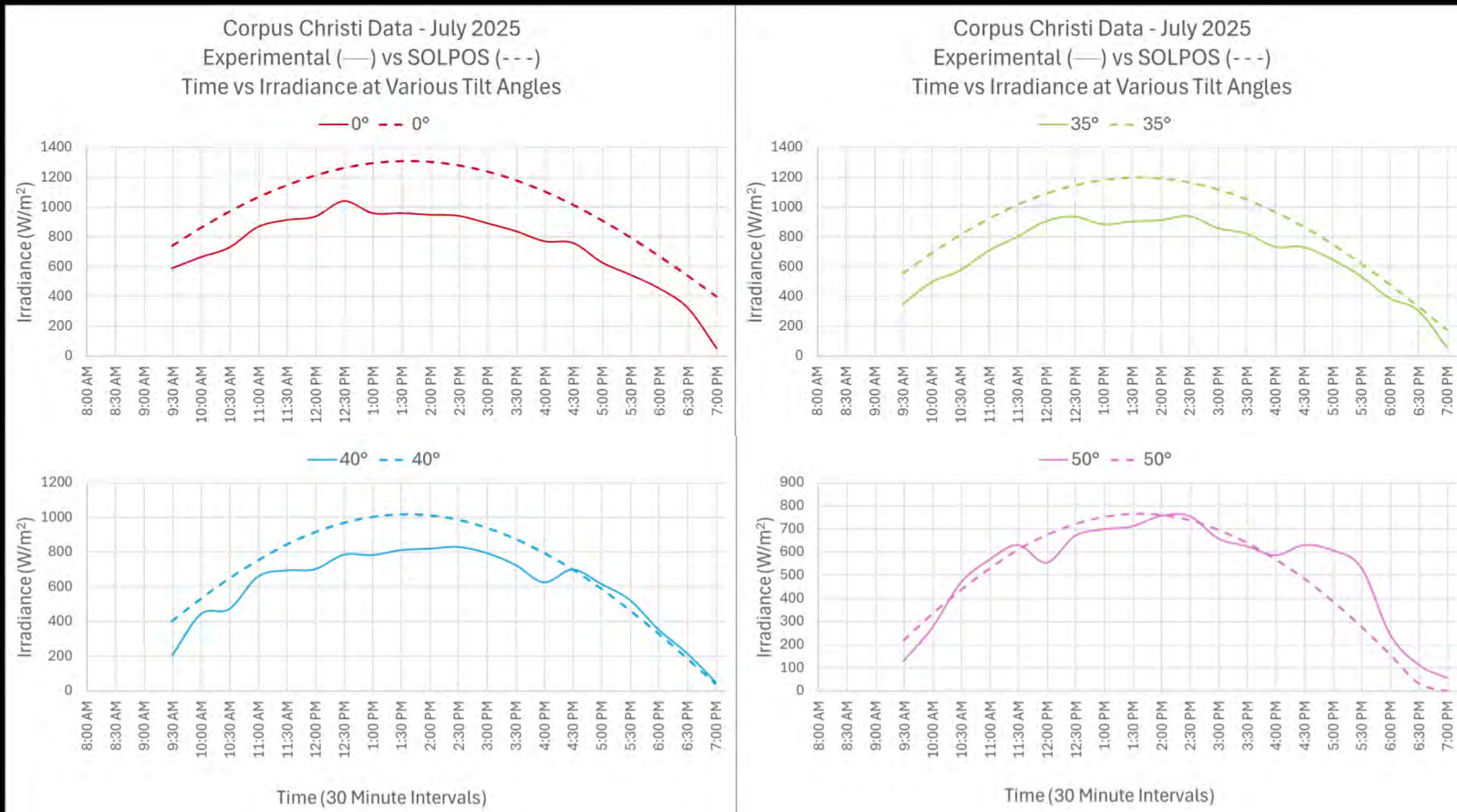
- 30-minute intervals
- 9:30 AM to 7:00 PM
- Time Zone: (-5)
- Azimuth: 180° South
- Clear days in July 2025
- Tilt Angles: 0°, 35°, 40°, 50°


Kingsville Experiment Location
27.526, -97.881

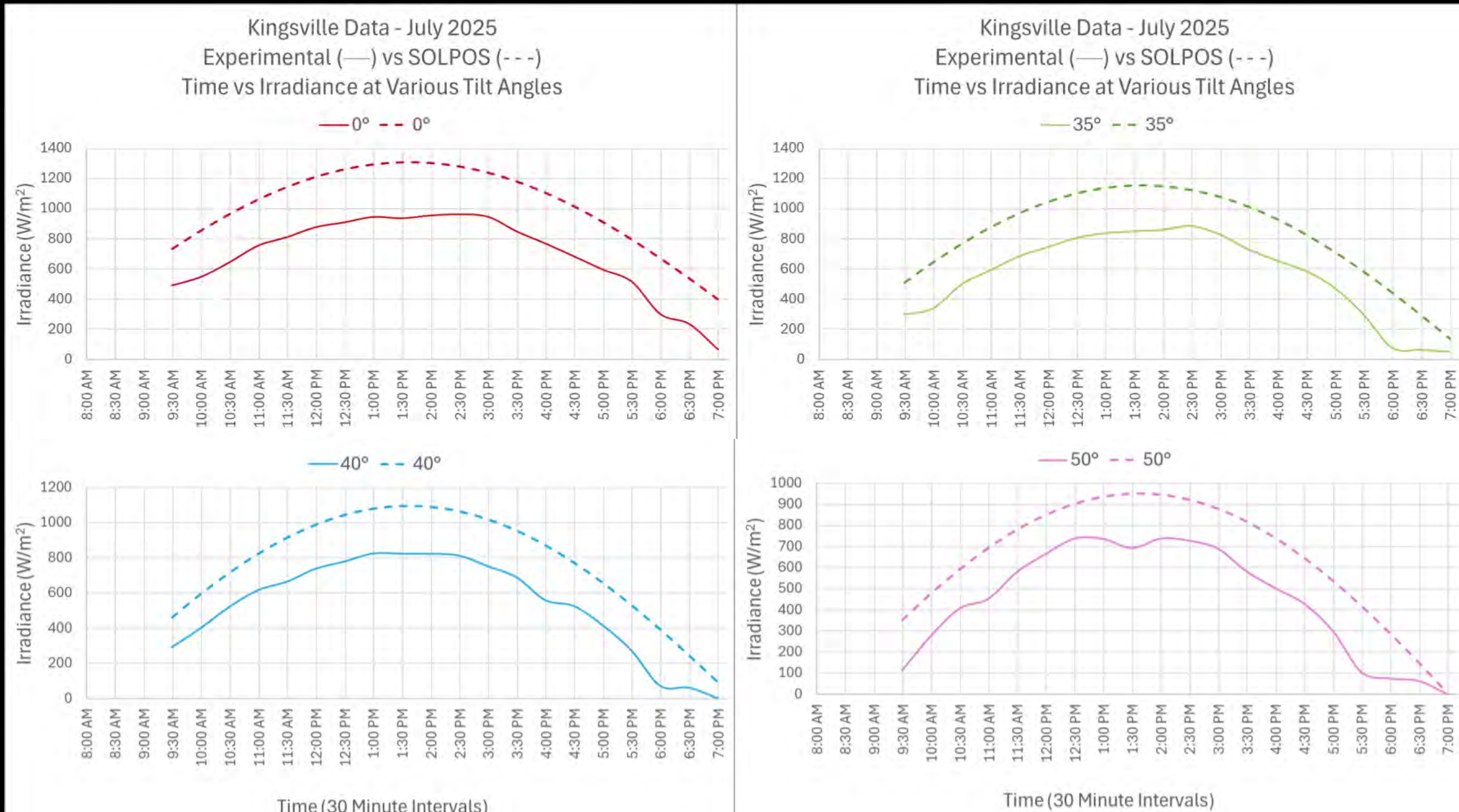
Corpus Christi Experiment Location
27.775 -97.401

Methods & Results
Corpus Christi Validation



- Irradiance trends observed for tilts (0°, 35°, 40°, 50°) on clear July days
- Experimental data aligns closely with SOLPOS simulations
- Validates SOLPOS for accurate modeling and classroom use

Methods & Results
Kingsville Validation



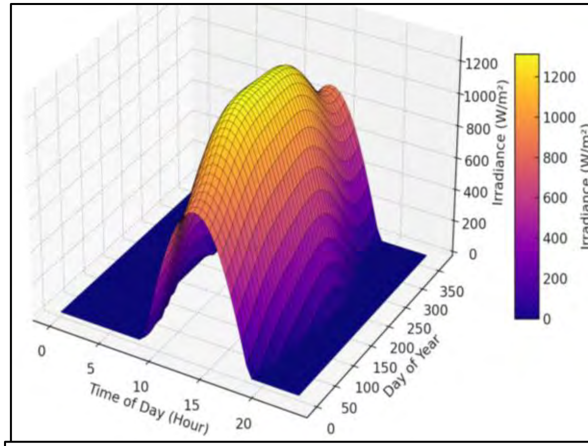
- Irradiance trends observed for tilts (0°, 35°, 40°, 50°) on a clear July day
- Minor deviations due to local weather variations
- Validates SOLPOS for accurate modeling and classroom use

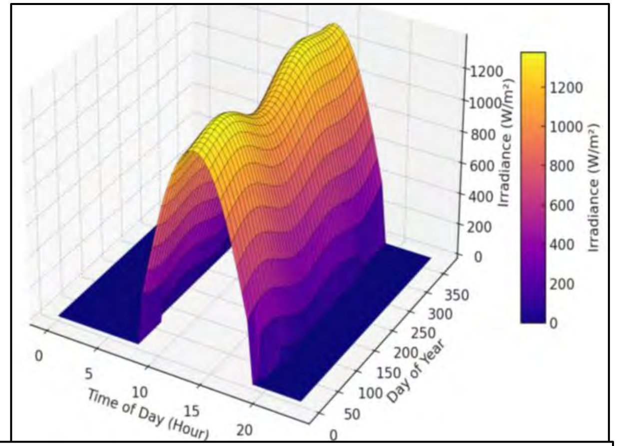
Methods - Analysis Parameters

- Downloaded irradiance (W/m²) & surface temperature (°F) in Kingsville using SOLPOS calculator.

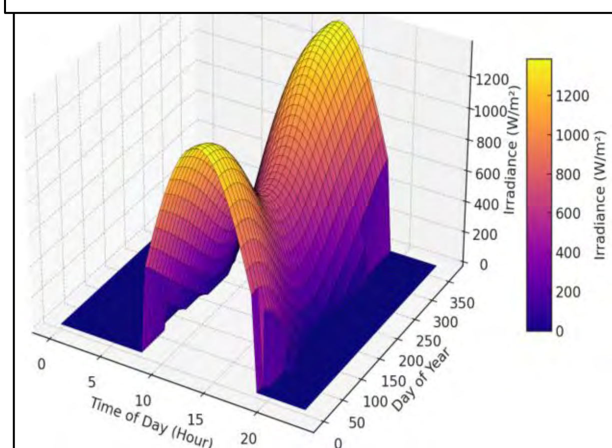
Kingsville Location: (27.526, -97.881)

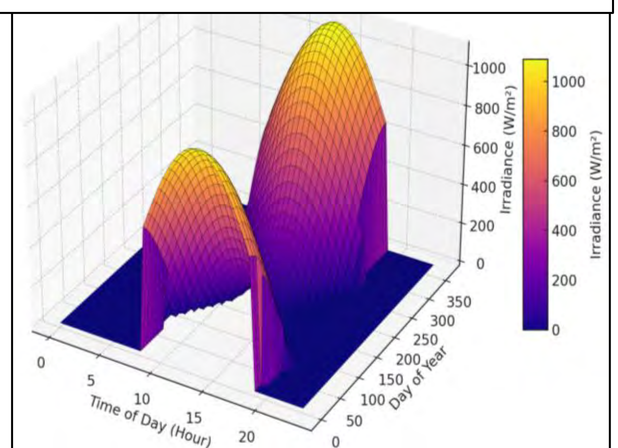
- 30-minute intervals
- 9:30 AM to 7:00 PM
- Time Zone: (-5)
- Azimuth: 180° South
- Full calendar rear (365 days) from Jan 1, 2024 – Jan 1, 2025
- Tilt angles: 0°, 15°, 30°, 45°, 60°, 75°, 90°

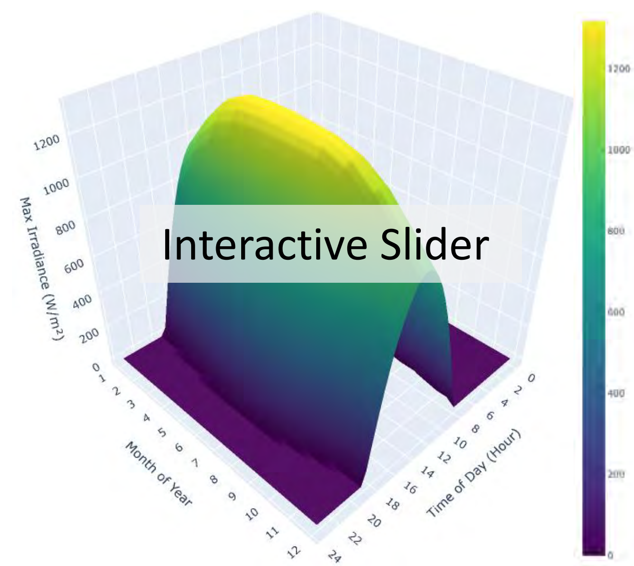




3D Surface: Irradiance vs Time vs Day of Year
Tilt angles: 0°, 30°, 60°, 90°







Seasonal Tilt Angle Insights

Optimal tilt angles shift monthly in South Texas

May–August: 0° tilt performs best (high solar elevation)

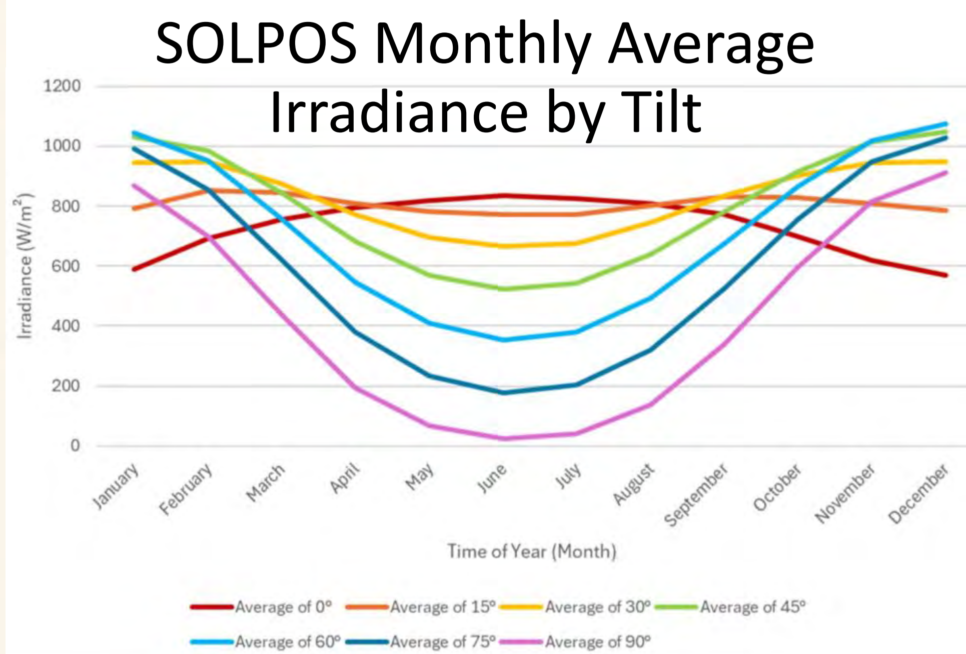
0°

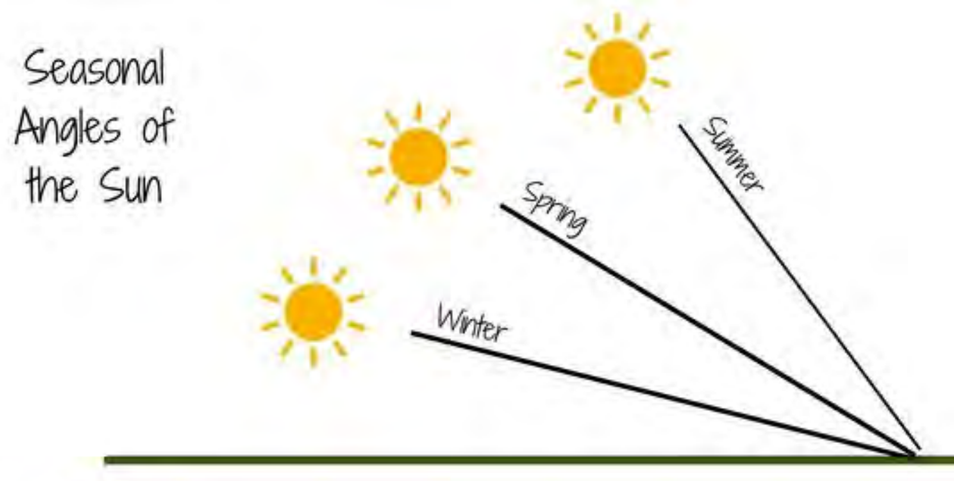
October–February: 60°–90° tilt yields highest irradiance

15°–30°: Strong year-round output, ideal for fixed panels

Highlights the benefit of tracking systems for maximum energy production

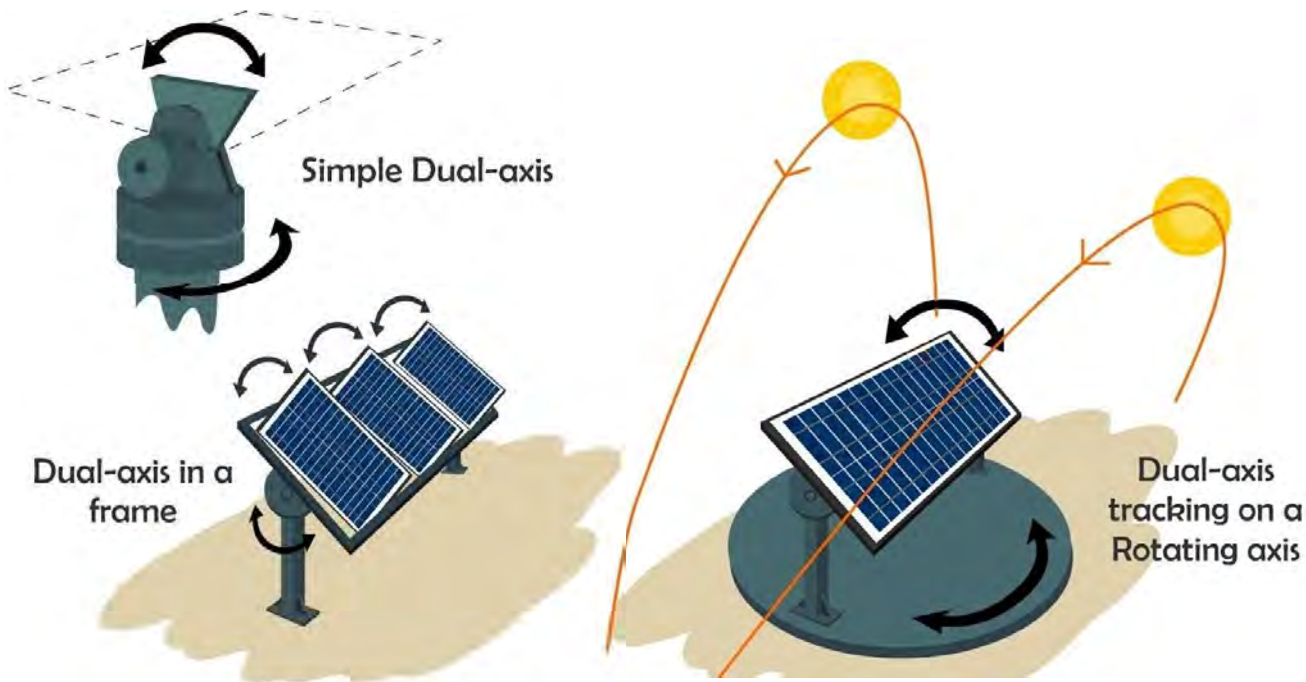
Conclusions



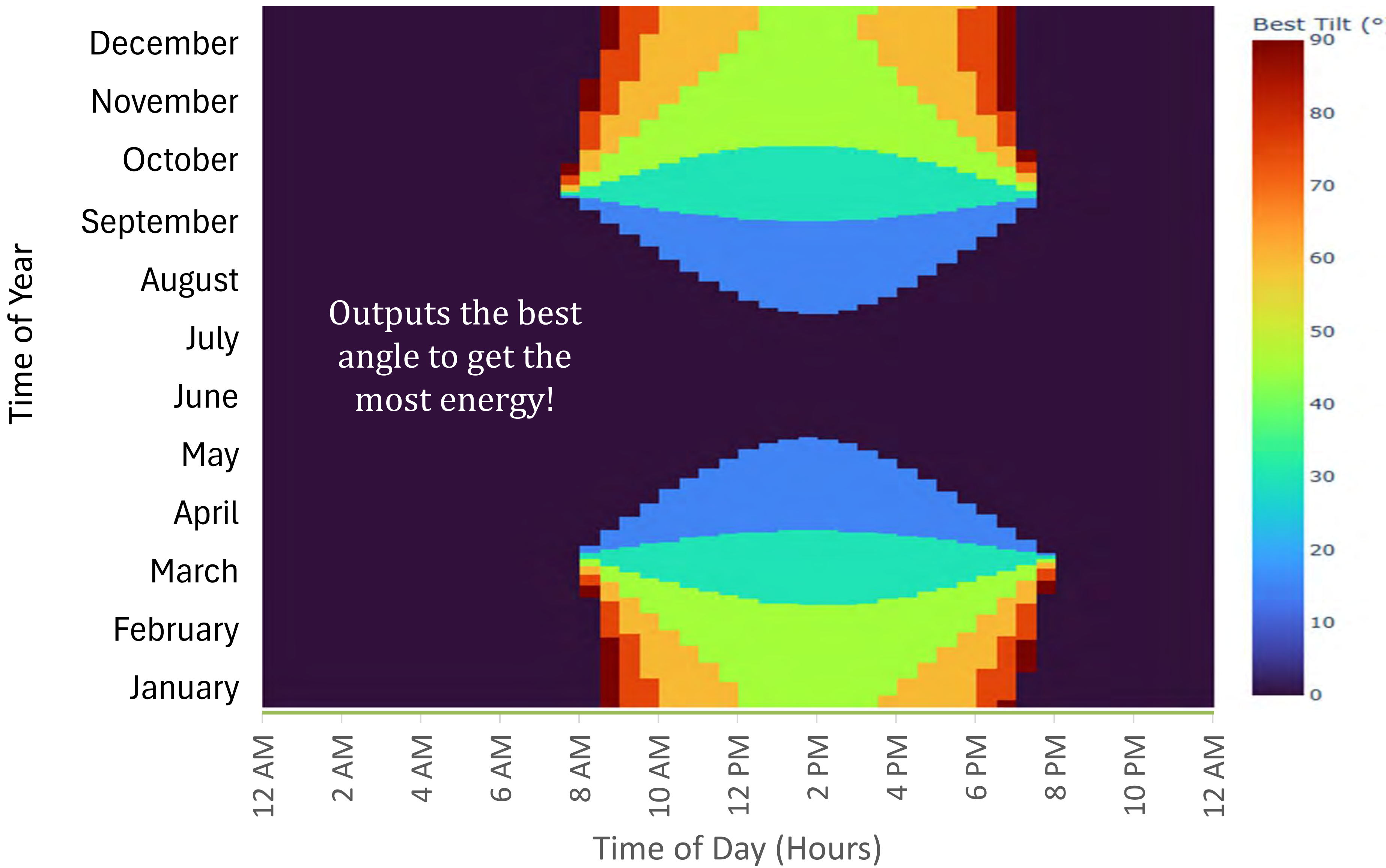


Tracking Systems

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



Best Tilt Angle Heatmap (SOLPOS)



Interactive Tool

SOLAR PANEL TILT CALCULATOR (HTML): ENTER TIME/DATE/DURATION FOR IDEAL TILT

Curriculum Modules

ALGEBRA 2

Data Meets Sunlight & Solar Panels

- **Objective:** Collect and model solar panel irradiance data using algebraic functions.
- **Key Concepts:** Linear/quadratic regression, graphing, trend analysis.
- **Activity:** Students record irradiance every 5 minutes for 40 minutes using various panel angles.
- **TEKS:** 111.39(c)(2)(A,D), (4)(A), (6)(B)
- **Real-World Link:** Algebra helps us model and predict energy output to improve solar tech.

Angles & Irradiance: Geometry in Solar Energy

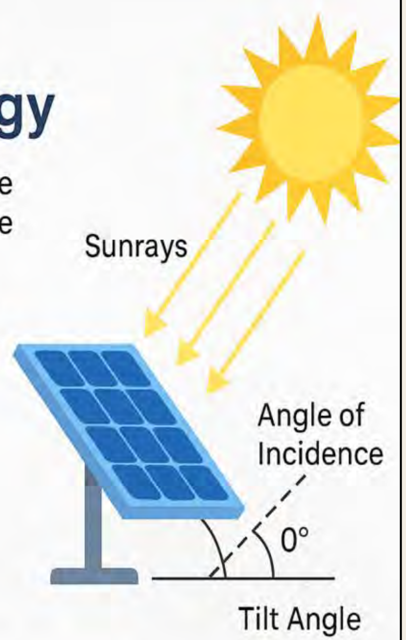
Objective: Use geometric concepts to analyze how tilt angle affects solar panel performance

Key Concepts: Angles, trigonometric ratios, real-world applications

Activity: Students test irradiance at different tilt angles (0°, 35°, 40°, 50°) and analyze the data

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

Real-World Link: Geometry helps optimize solar energy collection based on angle of incidence



PRECALCULUS

Maximizing Solar Output

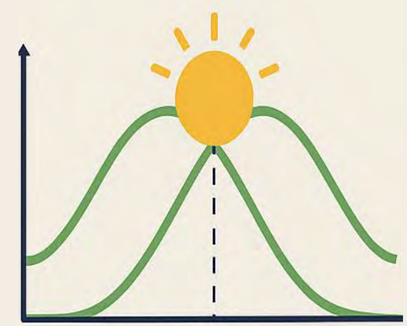
Solar Elevation Modeling with Sine Functions

Objective: Model sun's path with sinusoidal functions and real solar irradiance data

Key Concepts: Sine and cosine function modeling, amplitude, midline, period, and phase shift; Solar elevation and tilt angles

Activity: Model solar elevation data and overlay graphs for panels tilts to analyze

Real-World Link: Connect trigonometric modeling to engineering and research Analysis for Strategic Positioning of Solar Panels, in renewable energy field.



HONORS EXTENSION: Explore amplitude and phase shifts to simulate different latitudes and seasons

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

Acknowledgements & References

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Predicting Wind Conditions using Machine Learning

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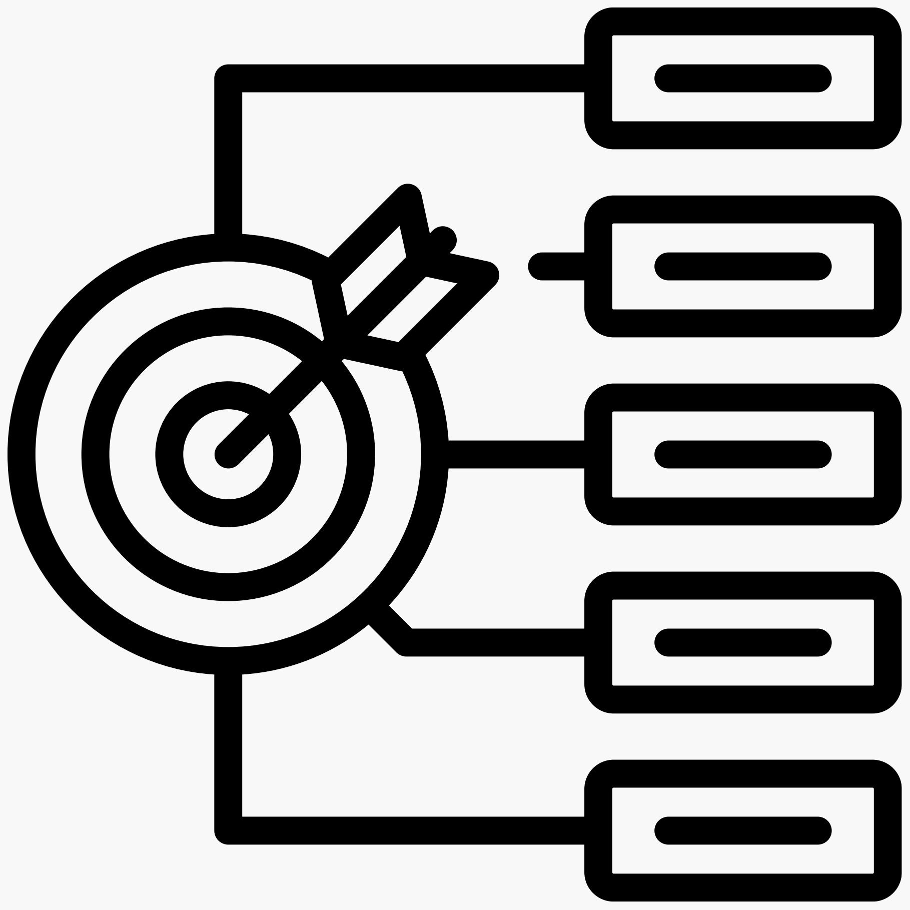
Student Mentor: Joaquin Haces-Garcia
Industrial Advisor: Rene Ramirez, Jr, P.E., PMP

TEXAS A&M UNIVERSITY KINGSVILLE® NSF

RESEARCH QUESTION:

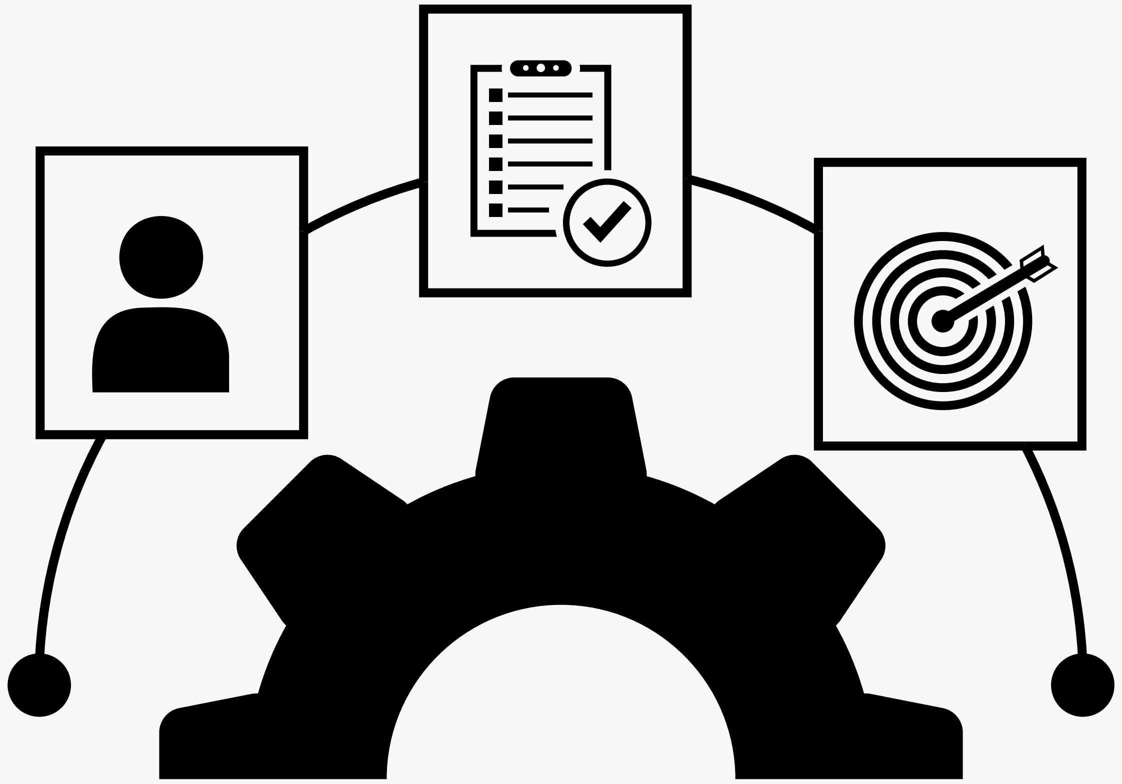
How do input window size and weather conditions affect the accuracy of machine learning models predicting next-day wind speeds at coastal and inland locations in Texas?

PROJECT OBJECTIVES:



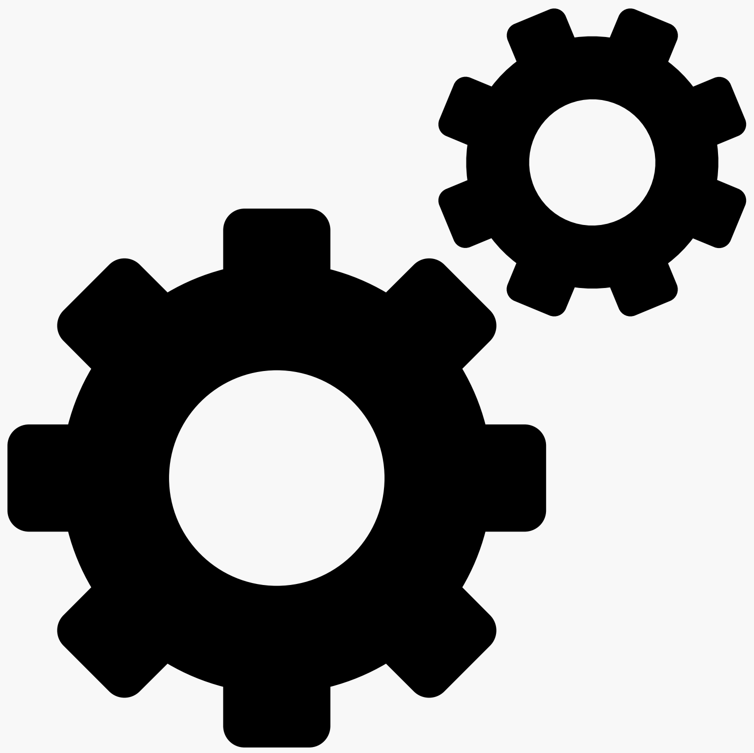
- ***Develop and test*** **machine learning models to predict next-day wind speeds using National Solar Radiation Database (NSRDB) data from (2017–2023).**
- ***Train*** **models across different weather conditions**
- ***Analyze*** **impact of input window sizes on prediction accuracy for next hour and next day wind speeds**
- ***Compare*** **forecasting accuracy between coastal and inland locations**
- ***Identify*** **the most effective model and configuration for day-ahead wind speed forecasting**

METHODOLOGY:

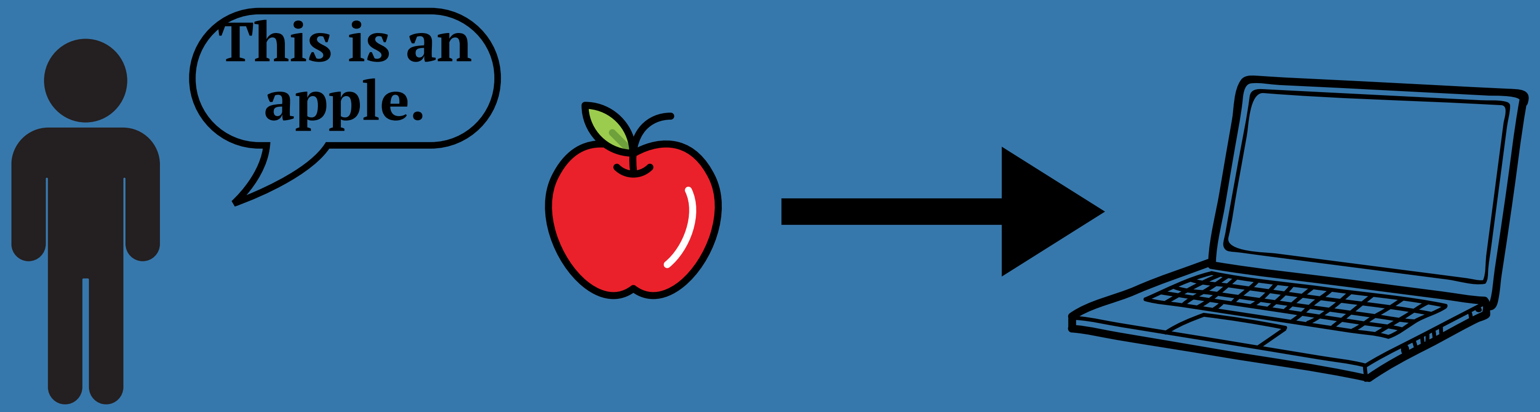


- Data Collection: National Solar Radiation Database (NSRDB) Wind Speed Data (2017–2023)
- Data Preprocessing
- Model Selection:
  - Random Forest (RF)
  - Support Vector Regression (SVR)
  - Long Short-Term Memory (LSTM)
- Model Training Phases:
  - Phase 1: Non-Hurricane Year (2022)
  - Phase 2: Hurricane Year (2020)
  - Phase 3: Combined Year Data (2020 & 2022)
- Input Window Sizes:
  - 24 hrs
  - 168 hrs (1 week)
  - 720 hrs (1 month)
- Prediction:
  - Stage 1: Next-Hour Wind Speed (All Models)
  - Stage 2: Next Day Wind Speeds (LSTM only)
- Evaluation: Root Mean Squared Error (RMSE)

WHAT IS MACHINE LEARNING AND HOW DOES IT WORK?

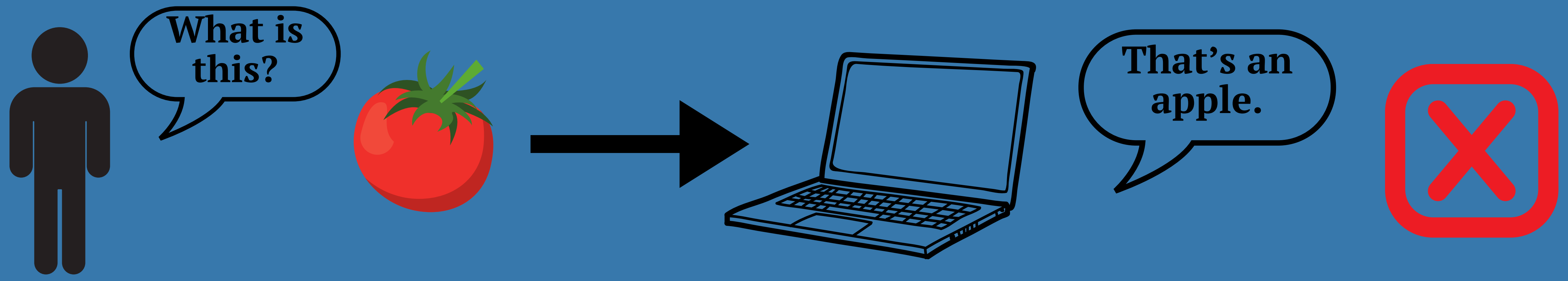


- Machine learning is when a computer learns from data instead of being told exactly what to do.
- "Train" the model by giving it data.



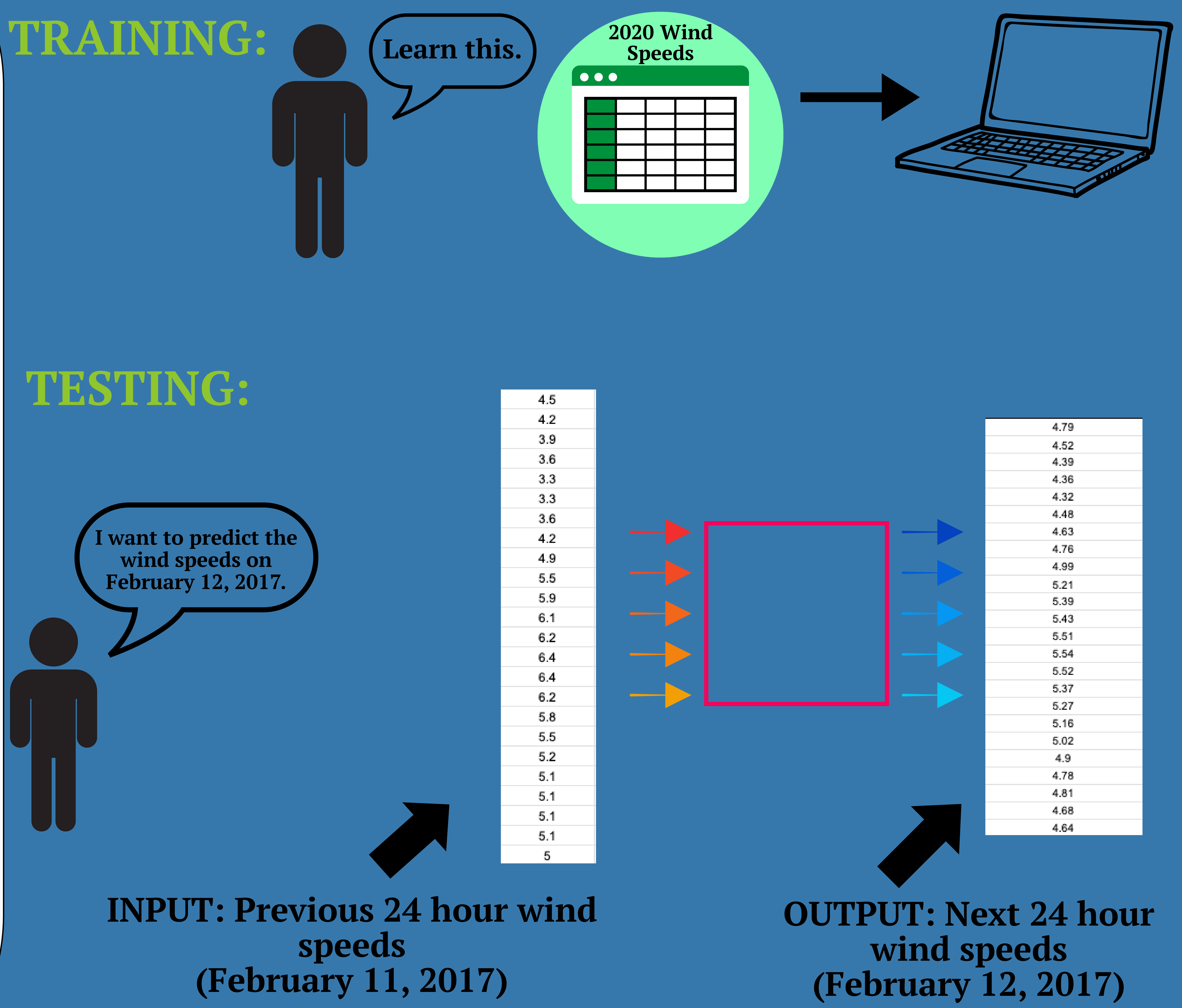
- The model learns from the data by looking for patterns .

- The model makes predictions.

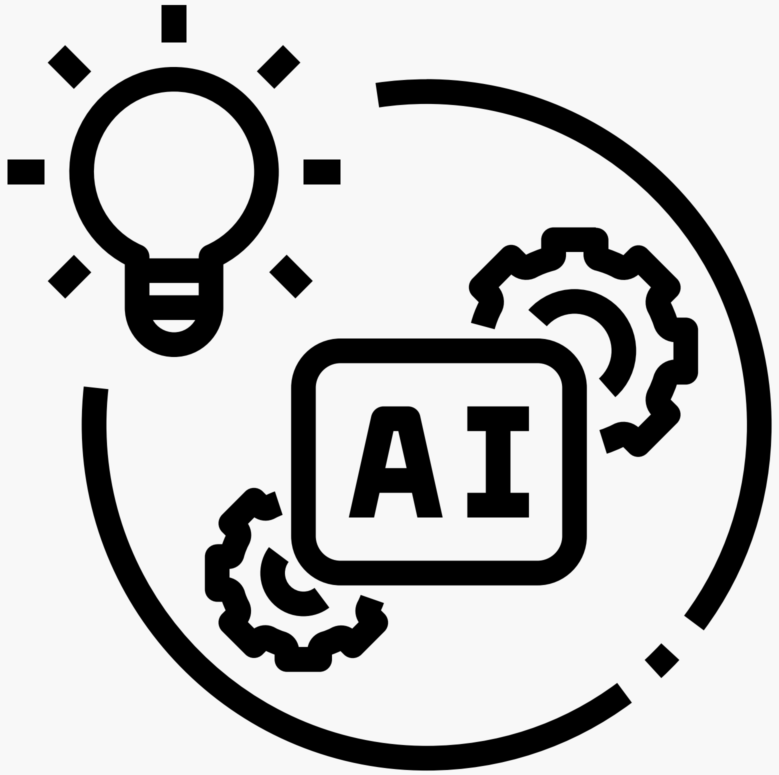


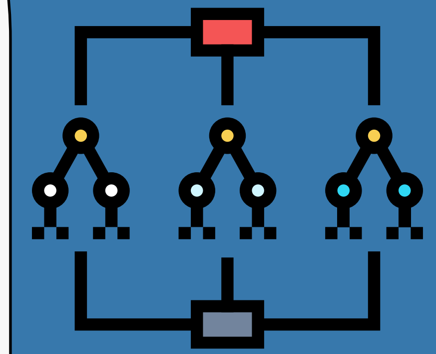
- We check if it was right, and help it improve by giving it more data.

PROJECT SPECIFIC EXAMPLE:

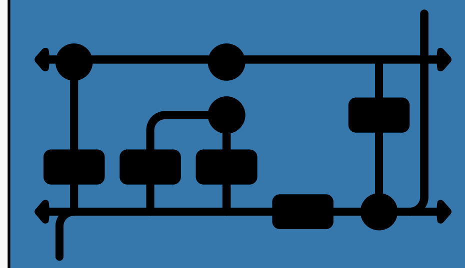


TYPES OF MACHINE LEARNING USED IN THIS PROJECT:

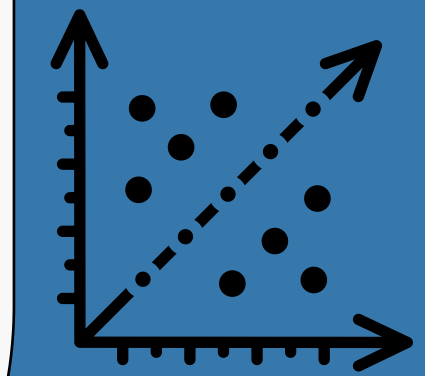




- Random Forest (RF)
  - A model that combines many decision trees to make more accurate and stable predictions.



- Long-Short Term Memory (LSTM)
  - A type of neural network designed to learn patterns in time-series data by remembering information across long sequences.



- Support Vector Regression (SVR)
  - A machine learning method that finds the best-fit line or curve within a margin of tolerance to predict continuous values.

LSTM CODE EXAMPLE:

SELECT TRAINING DATA:

```
# Apply filters

#hour_filter = df['Hour'].between(0, 6)
#day_filter = df['Day'].between(1, 7)
#month_filter = df['Month'].isin([1])
year_filter = df['Year'].isin((2020))
df = df[year_filter]
```

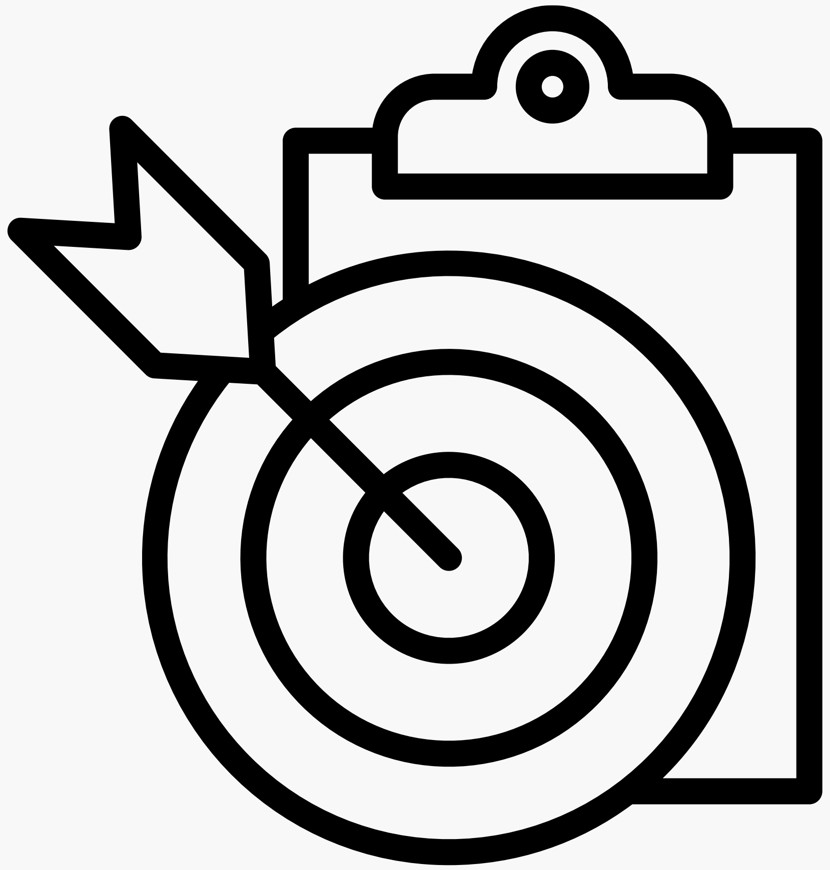
LAYERS OF THE MODEL:

```
# Define LSTM model
model = Sequential()
model.add(LSTM(64, activation='relu', input_shape=(X_train.shape[1], 1)))
model.add(Dense(32, activation='relu'))
model.add(Dense(output_seq_length))  # Output layer
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
model.summary()
```

SELECT TESTING DATA:

```
input_seq_length = 24 # New Window Size
output_seq_length = 24 # Number of Desired Outputs
```

HOW WE CALCULATED ACCURACY OF MODELS:



- Root Mean Squared Error (RMSE)
  - a way to measure how far off your predictions are from the actual values.
- How it works:
  - For each hour, the model predicts a wind speed.
  - RMSE looks at the difference between the predicted and actual wind speed.
  - It squares each difference.
  - Then it takes the average of those squared errors.
  - Finally, it takes the square root of the average.

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

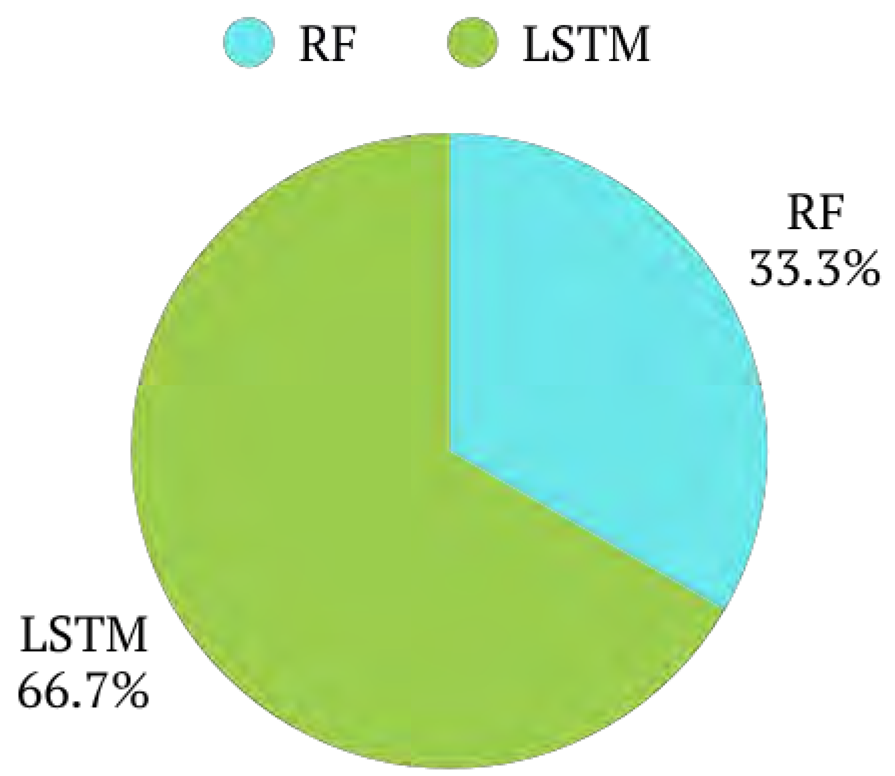
- What does the RMSE value mean?
  - RMSE is in the same units as your target — in this case, meters per second (m/s) for wind speed.
  - Lower RMSE = better accuracy

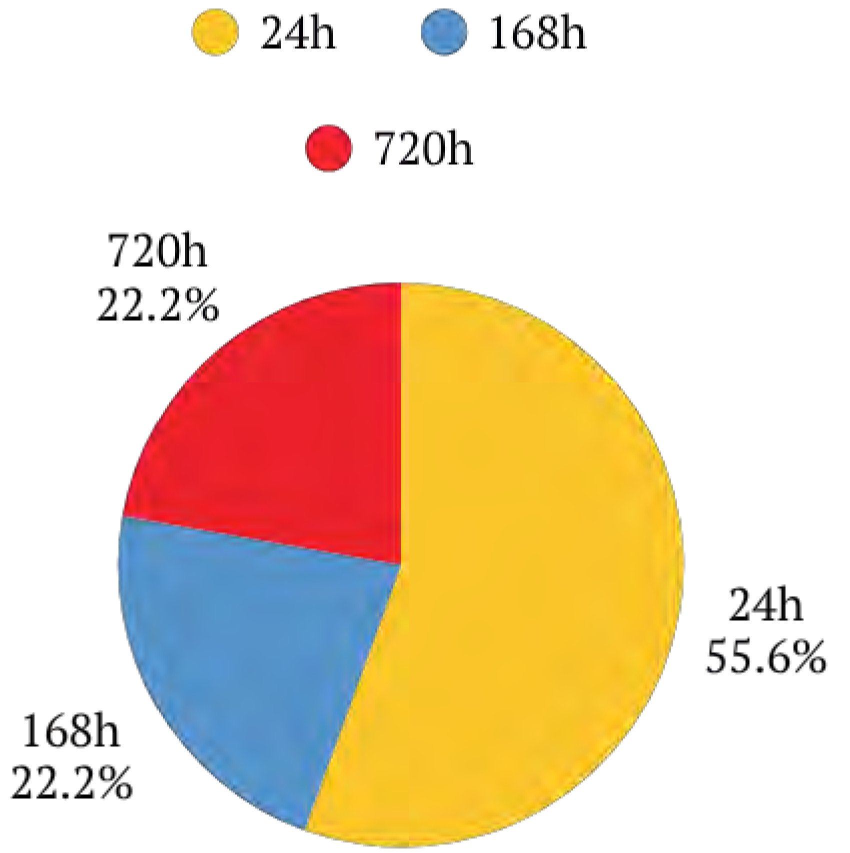
Stage 1 Predictions: Next-Hour Wind Speed RMSE Port Aransas, TX

Port A---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	0.12	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 YEAR		
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 YEAR		
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





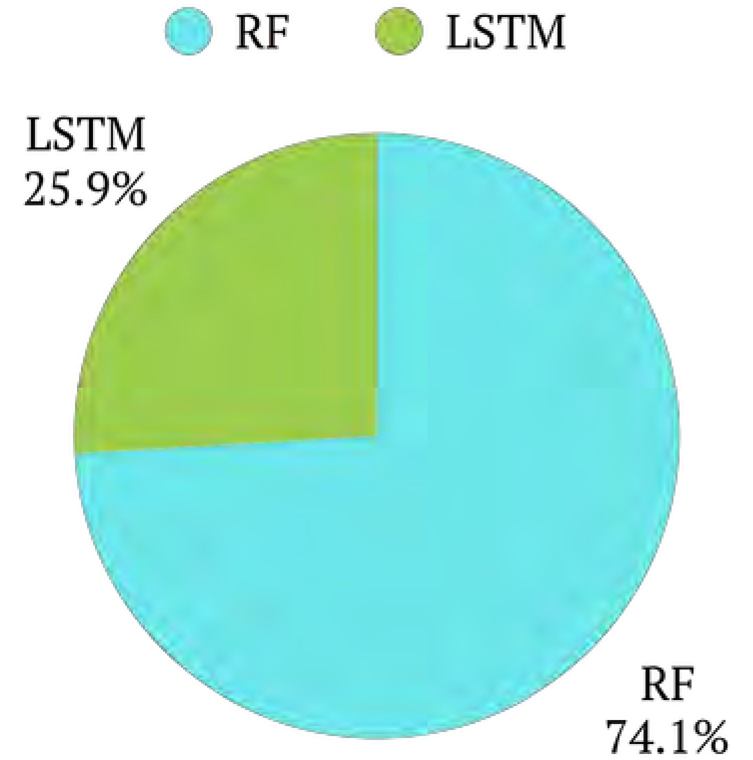
Stage 1 Predictions: Next-Hour Wind Speed Graphs Port Aransas, TX

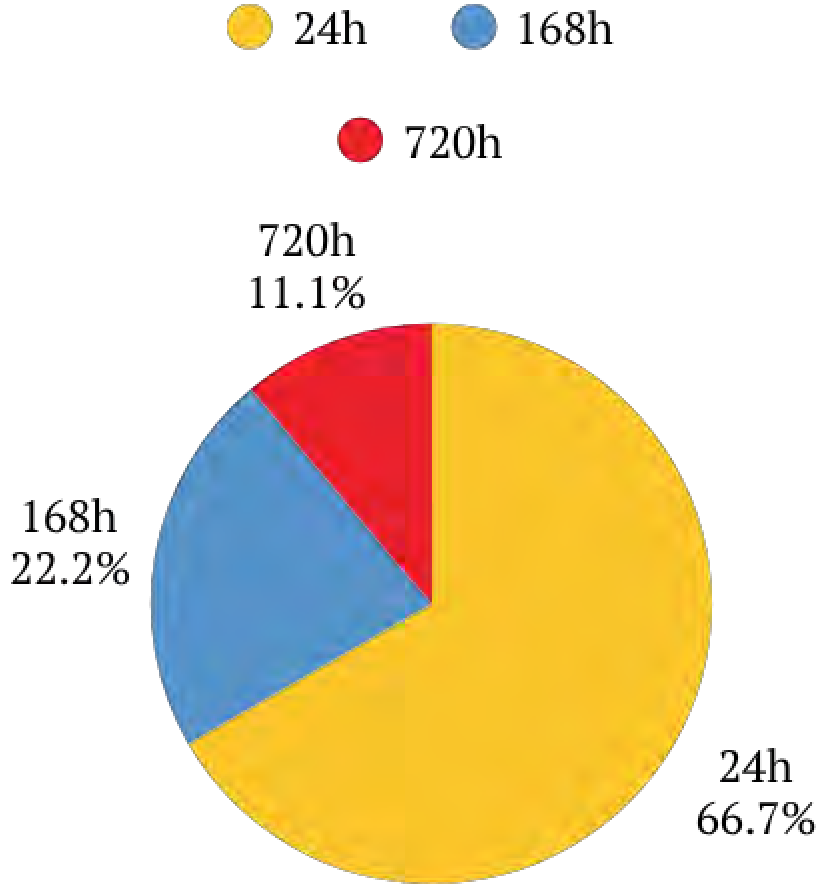
Stage 1 Predictions: Next-Hour Wind Speed RMSE Sinton, TX

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





Stage 1 Predictions: Next-Hour Wind Speed Graphs Sinton, TX

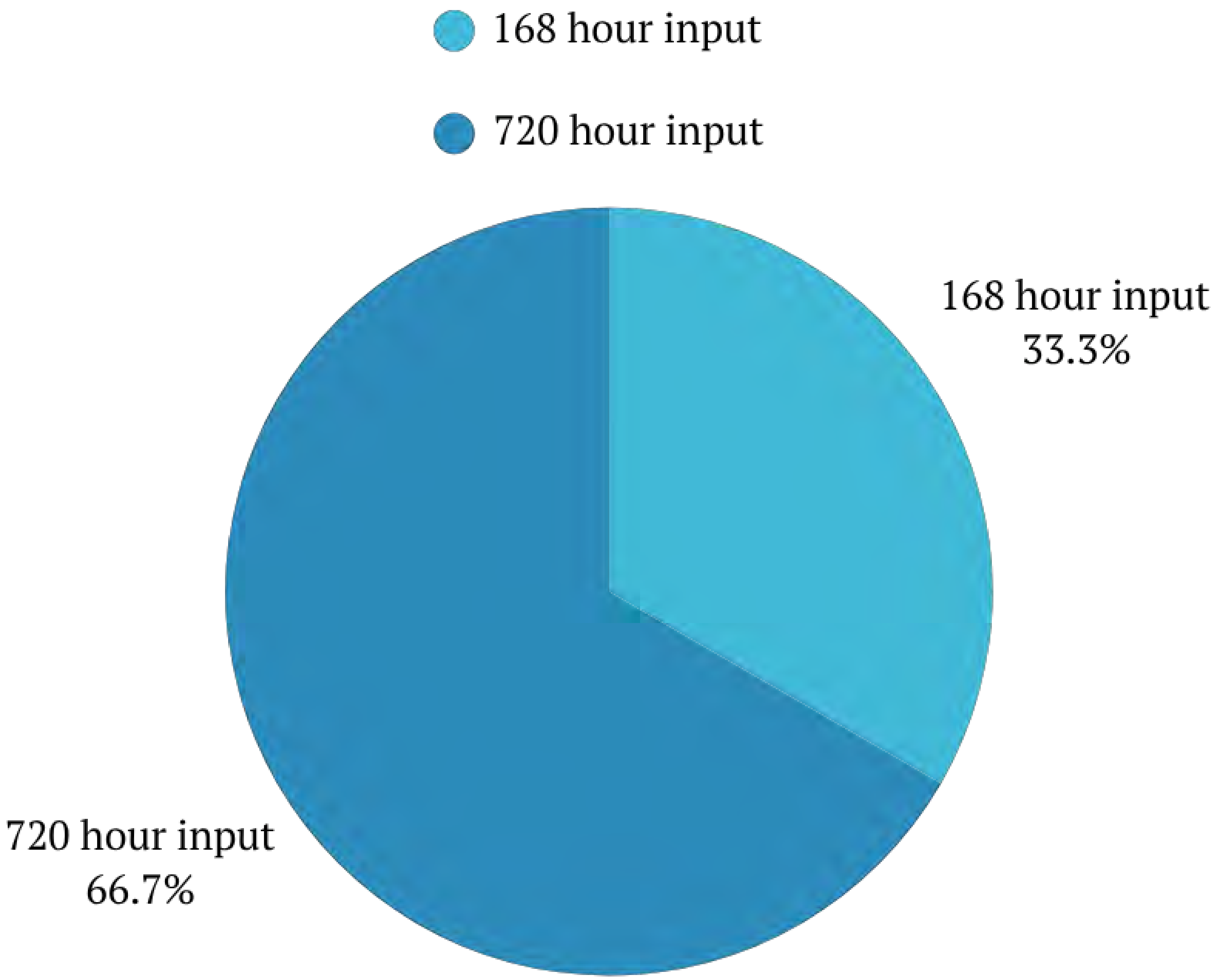
SO, WHY IS IT IMPORTANT TO PREDICT NEXT-DAY?

- The day-ahead wind market is a segment of the electricity market where energy produced from wind resources are traded a day in advance.
- Machine learning plays a crucial role in optimizing energy use by analyzing historical data, allowing for more efficient management of resources.
- By predicting wind conditions such as wind speeds, machine learning enhances decision-making processes for energy providers.

Stage 2 Predictions: Next-Day Wind Speed RMSE

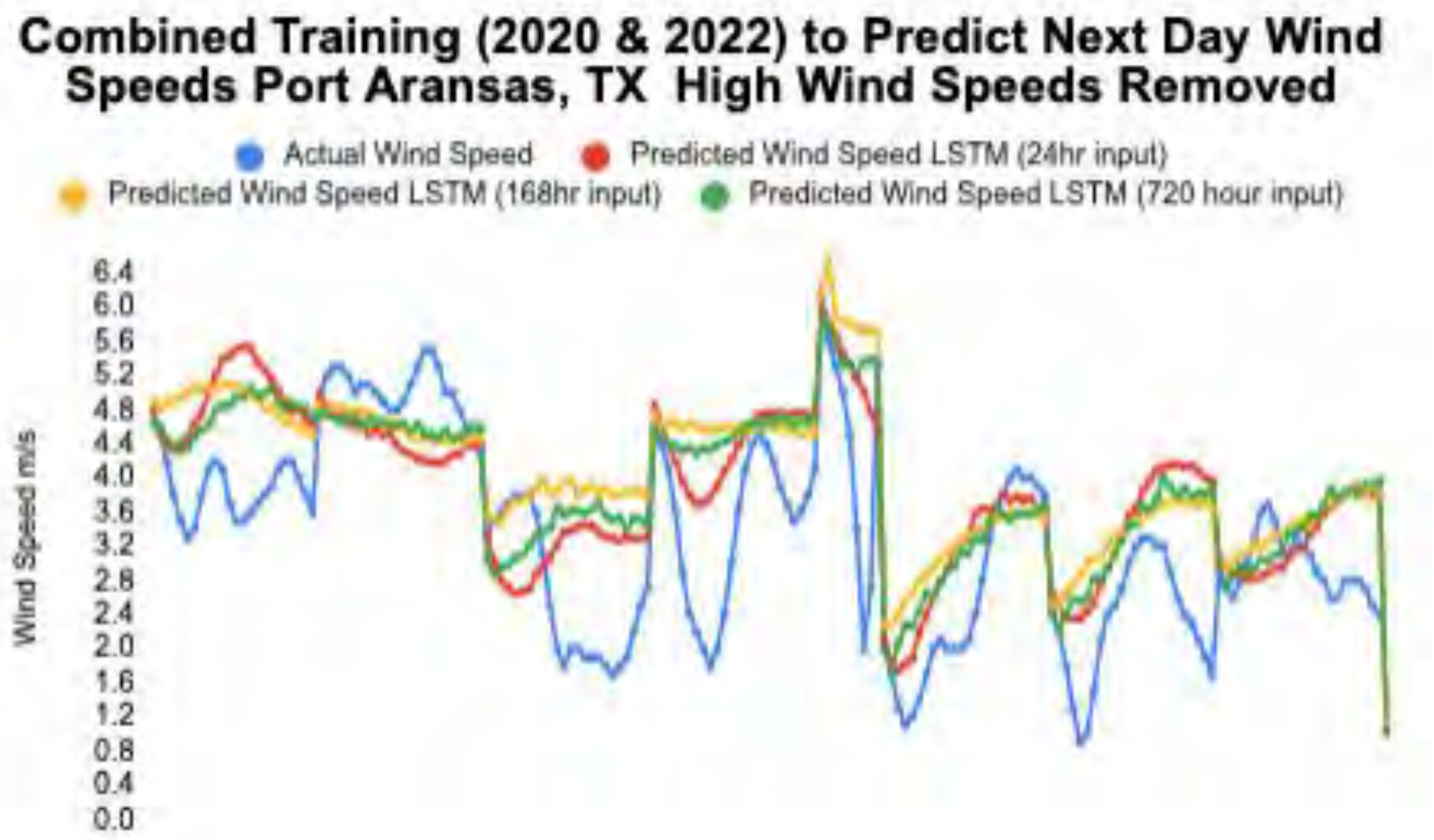
LSTM Model Combined Year Training (2020 & 2022) Port Aransas,TX			
Input Size	Hurricane and Non-Hurricane Year Predictions	Non-Hurricane Year Predictions	Hurricane Year Predictions
24 hours	1.49	1.63	0.97
168 hours (1 week)	1.26	1.37	0.85
720 hours (1 month)	1.16	1.27	0.76

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

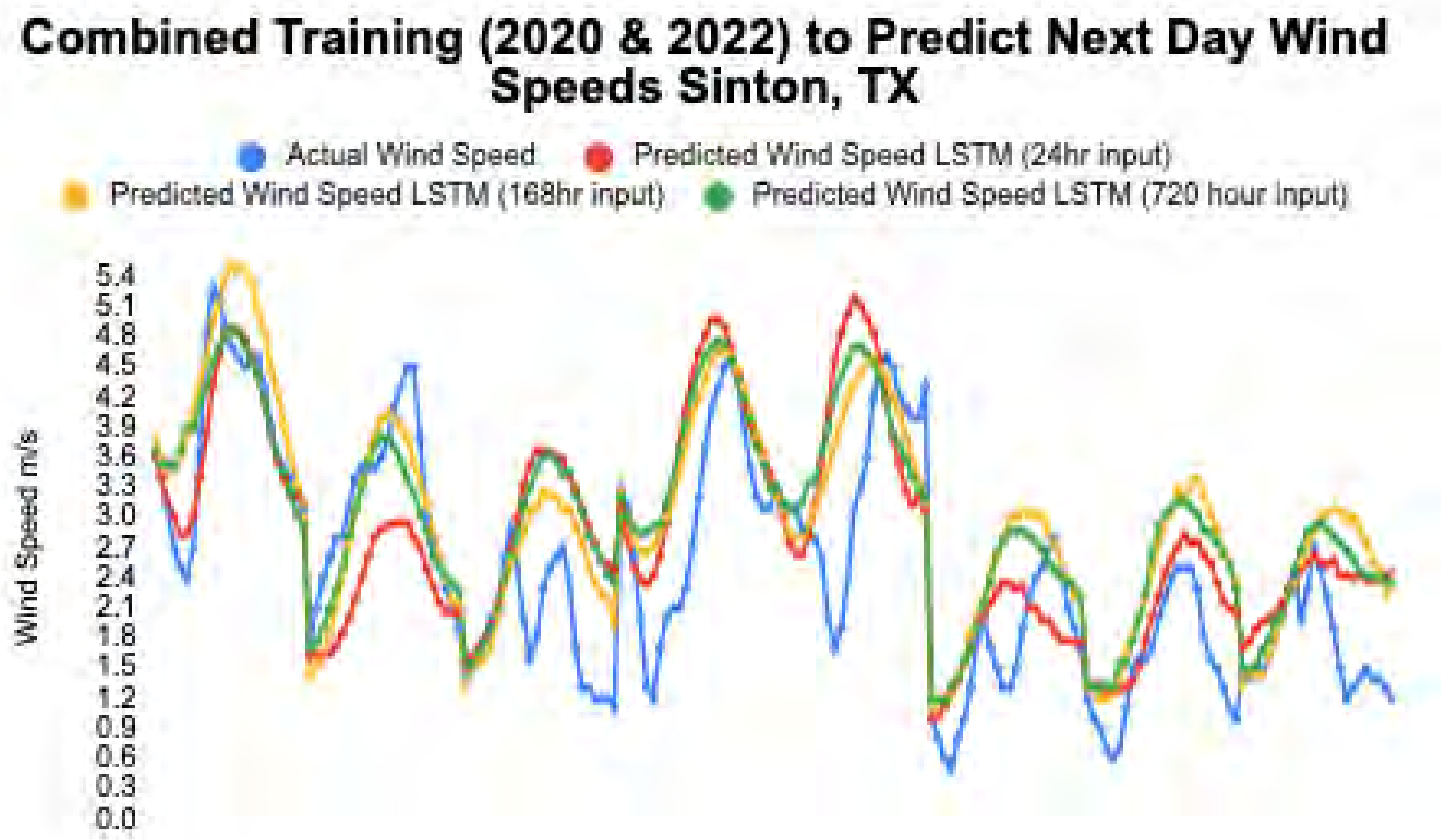


Next-Day Wind Speed Predictions Port Aransas, TX

Next-Day Wind Speed Predictions
Port Aransas, TX



Next-Day Wind Speed Predictions Sinton, TX



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 Aransas.
- 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.

Algebra 1 Curriculum Module Overview

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

6th Grade Math Curriculum Module Overview

In this data-driven STEM lesson, students will analyze a set of real or simulated wind speed data. They will represent the data using dot plots and calculate key statistical measures such as mean, median, mode, and range. By identifying patterns and trends, students will make predictions and better understand how data analysis can be used in real-world situations.

6.12(A) – Represent numeric data graphically, including dot plots, stem-and-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.

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Questions?