Demonstration of Long-Term Representativeness of On-Site Meteorological Data

Jackpile-Paguate Uranium Mine

January 2020

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Background

The purpose of this report is to evaluate the long-term representativeness of a single baseline year of meteorological monitoring at the Jackpile-Paguate uranium mine near Laguna, New Mexico. In particular, it is useful to know whether hourly average wind patterns measured from December, 2018 through November, 2019 are typical of the longer term. The approach uses hourly wind data from a nearby reference site, the Grants-Milan Municipal Airport (Grants), approximately 30 miles away. These data are analyzed to ascertain the relationship between wind speed, wind direction, and joint frequency distributions during the baseline year identified above and during a longer period of record (15 years). This report summarizes the application of multiple statistical tests to the comparison of these short and long-term wind data at Grants. The report documents and evaluates these alternative tests for their appropriateness in comparing meteorological frequency distributions. The analytical methods employed include graphical comparisons, summary statistics, the chi-square test, and linear regression analysis.

Data Sources

Hourly meteorological data have been collected at the Jackpile-Paguate site from October, 2018 to the present. For the purposes of this analysis, the baseline year extends from December 1, 2018 through November 30, 2019. For comparing long-term meteorological conditions to short-term conditions, hourly data from Grants, New Mexico (NOAA 2020) were used. Grants was selected as the reference site due to several factors:

1. Proximity to the Jackpile-Paguate site (50 kilometers to the west), similar elevation and similar terrain
2. Longest period of record within a 50-kilometer radius, with 15 years of continuous hourly data available in electronic form
3. Instruments meet National Weather Service standards; compliant with EPA's Meteorological Monitoring Guidance for Regulatory Modeling Applications (EPA 2000)

Laguna, New Mexico is approximately 7 miles south of the Jackpile-Paguate site. Meteorological data from Laguna were also evaluated for possible use in this demonstration. However, since the weather station does not meet EPA guidelines and the hourly data do not meet quality assurance criteria, this dataset was not used.

The short-term period at Grants is synchronous with the baseline monitoring year at the Jackpile-Paguate site, from December 1, 2018 through November 30, 2019. The long-term period is defined as 2005 through 2019, or 15 calendar years. The short-term, or baseline period is entirely contained within the long-term data set. These overlapping time periods do not significantly compromise sample independence since the baseline period represents only 7% of the long term. Hourly wind speed and wind direction are categorized to form short and long-term frequency distributions. Wind speeds are divided into 6 classes (according to Nuclear Regulatory Commission guidance) plus a 7th calm class; wind directions are divided into 16 classes (16 cardinal directions) plus a 17th calm class. Together these classification schemes correspond directly to the joint frequency distribution. The statistical tests enumerated above, are employed to determine if there is a significant difference between the short and long-term distributions of classified Grants data.

Hourly electronic data are available for Grants from as early as 1990 (30 years) and the entire period of record extends back to 1948, but there are many gaps as well as sub-hourly data in the earlier record. The most recent 15 years of continuous hourly data are deemed appropriate to represent long-term meteorological data. Others have noted the risks of using too long a period of record (POR). In particular, a publication from the U.S. Air Force Climatology Center (Coffin 1996) states, “As the POR expands, maintaining homogeneity of the data becomes more difficult. Climatological statistics obtained from too long a period may not be representative of contemporary conditions.” The authors cite Panofsky and Brier, who claim that a mean based on 15 years of data gives the best estimate for next year’s mean and is therefore preferable to a climatic normal based on more than 15 years.

Graphical Methods

Histograms, scatterplots and wind roses provide a visual demonstration of the similarities between short and long-term meteorological data at the Grants weather station. Figure 1 compares the 1-year (baseline) and 15-year wind frequency distributions. It can be seen that both wind speed and wind direction frequencies are distributed similarly over the two time periods.

Figure 1 – Grants Long-Term and Short-Term Wind Frequency Distributions

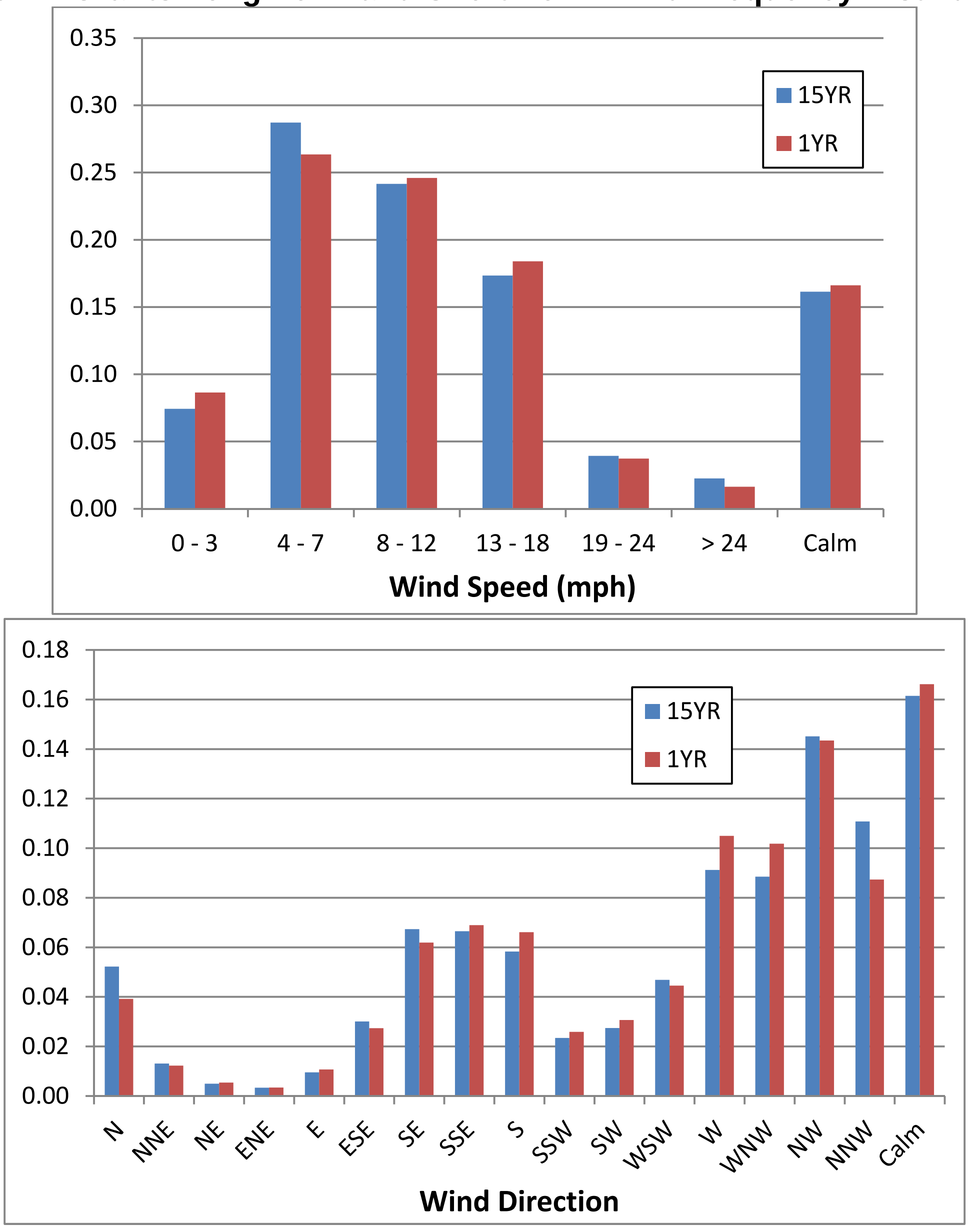
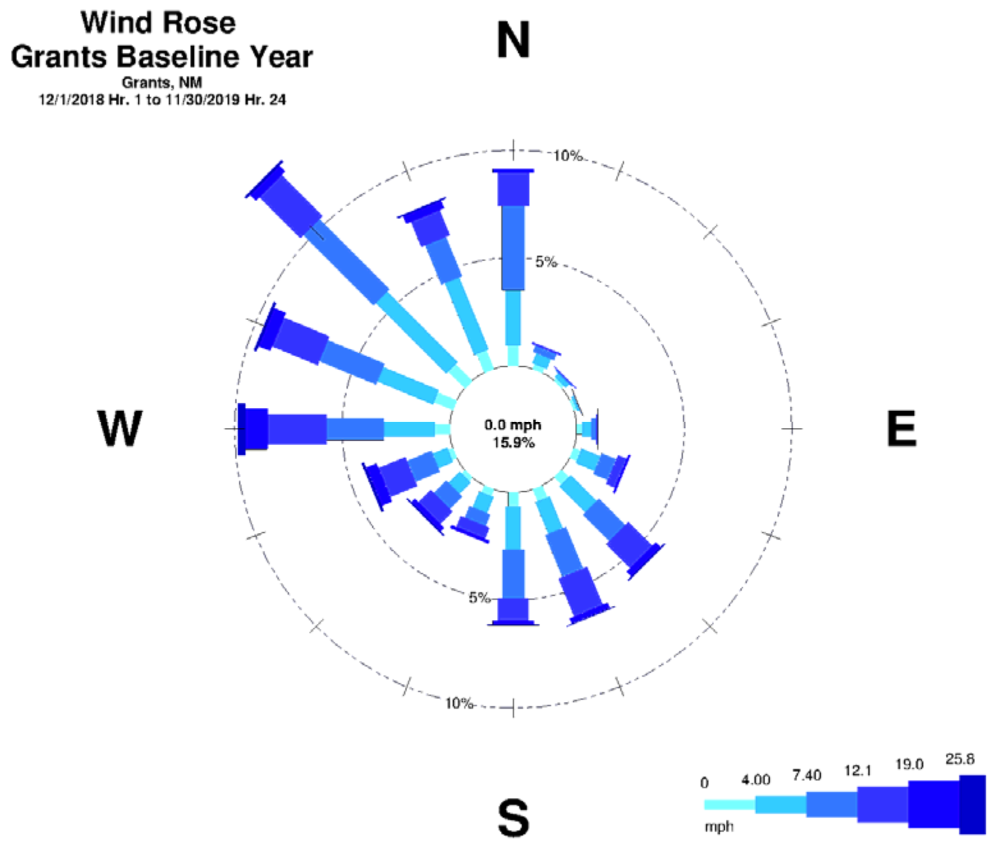


Figure 2 shows the wind roses from Grants for the same periods. The wind rose provides a polar graph of the joint distribution of wind speed and wind direction frequencies.

Figure 2 – Grants Short-Term and Long -Term Wind Roses



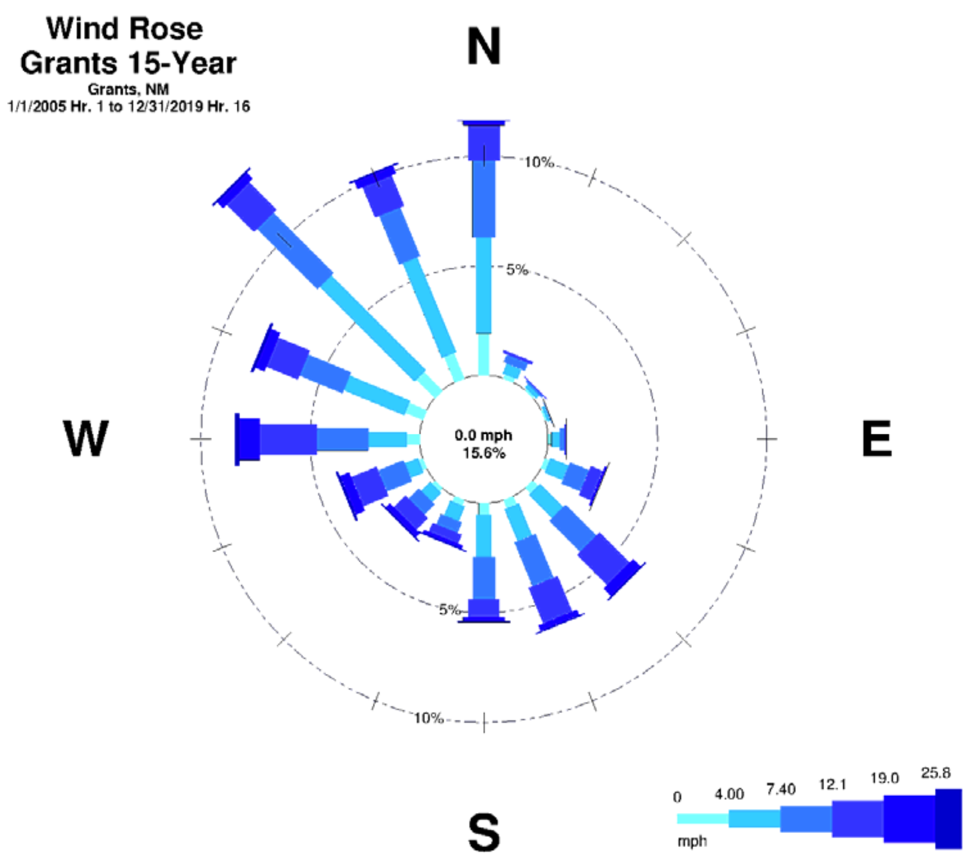


Figure 3 graphs the short-term vs. long-term wind frequencies, demonstrating close correlation between the two wind speed distributions and between the two wind direction distributions. In this instance, the right-most point on the wind speed graph corresponds to the 4-7 mph category, which accounts for 26.4% of the hourly wind speeds for the baseline year (y-axis), and 28.7% of the hourly wind speeds over the last 15 years (x-axis). The other points correspond to the remaining 6 wind speed categories. The wind direction graph plots the 17 direction categories in similar fashion.

Figure 3 – Grants Long-Term and Short-Term Wind Speed and Direction Scatterplots

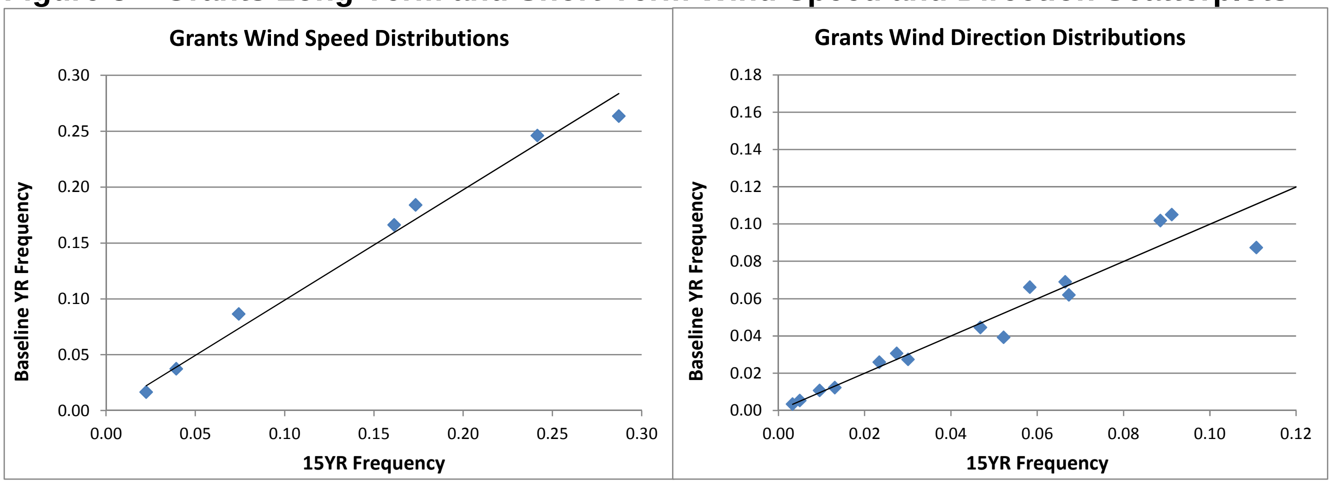
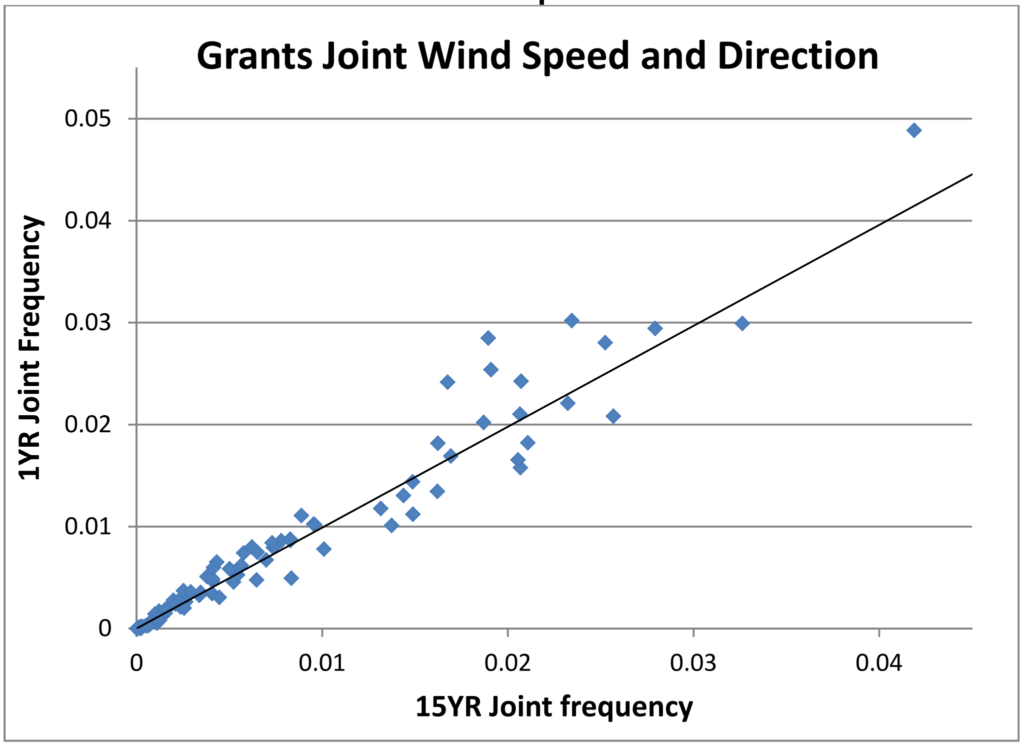


Figure 4 graphs the short-term vs. long-term joint wind speed and direction frequencies, once again demonstrating close correlation between the two periods for each of the 97 joint categories. Figure 4 substantiates the similarity between wind roses in Figure 2.

Figure 4 – Grants Long-Term and Short-Term Joint Wind Speed and Direction Scatterplot



Summary Statistics

Table 1 shows the average wind speed and unit-vector averaged wind direction for the 15-year monitoring period and for the 1-year baseline period. For wind speed, the baseline year mean is less than one standard deviation from the long-term mean. For wind direction, this difference is nearly two standard deviations, but both periods exhibit a northwesterly average.

Table 1 – Grants Wind Speed and Direction Summary Statistics

Statistic	Average Wind Speed (mph)	Vector Average Wind Direction (°)
2005 through 2019 Mean	8.0	316.0
Baseline Year	8.2	324.7
2005-2019 Standard Deviation of Yearly Means	0.4	4.9

Application of the Chi-Square (χ^2) Test

The χ^2 test can be used in meteorology to evaluate the null hypothesis (H_0) that two frequency distributions are similar (Lowther 1991). It is particularly useful in testing the similarity of frequency distributions of two or more sets of meteorological observations

(Brooks 1978). The χ^2 test has some limitations when applied to frequency distributions derived from large samples. It is useful to convert relative frequencies to equivalent annual hours, then adjust the χ^2 value for large sample size by means of the phi coefficient (Lowther 1991). The phi coefficient for *n* total observations is calculated as:

$$\emptyset = \sqrt{\frac{\chi^2}{n}}$$

In this analysis, the χ^2 test regards long-term values as the expected hourly counts per year, and short-term (baseline period) values as the observed counts per year. Table 2 shows the resulting analysis of wind speeds at Grants. The calculated χ^2 value of 57.52 is more than the 95% confidence statistic for 6 degrees of freedom (12.59). Thus, for this sample size (8,760) we reject H_0, which states that the short-term wind speed distribution comes from the same population as (i.e., is representative of) the long-term distribution. However, due to the liabilities of the Chi-Square test in treating large samples, we compute the phi coefficient, which adjusts the χ^2 result for large sample sizes, yielding 0.08. This infers similarity between the two wind speed distributions. An analysis of categorized cloud cover by the U.S. Air Force established a critical phi coefficient of 0.20, below which "a large degree of similarity" between distributions is indicated (Lowther 1991). Note that the minimum annual count of 144 (calm category) is larger than the minimum recommended by NRC (NRC 2011) for a valid χ^2 test. NUREG-1475 states that no expected count should be smaller than 2 for any class.

Table 2 – χ^2 Test for Annualized Wind Speed Distributions

Wind Speeds - Grants LT/ST Frequency x 8,760				
mph	15yr WS	1Yr WS	$(LT-ST)^2/LT$	Chi-Square
0 - 3	651	757	17.207	57.52
4 - 7	2516	2308	17.085	$\chi^2_{0.95}(6) = 12.59$
8 - 12	2117	2156	0.706	**Reject H_o**
13 - 18	1519	1612	5.649	p-value = 0.000
19 - 24	345	327	0.880	Min Count = 198
> 24	198	144	14.773	Phi-value = 0.08
Calm	1414	1456	1.224	**Adj: Do Not Reject**

Table 3 shows a similar test for 15-year vs. 1-year wind directions at Grants. The calculated χ^2 value of 133.49 is more than the 95% confidence statistic for 16 degrees of freedom (26.30), so we initially reject the null hypothesis (H_0) that the short-term wind direction distribution comes from the same population as the long-term distribution. The resulting phi coefficient of 0.12, however, suggests a strong similarity between the two wind direction distributions. As with wind speeds, the minimum annual count of 29 (ENE category) is sufficient for a valid χ^2 test.

If the wind direction frequencies are multiplied by 500 rather than by 8,760, the χ^2 test in Table 3 produces a different outcome (Table 4). The scaling factor of 500 was chosen to meet a minimum count requirement of 2. In this case the calculated χ^2 value of 7.62 is less than the critical value, so we cannot reject H_0 with 95% confidence. As others have noted, the χ^2 test is sensitive to large sample sizes. In a smaller sample the differences would not be enough to be statistically significant. Dealing with a large number of observations, Hessen, Dolan, and Wicherts noted that χ^2 values are inflated by large total sample sizes rendering the test results "of little use" under these circumstances (Hessen 2006). A statistical text (Sharpe 2012) warns: "Beware large samples! With a sufficiently large sample size, a chi-square test can always reject the null hypothesis." The phi coefficient removes this sensitivity. Values [of phi] close to zero indicate the distributions are nearly identical, while those approaching either 1 or -1 are significantly distinct. A phi coefficient less than or equal to 0.20, implies "a large degree of similarity in the two distributions" (Lowther 1991). Though the χ^2 statistics are different, a sample size of 500 (Table 4) and a sample size of 8,760 (Table 3) both yield the same phi coefficient of 0.12. Neither version of the test ultimately provides sufficient evidence to reject H_0, so we cannot conclude the frequencies are different.

Table 3 – χ^2 Test for Annual Wind Direction Distributions

Wind Directions - Grants LT/ST Frequency x 8,760				
Direction	15yr WD	1Yr WD	$(LT-ST)^2/LT$	Chi-Square
N	457	343	28.452	133.49
NNE	114	107	0.428	$\chi^2_{0.95}(16) = 26.30$
NE	44	47	0.293	**Reject H_o**
ENE	29	30	0.018	p-value = 0.000
E	84	94	1.208	Min Count = 29
ESE	263	240	2.131	Phi-value = 0.12
SE	590	542	3.815	**Adj: Do Not Reject**
SSE	583	604	0.764	
S	510	579	9.163	
SSW	205	226	2.225	
SW	240	269	3.335	
WSW	410	390	1.006	
W	799	920	18.289	
WNW	775	892	17.485	
NW	1271	1257	0.164	
NNW	971	765	43.492	
Calm	1414	1456	1.224	

The same demonstration can be made for wind speed distributions by multiplying the wind speed frequencies by 500 instead of 8,760. The resulting phi-coefficient is still 0.08 as in Table 2.

Table 4 – χ^2 Test for Smaller Scaling Factor

Wind Directions - Grants LT/ST Frequency x 500				
Direction	15yr WD	1Yr WD	$(LT-ST)^2/LT$	Chi-Square
N	26	20	1.624	7.62
NNE	7	6	0.024	$\chi^2_{0.95}(16) = 26.30$
NE	2	3	0.017	**Can't reject H_o**
ENE	2	2	0.001	p-value = 0.959
E	5	5	0.069	Min Count = 2
ESE	15	14	0.122	Phi-value = 0.12
SE	34	31	0.218	**Adj: Confirm**
SSE	33	34	0.044	
S	29	33	0.523	
SSW	12	13	0.127	
SW	14	15	0.190	
WSW	23	22	0.057	
W	46	52	1.044	
WNW	44	51	0.998	
NW	73	72	0.009	
NNW	55	44	2.482	
Calm	81	83	0.070	

The χ^2 test results above indicate insufficient evidence to infer a statistical difference between short and long-term wind speed and wind direction distributions. This is not always the case. Even when corrected for large samples, the χ^2 test generally infers a significant difference between wind frequency distributions from different sites.

Application of Linear Correlation and Linear Regression

The following discussion combines linear correlation and regression since they yield closely related statistics. Under the assumptions applied to wind frequency distributions the Pearson's correlation coefficient R is equal, or very nearly equal to the square root of the linear regression coefficient of determination R^2. While linear regression has not been commonly employed to demonstrate the degree of similarity between two meteorological frequency distributions, linear correlation coefficients have (Coffin 1996). Using either approach to assess a linear association between two relative frequency distributions is indicated, since their component frequencies each sum to 1. If two such distributions are similar, they will necessarily be linearly associated and the scatterplot of their frequencies will cluster around the identity line.

A correlation coefficient is merely a mathematical expression of the "correspondence" between two distributions (Brooks 1978). In the present application, the short and long-term data distributions both approximate a third variable, the true long-term distribution. If any two relative frequency distributions of a categorized meteorological parameter are linearly correlated, they are also substantially equivalent since the frequencies sum to 1 for both distributions. And if they are equivalent, then either they both represent the true long term distribution, or neither does. As indicated above, 15 years inherently represent the long term.

Two refinements to the regression analyses apply to the comparison of the baseline year to the long term at Grants:

1. Adopting the convention of assigning long-term frequencies to the independent variable. This is consistent with assigning the dependent variable to the unknown or most uncertain of the two (Brooks 1978). But because both variables are measurements with nonparametric distributions of roughly equal variances, reversing this assignment will also work.
2. Forcing the regression line to pass through the origin (zero intercept) in recognition of the fact that two relative frequency data sets that each sum to 1 cannot exhibit a systematic bias. If a zero intercept is enforced, the slope of the regression line approaches unity as the linear relationship approaches equality.

Figure 5 illustrates the linear association between short and long-term wind speed frequencies at Grants. The hourly data for each distribution fall into one of 7 categories. The graph illustrates the degree to which the 1-year frequencies match the 15-year frequencies. The R^2 value of 0.985 confirms a very strong linear relationship, and the slope of 0.988 indicates substantial equivalence between short and long-term frequencies. A p-value of zero establishes a near-100% confidence level that this relationship is significant.

Figure 5 – Grants Short and Long-Term Wind Speed Frequency Distributions

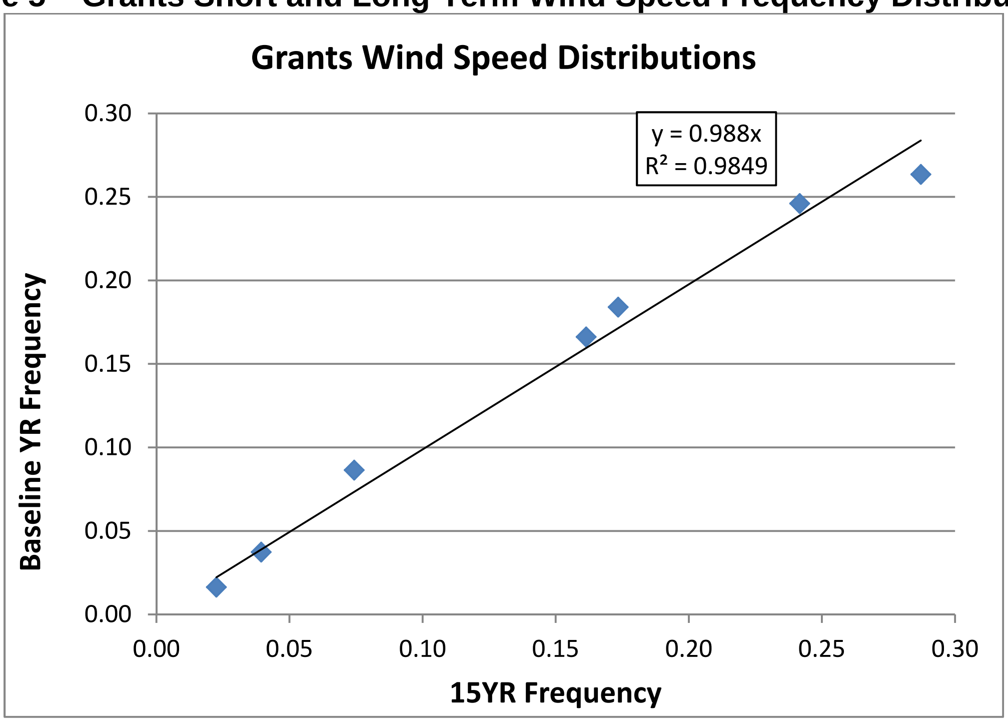
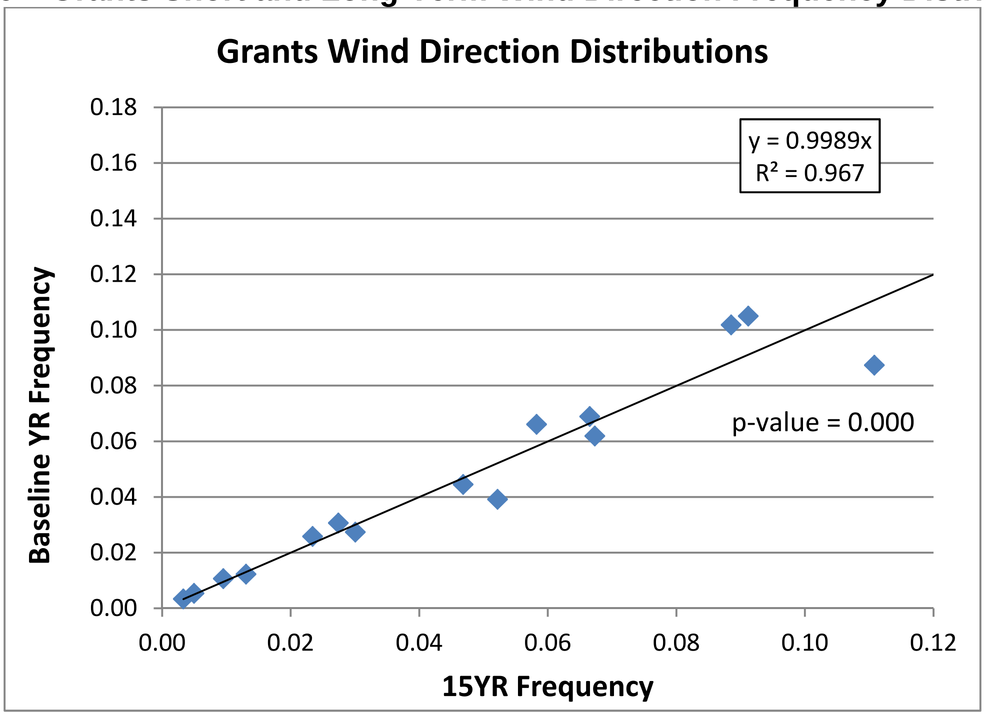


Figure 6 illustrates the linear association between short and long-term wind direction frequencies at Grants. The hourly data for each distribution fall into one of 17 categories (16 cardinal directions plus calm). The graph illustrates the degree to which the 1-year frequencies match the 15-year frequencies. The R^2 value of 0.967 confirms a very strong linear relationship, and the slope of 0.999 indicates substantial equivalence between short and long-term frequencies. A p-value of zero leaves little doubt that this relationship is significant.

Figure 6 – Grants Short and Long-Term Wind Direction Frequency Distributions

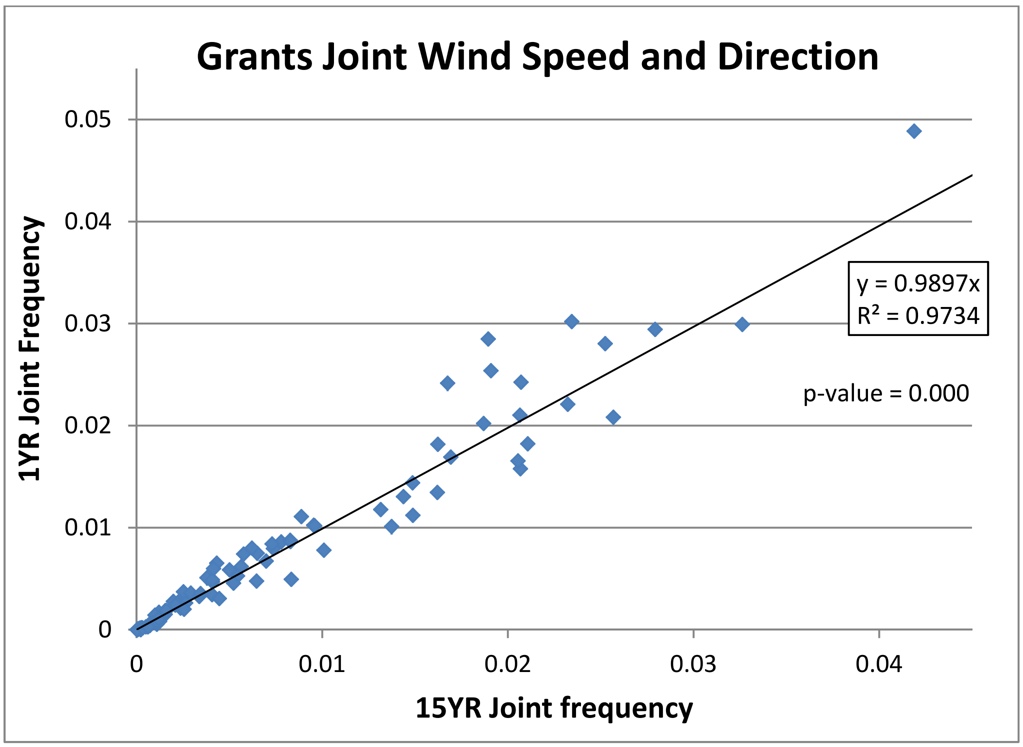


The wind roses in Figure 2 provide a graphical representation of joint wind speed and wind direction distributions. This two-way wind classification categorizes hourly wind data by both speed and direction. Hypothesis testing is generally unworkable in comparing joint wind speed and direction frequencies because the wind data are partitioned into too many categories. In general, the number of categories in hypothesis testing should not exceed $5*\log_{10}(N)$, where N is the sample size (Brooks 1978). For a one-year sample of hourly averages (N = 8,760) the maximum number of categories would be 20. This limit is consistent with 7 wind speed classes or 17 wind directions, but not with 97 joint frequency categories. Therefore the χ^2 test is not appropriate for evaluating similarities between joint frequency distributions.

Joint wind speed and direction distributions are amenable to linear regression or correlation analysis. Examining these two-way distributions can strengthen the case for long-term representativeness of baseline wind data. The joint analysis offers a more rigorous comparison between short and long-term wind frequency distributions, than individual speed and direction analyses by themselves. This comparison also offers the best quantitative measure of the similarity between the associated wind roses (see Figure 2).

Figure 7 shows the linear relationship between short and long-term joint frequencies at Grants. The hourly data for each distribution fall into one of 97 categories. The graph illustrates the degree to which the 1-year joint frequencies match the 15-year frequencies. The R^2 value of 0.973 confirms a very strong linear relationship, and the slope of 0.990 indicates substantial equivalence between short and long-term frequencies. A p-value of zero leaves little doubt that this relationship is significant.

Figure 7 – Grants Short and Long-Term Joint Frequency Distributions



Linear regression also isolates the sources of variation among category frequencies. When multiplied by 100, R^2 signifies the percent of the departure from a mean frequency that is common to both short and long-term distributions. In Figure 7, for example, 97.3% of the variation among 1-year joint frequencies can be predicted based on measured long-term frequencies, while only 2.7% is attributed to random, year-to-year fluctuations and/or measurement error.

Linear correlation produces Pearson's correlation coefficient R, based on the assumption of normally distributed data. Wind speed and direction distributions at Grants are roughly normal. The normality assumption can be relaxed, however, by ranking the data and computing Spearman's correlation coefficient, a method commonly applied to nonparametric data. A value of 1.000 for either coefficient reflects a perfect correlation. The Grants wind speed comparison yields a Pearson's R of 0.993 and a Spearman's R of 1.000. The Grants wind direction comparison yields a Pearson's R of 0.983 and a Spearman's R of 0.980. Therefore, the assumption of normally distributed data does not compromise the results.

Conclusion

The combination of visual evidence, summary statistics, linear correlation and hypothesis testing provides a comprehensive demonstration of long-term representativeness of baseline meteorological data at the Jackpile-Paguate site. For the nearby Grants site, the baseline-year, hourly wind data are statistically no different than the most recent 15 years of data. This conclusion is supported by graphical analyses and by two statistical tests, which have been jointly applied by others to categorize meteorological data (Lowther 1991):

1. χ^2 test (with the phi coefficient to adjust for large sample size)
2. Linear correlation coefficient R (or regression coefficient of determination R^2)

Table 5 summarizes the test results for the Grants site. For wind speed, wind direction, and joint frequency distributions, all relevant statistical tests infer the absence of a significant difference between short and long term data.

Table 5 – Summary of Statistical Analysis of Frequency Distributions at Grants

15-Yr vs. 1-Yr Frequency Distributions	Statistical Method						Overall Conclusion
	χ^2 at 8,760 hrs.	Ø-Coeff.	χ^2 at 500 hrs.	Ø-Coeff.	Linear Regress. R^2	p-value for R^2	
Wind Speed	58	0.08	3.3	0.08	0.98	0.000	No statistical difference
Wind Direction	133	0.12	7.6	0.12	0.97	0.000	No statistical difference
Joint Wind Speed and Wind Direction	N/A	N/A	N/A	N/A	0.97	0.000	No statistical difference

The χ^2 test gives a yes/no answer: either the computed statistic results in 95% confidence in a significant difference, or it does not. Linear regression supplies the best measure of the *degree* of similarity between short-term and long-term wind speed and wind direction distributions. Moreover, it is uniquely suited to testing joint wind speed and direction frequencies due to the large number of categories.

Grants is considered representative of the Jackpile-Paguate site due to its proximity, similar elevation, and comparable terrain. While local terrain features produce slightly different wind patterns between the two sites, it is reasonable to conclude that since the baseline year at

Grants exhibited wind characteristics very similar to the longer term, the same would hold true for the Jackpile-Paguate site. Both sites are susceptible to the same regional climatological factors from year to year, and it has been demonstrated above that during the baseline year those factors differed very little from the most recent 15-year period.

References

Brooks 1978, Handbook of Statistical Methods in Meteorology, C. E. P. Brooks and N. Carruthers, Reprint of 1953 Edition, 1978.

Coffin 1996, Consolidated Statistical Background Papers, U.S. Air Force Climatology Center, Charles R. Coffin, November 1996

EPA 2000, Meteorological Monitoring Guidance for Regulatory Modeling Applications, EPA-454/R-99-005, February 2000

Gardiner 1979, Analysis of Frequency Distributions, Concepts and Techniques in Modern Geography, V. Gardiner & G. Gardiner, 1979.

Hessen 2006, The Multigroup Common Factor Model With Minimal Uniqueness Constraints and the Power to Detect Uniform Bias, Applied Psychological Measurement, Vol. 30 No 3, Hessen, D. J., Dolan, C. V., and Wicherts, J. M., May 2006.

NOAA 2020, Meteorological Database for Grants, New Mexico, Data Tools: Local Climatological Data (LCD), National Oceanic and Atmospheric Administration, Accessed January 2020.

Lowther 1991, RTNEPH Total Cloud Cover Validation Study, Capt. Ronald P. Lowther, Mr. Mark T. Surmeier, Capt. Richard W. Hartman, Mr. Charles R. Coffin, Capt. Anthony J. Warren, November 1991.

Sharpe 2012, Business Statistics Second Edition, Chapter 15, Inference for Counts: Chi-Square Tests, Sharpe, DeVeaux and Velleman, 2012.

Lowther 1991, RTNEPH Total Cloud Cover Validation Study, Capt. Ronald P. Lowther, Mr. Mark T. Surmeier, Capt. Richard W. Hartman, Mr. Charles R. Coffin, Capt. Anthony J. Warren, November 1991.