BNSF Railway San Bernardino Railyard

Blair Blokzyl

December 2013 – January 2014

California State University of San Bernardino

Dr. Robert Phalen, California State University of San Bernardino

January 21, 2014

Table of Contents

Acknowledgements

I would like to first thank the Louis Stokes Alliance for Minority Participation for notifying many students, including me, about this opportunity. The two main people I would like to thank are Julie Lappin and Dr. Phalen. Julie was consistently there to answer any questions and make the application process run smoothly. As for Dr. Phalen, he made sure he made time no matter how conflicting schedules were and made sure to train to use any equipment that were unfamiliar. From this I was able to learn new programs, operate equipment and have input for information in my field. This project was supported by a United States Department of Education Grant No. P120A100072-11.

Executive Summary

Data has been observed with the San Bernardino community that is impacted by local air pollution. Data was collected from regional air pollution data instead of local air pollution data. It was shown residents in downwind and near multiple air pollution sources increase in pollution exposure. In order to confirm, data was collected and analyzed in selected areas in San Bernardino through a weather site, in person in selected areas and an air quality website.

Project Objectives

Wunderground, a weather website (www.wunderground.com), was initially used to analyze the average monthly wind speed and direction per location throughout the year. To find the resultant vector of wind direction and speed in multiple destinations in one city, triangulation must be used. This technique allows the use of Physics and Mathematics for a potential STEM focused career pathways. Once resultant direction and speed are found based off the data taken manually, it is entered on the GIS map built. Resultant direction and speed were also compared to an accredited website to AQMIS2.

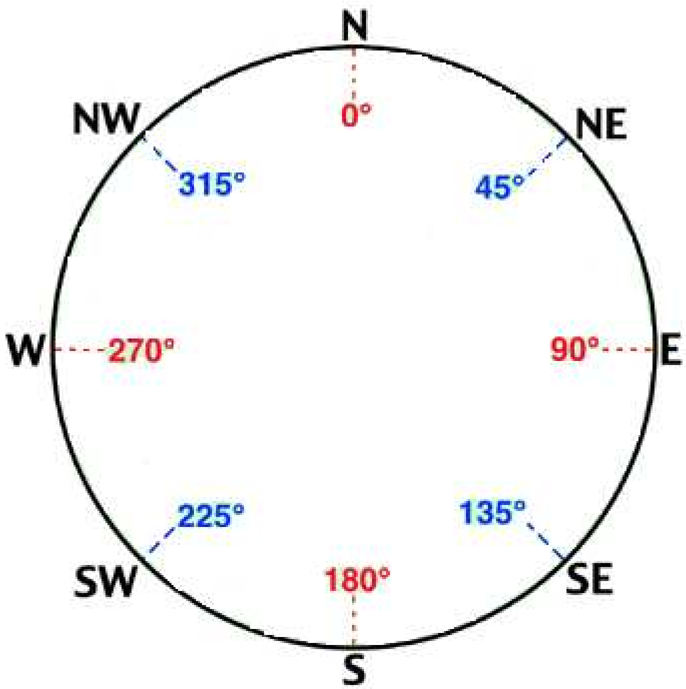
Project Approach

Field Measurements of Wind Speed and Direction

Measurement used to conduct wind speed is a Thermo anemometer Equipment mfg. For wind direction, a handheld compass and a Google Play app *Compass* (https://play.google.com/store/apps/details?id=com.apksoftware.compass&hl=en) were used.

These measurements were different areas in San Bernardino that were alternated to avoid being taken at the same time. When taken, one minute intervals for ten minutes would be collected to not have bias data of any sort.

To find the resultant vector, in this case the resultant wind speed, the compass directions must be converted into degrees (α) using the unit circle. The picture below demonstrates this conversion.



The x and y components are calculated for each wind direction by:

X = β*cos(α) where β is the wind speed and X is the x component

Y = β*sin(α) where Y is the y component

After each x and y components are calculated, the average is then taken for each set of intervals. From there, each average is summed up per destination.

The resultant vector (V) is then calculated as

$V = \mathrm{sqrt}(X^2 + Y^2)$

The x and y components also calculate the resultant wind direction by the equation

$\alpha = \tan^{-1}(\frac{Y}{X})$

The units are in degrees hence why wind direction is equaled to α.

Predicted Average Wind Speed

In order to verify results, AQMIS2's (http://www.arb.ca.gov/aqmis2/map_pages/gmap.php) wind speed data was used. Three of AQMIS2's closest meteorological stations were selected to compare with actual results. Distances were measured by using Google Maps Labs Distance Measurement Tool (https://maps.google.com/maps?hl=en&tab=wl). Distance fraction used is:

$\frac{d_1 * d_2 * d_3}{d_1 + d_2 + d_3}$ where d_1 is first distance, d_2 is second distance and d_3 is third distance

From this equation we can derive speed equation by:

s = d*v where s is the speed with distance, d is the total three distances and v is the speed in m/s from entered data

Finally, the actual wind speed equation can be derived by summing up all of the speed equations:

$S_T = s_1 + s_2 + s_3$ where S_T is the total speed

Predicted Average Wind Direction

Similarly, AQMIS2 is used to retrieve wind direction data. Since AQMIS2 starts counterclockwise a formula is produced for each quadrant to convert to clockwise to compare with data:

Quadrant 1: when $90<\theta$ then $90-\theta$

Quadrant 2: when $91<\theta<180$ then $180-\theta+270$

Quadrant 3: when $181<\theta<270$ then $270-\theta+180$

Quadrant 4: when $271<\theta<360$ then $360-\theta+90$

The corrected wind direction data is then used for deriving an equation with the distance fraction formula. This formula is expressed by:

$F = d*\theta$ where F is the direction of the wind, d is the total three distances and θ is the corrected degrees.

Once each wind direction is calculated, the sum is taken for each set of destinations to give the equation:

$F_T = F_1 + F_2 + F_3$ where F_T is the total of direction of the wind

The sum of the wind directions is used for comparison to the actual wind direction data.

Predicted Vector Sum Wind Speed and Direction

The predicted vector sum wind speeds are similar to average wind speed predictions. For the vector formulas, the x any y components are calculated by:

$X = v*\cos(\Theta)$ where x is denoted for the x component

$Y = v*\sin(\Theta)$ where y is denoted for the y component

After each x and y components are calculated, the average is then taken for each set of intervals. From there, each average is summed up per destination.

Project Outcomes

Wind Speed

A summary of actual (measured) wind speed and predicted wind speed data are shown in Table 1. Paired t-tests were conducted on the data. Based on these tests, the predicted wind speeds were about double the actual speed ($p \leq 0.05$). The predicted average wind speed was 140% higher than the actual wind speed, and the predicted vector sum wind speed was 110% higher than the actual wind speed. The Spearman's rank order correlation coefficient (rho) for actual and predicted wind speed data are presented in Table 2. The rules for interpreting the strength of the correlation are as follows: little to no association if rho ≤ 0.39, weak to moderate association if 0.4 ≤ rho ≤ 0.69, strong association if rho ≥ 0.7. There was a strong association between actual wind speed and both the predicted average (rho = 0.70; $p > 0.05$) and vector sum (rho = 0.66; $p > 0.05$) wind speeds.

Table 1. Descriptive data for wind speed

	Mean (m/s^2)	Standard Deviation (m/s^2)	Coefficient of Variation (%)	Sample Size (N)
Actual speed	1.5	1.1	76.5	30
Predicted based on average	3.6	2.3	65.4	30
Predicted based on vector sum	3.2	2.6	78.8	30

Table 2. Spearman's correlation for wind speed

	rho	*p*-value
Predicted average	0.70	< 0.001
Predicted vector sum	0.66	< 0.001

Figure 1. Actual Versus Average Predicted Wind Speed

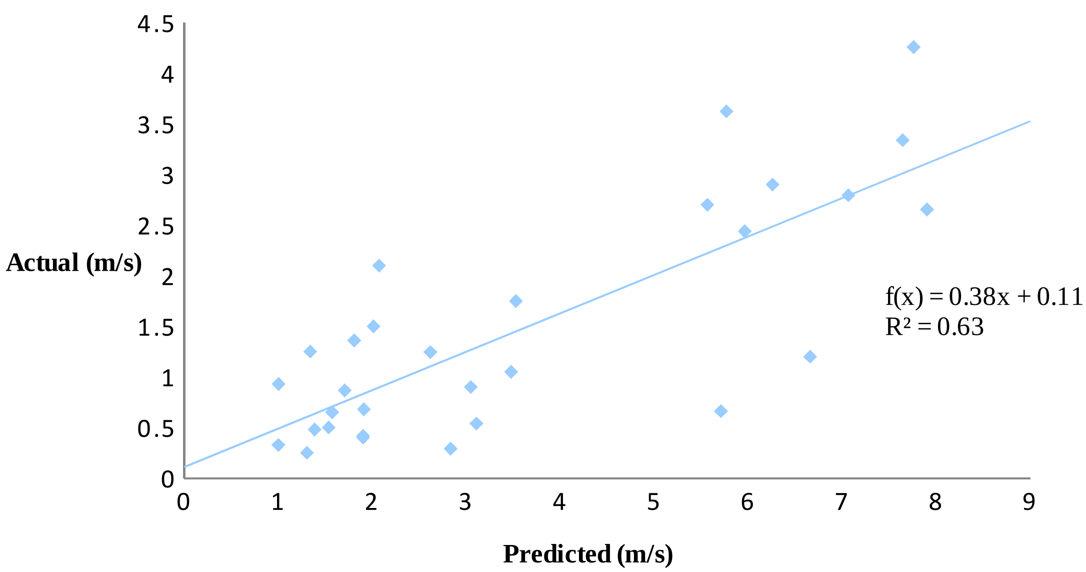
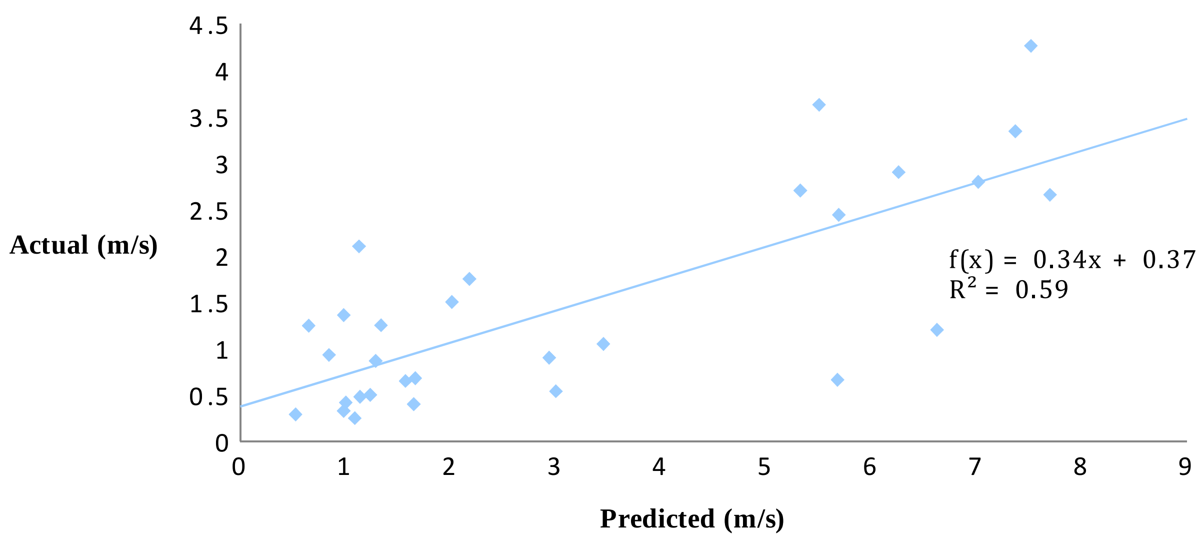


Figure 2. Actual Versus Vector Predicted Wind Speed



Wind Direction

A summary of actual wind direction and predicted wind direction data are presented in Table 3. As with wind speed, paired t-tests were conducted on the data. Based on these tests, the predicted wind directions were not significantly different from the actual direction ($p > 0.05$). Both the average and vector sum predictions were similar to the measured location wind directions.

Table 3. Descriptive data for wind direction

	Mean (degrees)	Standard Deviation (degrees)	Coefficient of Variation (%)	Sample Size (N)
Actual direction	196	91	47	30
Predicted based on average	143	94	65	30
Predicted based on vector sum	175	118	68	30

The Spearman's rank order correlation coefficient (rho) for actual and predicted wind direction data are presented in Table 4. There was little to no association between actual wind direction and both the predicted average (rho = -0.39; $p > 0.05$) and vector sum (rho = -0.48; $p \leq 0.05$) wind directions.

Table 4. Spearman's correlation for wind direction

	rho	*p*-value
Predicted average	-0.39	0.031
Predicted vector sum	-0.48	0.007

Figure 3. Actual Versus Average Predicted Wind Direction

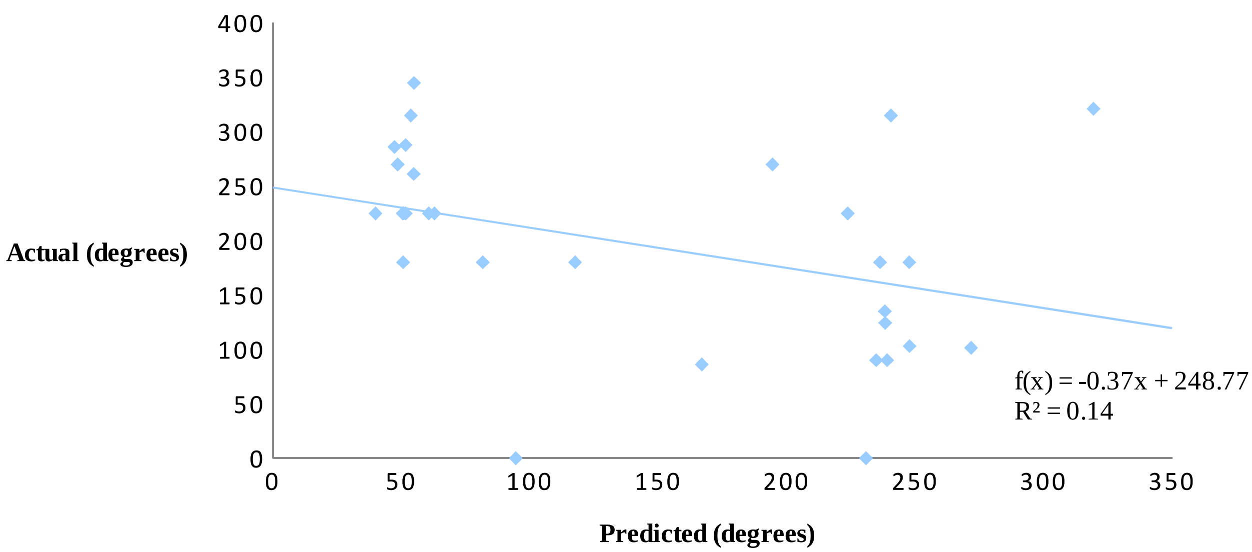
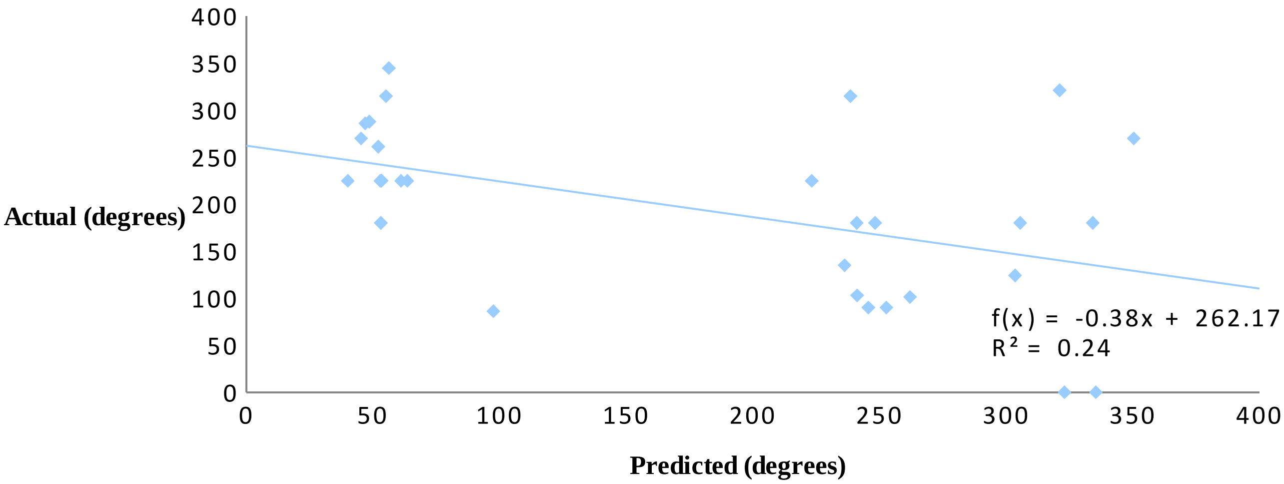


Figure 4. Actual Versus Vector Predicted Wind Direction



The linear regression plots for actual wind direction versus predicted wind direction data are shown in Figures 3 and 4. The Pearson correlation coefficient (r) was 0.38 ($p \leq 0.05$) for the predicted average wind direction and 0.49 ($p \leq 0.05$) for the predicted vector sum wind direction. These results were consistent with the Spearman's correlation coefficients of -0.39 and -0.48, respectively. As discussed earlier. The Spearman's correlation coefficients were preferred measures of association in this study. The plots in Figures 1-4 were provided for visual representation of the associations.

Conclusions

Wind data speeds have been shown to be successfully correlated. However, wind data direction is still in need of improvement. Further research of possibly finding better methods or equipment would improve finding an accurate average direction. Once the wind data directions have a strong correlation, then the correlation between areas with high air pollution and the travel of pollution from factories can be analyzed. Just from the research that was accomplished in this time period, an application of mathematics and physics was able to be seen and worked with using programs companies would use on a day to day basis.