Identifying NAM Points with Wind Speed Discrepancies Through Time-Series Analysis and Optimizing VRI Polygon

Kenneth Hidayat khidayat@ucsd.edu
Steven Sahar ssahar@ucsd.edu
Mentor: Kasra Mohammadi KMohamma@sdge.com
Mentor: Jacob Wigal JWigal@sdgecontractor.com
Mentor: Phi Nguyen pnguyen@sdge.com

UC San Diego HALICIOĞLU DATA SCIENCE INSTITUTE

Our Goal: To Leverage North American Mesoscale (NAM) Model to Address Wind Speed Inaccuracies and Improve the Accuracy of VRI Polygons

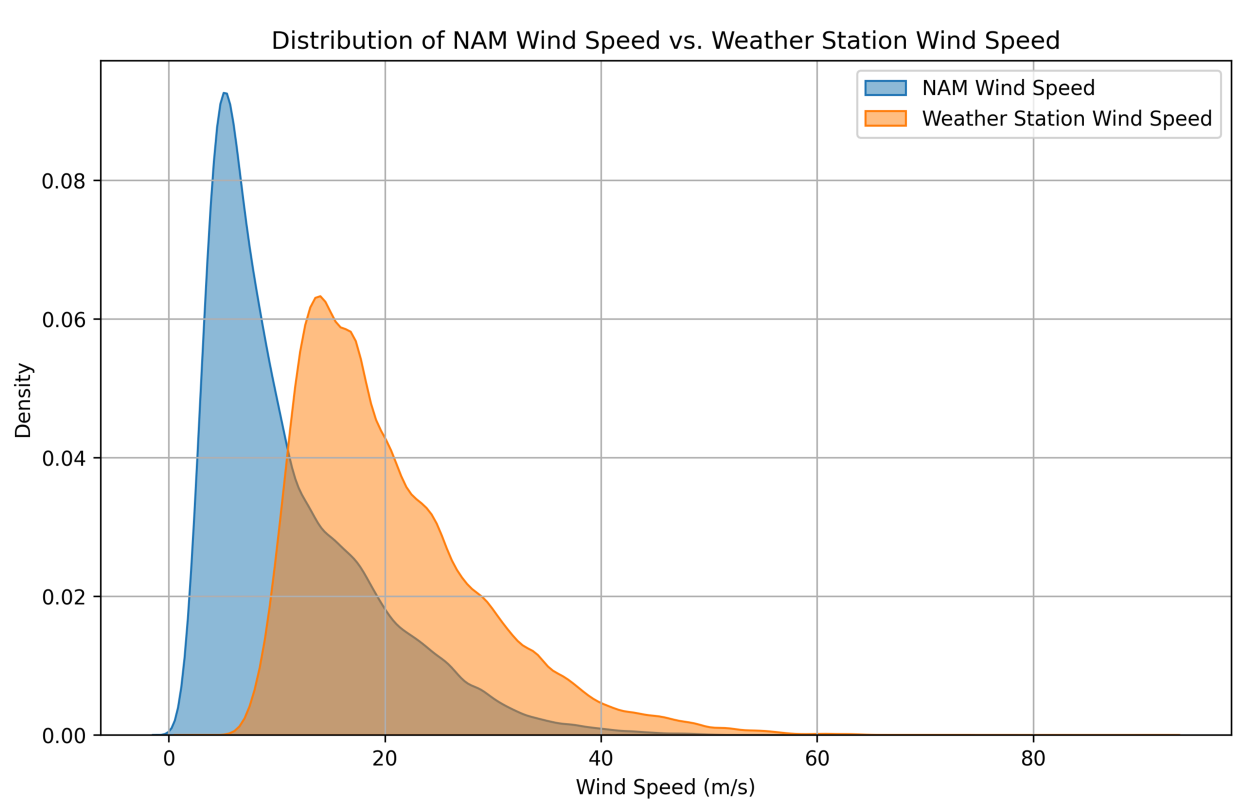
MOTIVATION

With the recent Palisade's Fire, wildfires are becoming more frequent and severe

- Accurate wind speed data are essential for mitigation strategies like Public Power Safety Shutoffs (PSPS)
- PSPS decisions rely on SDG&E weather stations, but large VRI polygons assume uniform wind conditions potentially leading to inaccuracies
- We aim to identify wind speed discrepancies between NAM points & weather stations through geospatial analysis
- We conducted an in-depth analysis of VRI polygon areas with high wind speed discrepancies to seek alternative VRI polygon assignments of NAM points with high errors

DATASET

- Datasets obtained from **SDG&E**: Weather Station Data, Weather Station Wind Speed Data & VRI Polygon Data
- Datasets obtained from **Public Datasets**: NAM Wind Speed Data, Elevation Data, San Diego County Boundary & Southern Orange County Boundary



- NAM Wind Speed points tend to underestimate Weather Station Wind Speeds showing **inconsistent measurements**
- Datasets were standardized, filtered for PSPS dates, merged with weather station, NAM, and VRI polygon data, missing values were handled using the nearest station, and key features like elevation and temporal factors were extracted

METHODS

Addressing Wind Speed Discrepancies

Implementing loss functions allow us to measure Wind Speed inconsistencies between a NAM point and its associated VRI polygon

- **Loss Function Implementation:** Standard error functions, such as Mean Absolute Error (**MAE**) are standard metrics used to measure discrepancies.
- To ensure errors in farther locations are weighted accordingly, we also utilize the Distance-Weighted Absolute Error (**DWAE**) metric.

Predicting Error of NAM Points Outside the VRI Polygon

To address Wind Speed errors for NAM points **not associated** to a VRI polygon, a LightGBM model is used to perform error prediction

- **Key Features:** Wind speed, elevation, distance from the nearest weather station, and temporal factors (month, day of year)
- **Why LightGBM?** It simply considers spatial variations to improve accuracy
- **Why predict Error?** To better capture variability in wind speed predictions and where direct records from weather stations aren't available

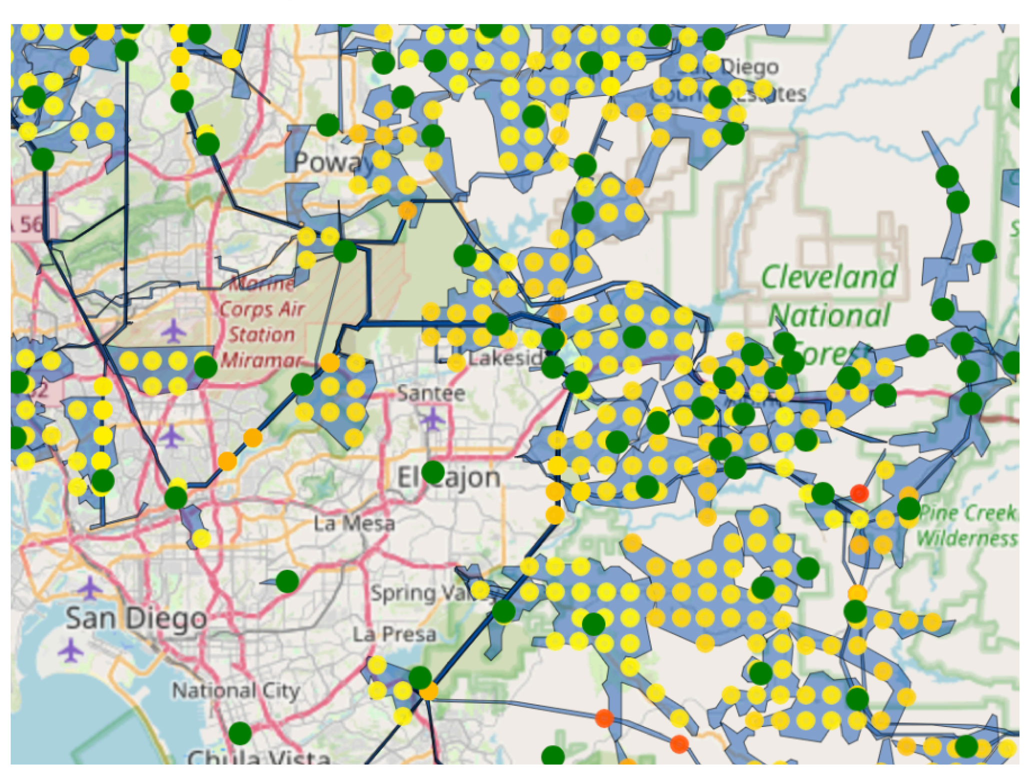
In Depth Analysis for Polygon Optimization

The VRI polygons associated to the **top 20** NAM point errors are areas of interest requiring polygon optimization

- **Optimization Implementation:** The Haversine distance are used to assign the nearest alternative VRI polygon to the NAM points
- **Error computation:** After the alternative polygons are assigned, the corresponding errors are recomputed and NAM points with lower errors are the newly optimized VRI polygons

RESULTS

Visualizing Wind Speed Discrepancies

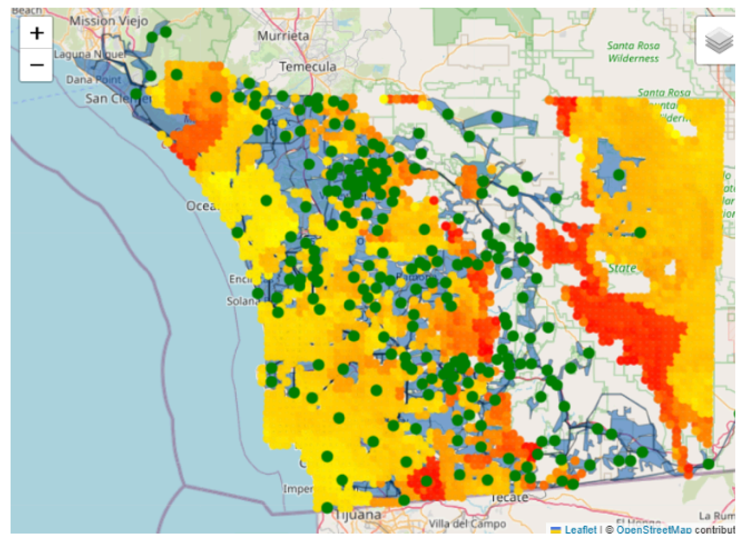


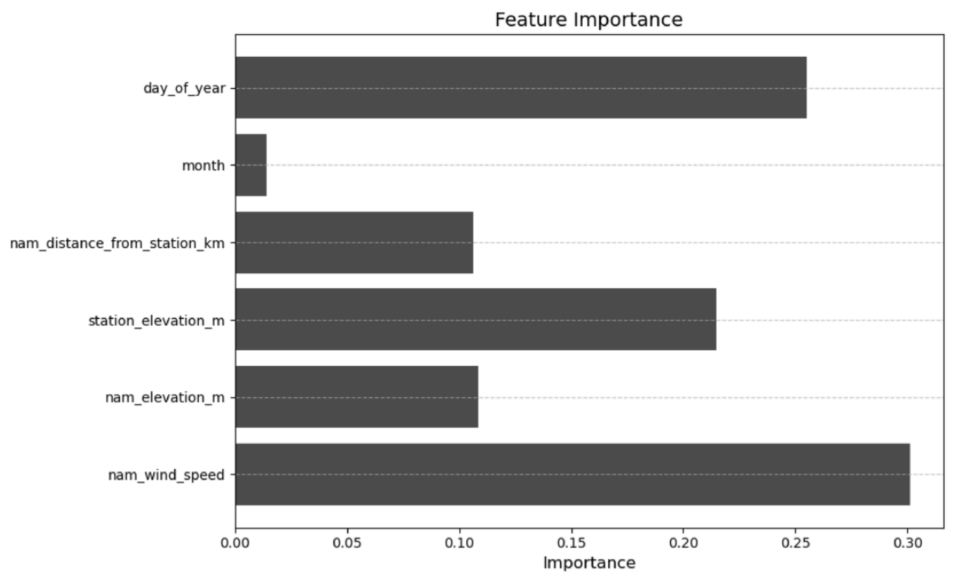
We developed a visualization to identify NAM point error locations where:

- **NAM points** are color-coded by error intensity (yellow for low, orange for moderate, and red for high discrepancies)
- **Weather stations** are marked as green points
- **VRI boundaries** are represented by blue polygons

LightGBM Error Prediction

Predicted errors of the selected NAM points are shown for potential areas with high errors for possible new weather stations

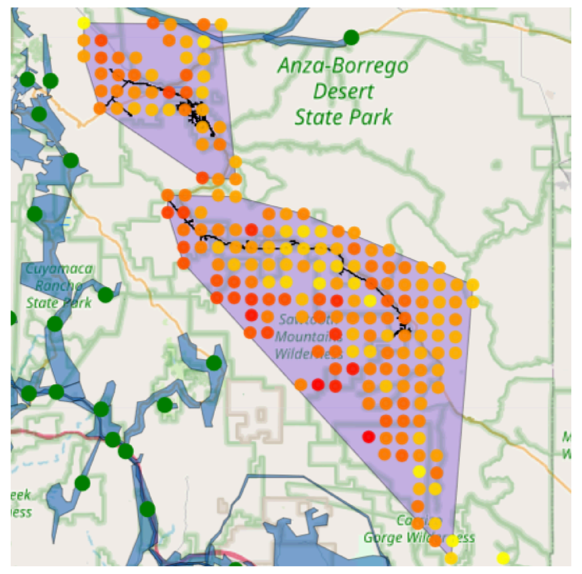




Mean Absolute Error: 2.7
R^2 Score: 0.66

Outlier Wind Speed Error

boundary_name	span_count	sum_of_customers
CA 78	459	232.0
Otay Mountains	60	16.0
Sawtooth Mountains	401	118.0



VRI Polygon Optimization

- The polygon optimization resulted in a notable reduction of MAE errors
- **18/20** of the selected NAM points with high errors experience error reductions by **55% on average**

Metric	Value
Mean Old MAE	25.74
Mean New MAE	11.68
Mean MAE Reduction	14.07
Percentage MAE Reduction (%)	54.64

CONCLUSION

Our analysis has brought insights to strengthen the infrastructure of wildfire mitigation by:

- **Identifying** areas within and outside VRI polygons with high wind speed measurement errors that potentially requires additional collection of weather station wind speeds
- **Understanding** how certain areas with high errors affect customers and the relationships of the infrastructure around it
- **Optimizing** VRI polygons which allows for better wind speed accuracy and relevance to its respective polygons

Our project scope allows SDG&E to be better informed to improve their weather station infrastructure allowing for better precision when performing wildfire mitigation strategies

Acknowledgements

We would like to give a deep and sincere appreciation to our mentors Kasra Mohammadi, Jacob Wigal and Phi Nguyen for providing useful feedback and guiding us through our project