

**Demonstration of Long-Term Representativeness of On-Site
Meteorological Data
Ross In-Situ Uranium Recovery Project**

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Background

In a recent evaluation report (NRC 2014), NRC provided Strata with additional guidance in meeting the requirement to demonstrate that the short-term data from the Ross ISR Project are representative of long-term trends pursuant to the acceptance criterion in NUREG-1569 and Regulatory Guide 3.63. The report states, “The NRC staff finds the linear regression analysis performed by Strata demonstrated that a linear relationship existed between the data sets. However, while NRC Staff found the linear regression analysis acceptable in the SER (NRC, 2013;2014), the NRC staff has determined subsequently that neither linear regression nor correlation analyses are appropriate statistical tests for representativeness of data sets. While linear regression and correlation analyses describe relationships between variables, a statistical test for representativeness requires an analysis of data populations (e.g., short- and long-term wind data at a given site).”

“Acceptable statistical methods to be used to substantiate representativeness are not addressed in RG 3.63 (NRC, 1988). The NRC staff finds the following statistical approaches acceptable: 1) testing summary statistics, such as the mean from the short- and long-term data (see, for example, Chapter 5 of Brooks and Carruthers, 1953), and 2) testing the statistics for similarity or validity of the data by using a statistical method such as the Student's T test, Chi square test for distribution, Kolmogorov-Smirnov test for distribution, etc., as appropriate (see, for example, Chapter 12 of NRC, 2011). Strata has not provided such tests; therefore, the NRC staff is requiring Strata to substantiate that the short-term meteorological data used for assessing impacts are representative of long-term conditions at or near the project by including a license condition to Strata’s operating license.”

In response to NRC’s latest requirement, this report applies alternative statistical tests to the comparison of short and long-term, hourly wind and atmospheric stability data at a representative site. Appendix A of this report documents and evaluates these alternative tests for their appropriateness in comparing meteorological frequency distributions. They include the chi-square test, the Student’s t-test, and the Kolmogorov-Smirnov test. Appendix A presents a case study based on three sites with available long-term meteorological data. This allows temporal comparisons for each site, as well as inter-site comparisons to assess how well each statistical test discriminates between visually similar and dissimilar frequency distributions. Also included in Appendix A is an in-depth discussion of the role that graphical methods, linear correlation and regression analysis can play in strengthening the required demonstration.

Data Sources

Strata Energy has collected over four years of hourly meteorological data at its Ross ISR Project site (IML 2014a). For the purposes of this analysis, the four-year period is treated as the baseline period. For comparing long-term meteorological conditions to short-term conditions, hourly data from the Eagle Butte Mine (IML 2014b) were used. Eagle Butte was selected due to several factors:

1. Proximity to the Ross site (30 miles to the west), similar elevation and similar rolling terrain
2. Longest period of record within a 50-mile radius, with hourly data available in electronic form
3. Highest data recovery within a 50-mile radius, for the entire period of record (98.5% recovery for joint wind speed and wind direction)
4. Low instrument thresholds and high data resolution compared to National Weather Service stations; complies with EPA’s Meteorological Monitoring Guidance for Regulatory Modeling Applications (EPA 2000)

Other sites considered for this analysis include the Dry Fork Mine, the Buckskin Mine and the Gillette airport. All three are located roughly 25 to 30 miles west of the Ross site. Meteorological data recovery at the Dry Fork Mine was lower than at Eagle Butte. The meteorological station at the Buckskin Mine was moved several miles in 2006, resulting in a shift in wind patterns due to topographic differences between the old and new sites. The NWS weather station at Gillette has only 15 years of electronic data, and wind direction resolution is extremely coarse at 10°. Since each of the 16 wind direction classes spans 22.5°, the categorization of wind direction data from Gillette is subject to considerable discretization error.

The short-term period is defined as 2010 through 2013 (coincident with the Ross data), and the long-term period is defined as 1995 through 2009. These non-overlapping time periods assure sample independence. Hourly wind speed, wind direction and atmospheric stability class data are categorized to form short and long-term frequency distributions. Wind speeds are divided into 6 classes (plus a 7th calm class), wind directions are divided into 16 classes (plus a 17th calm class), and atmospheric stability is divided into 6 classes. All three classification schemes correspond directly to the MILDOS STAR 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 Eagle Butte data.

Appendix A discusses why 15 to 20 years are appropriate to represent long-term meteorological data, and documents 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.”

Graphical Methods

Histograms, scatterplots and wind roses provide a visual demonstration of the similarities between short and long-term meteorological data at the Eagle Butte Mine (EBM). Figure 1 compares the 4-year (2010-2013) and 15-year (1995-2009) 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 – EBM Long-Term and Short-Term Wind Frequency Distributions

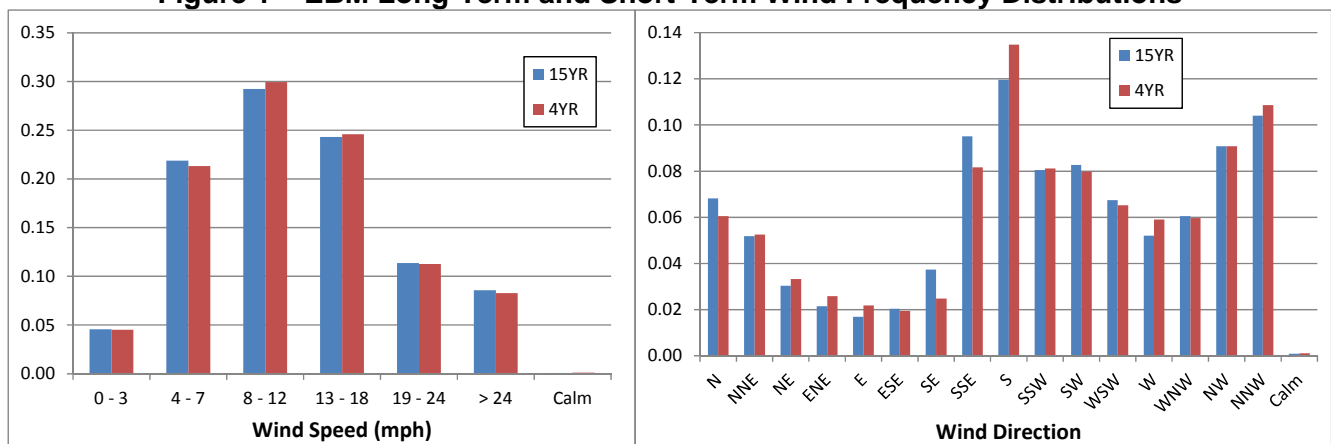


Figure 2 shows the wind roses from Eagle Butte for the same periods. The wind rose provides a polar graph of the joint distribution of wind speed and wind direction frequencies.

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

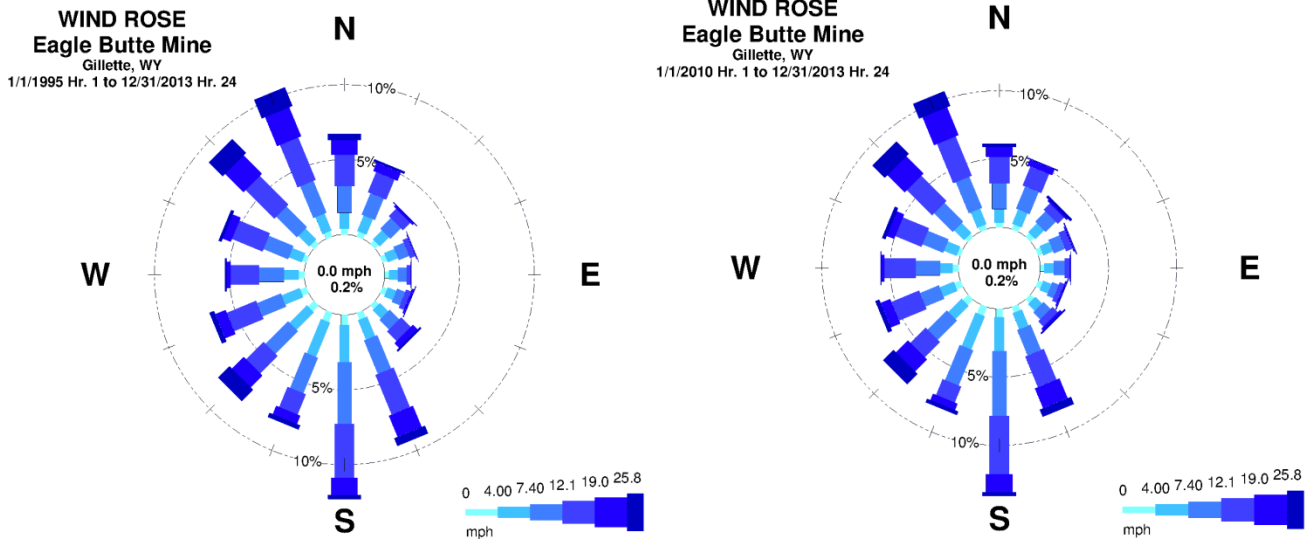


Figure 3 graphs the short-term vs. long-term wind frequencies, demonstrating close correlation between the two wind speed distributions and between the two wind direction distributions. In this instance, the right-most point on the wind speed graph corresponds to the 8-12 mph category, which accounts for 29.9% of the hourly wind speeds from 2010 through 2013 (y-axis), and 29.2% of the hourly wind speeds over the previous 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 – EBM Long-Term and Short-Term Wind Speed and Direction Scatterplots

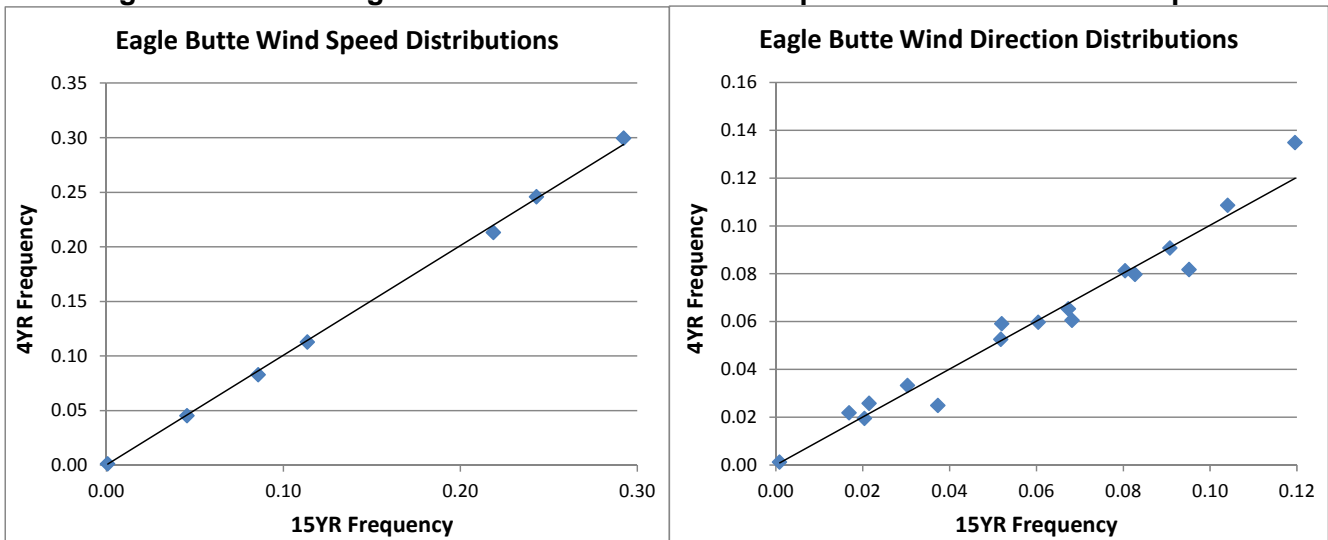


Figure 4 graphs the short-term vs. long-term joint wind speed and direction frequencies, once again demonstrating close correlation between the two periods for each of the 97 joint categories. Figure 4 substantiates the similarity between wind roses in Figure 2.

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

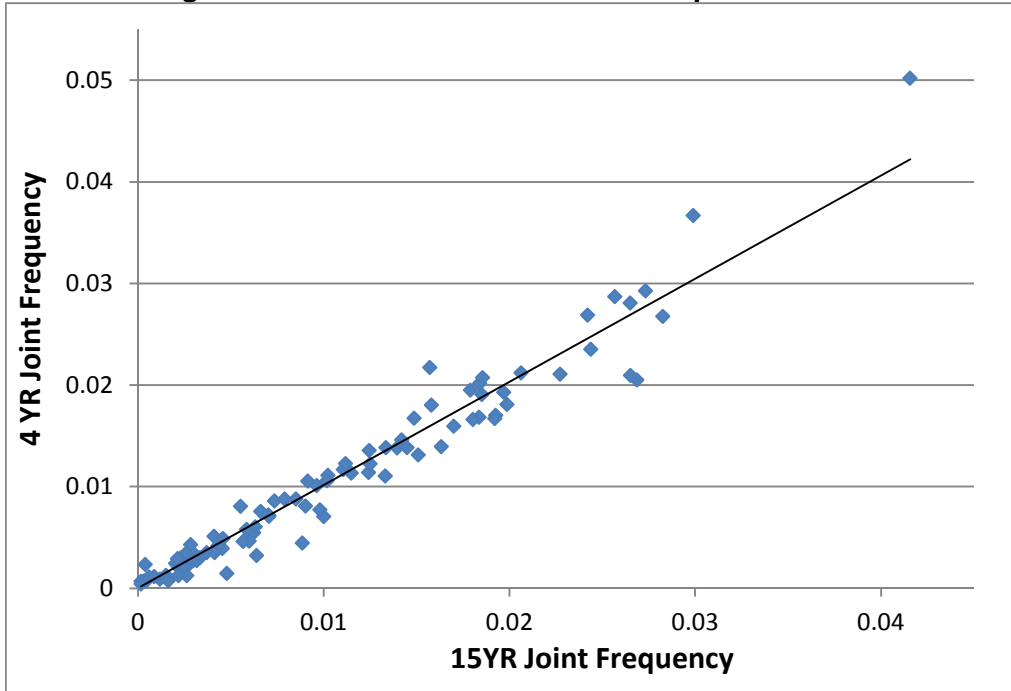
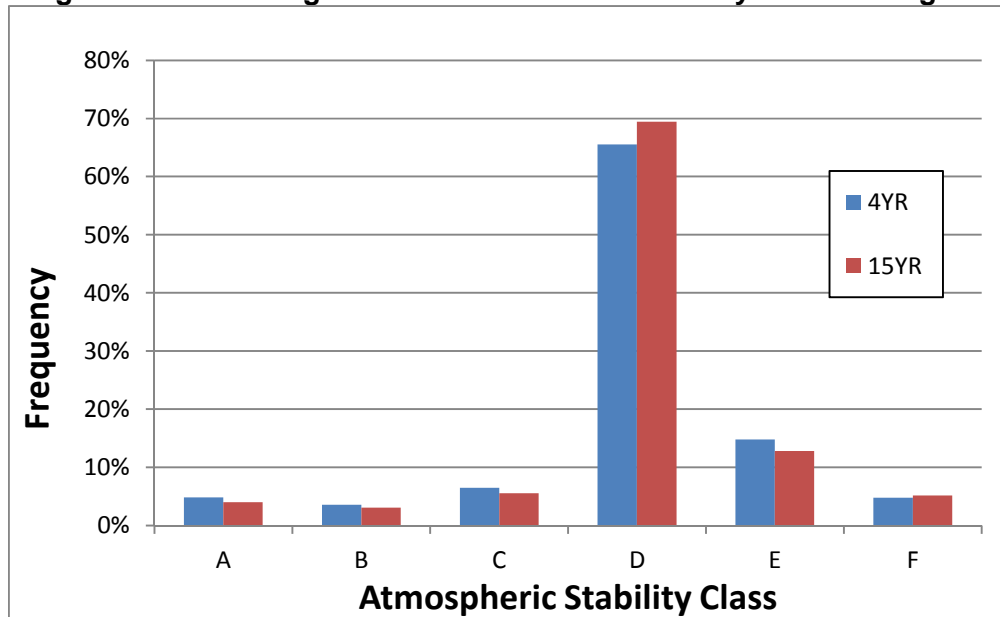


Figure 5 shows the histogram for short and long-term atmospheric stability class distributions at Eagle Butte. The stability classes were assigned according to the σ_θ method (EPA 2000). Both periods are dominated by stability class D, representing neutral to slightly unstable conditions.

Figure 5 – EBM Long-Term and Short-Term Stability Class Histogram



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

The χ^2 test can be used to evaluate the null hypothesis (H_0) that two frequency distributions are similar. Appendix A demonstrates some limitations in the χ^2 test when applied to frequency distributions derived from large samples. It discusses the usefulness of converting relative frequencies to equivalent annual hours, then adjusting the χ^2 value for large sample size by means of the phi coefficient.

In this analysis, the χ^2 test regards long-term values as the expected counts, and short-term (baseline period) values as the observed counts. Table 1 shows the resulting analysis of wind speeds at Eagle Butte. The calculated χ^2 value of 4.81 is less than the 95% confidence statistic for 6 degrees of freedom (12.59). Thus, we cannot 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. The phi coefficient, which adjusts the χ^2 result for large sample sizes, is 0.02. This confirms the 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 8 (Calm category) is larger than the minimum recommended by NRC (NRC 2011) for a valid χ^2 test.

Table 1 – χ^2 Test for Annual Wind Speed Distributions

Wind Speeds - Eagle Butte LT/ST Frequency x 8,760				
<u>mph</u>	<u>15Yr WS</u>	<u>4Yr WS</u>	<u>(LT-ST)²/LT</u>	<u>Chi-Square</u>
0 - 3	399	395	0.038	4.81
4 - 7	1916	1867	1.251	$\chi^2_{0.95}(6) = 12.59$
8 - 12	2560	2623	1.529	Can't reject H_0
13 - 18	2129	2154	0.279	p-value = 0.569
19 - 24	996	987	0.074	Min Count = 8
> 24	752	724	1.019	Phi-value = 0.02
Calm	8	10	0.615	Confirm

Table 2 shows a similar test for 15-year vs. 4-year wind directions at Eagle Butte. The calculated χ^2 value of 113 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 phi coefficient of 0.11, however, suggests a strong similarity between the two wind direction distributions. As with wind speeds, the minimum annual count of 8 (Calm category) is sufficient for a valid χ^2 test.

If the wind direction frequencies are multiplied by 2,000 rather than by 8,760, the χ^2 test in Table 2 produces a different outcome (Table 3). The scaling factor of 2,000 was chosen to meet the minimum count requirement of 2. In this case the calculated χ^2 value of 25.81 is just less than the critical value, so we cannot reject H_0 with 95% confidence. As pointed out in Appendix A, the χ^2 test is sensitive to large sample sizes. The phi coefficient removes this sensitivity. Though the χ^2 statistics are different, a sample size of 2,000 (Table 3) and a sample size of 8,760 (Table 2) both yield the same phi coefficient of 0.11. Neither version of the test ultimately provides sufficient evidence to reject H_0 .

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

Wind Directions - Eagle Butte LT/ST Frequency x 8,760				
Direction	15Yr WD	4Yr WD	(LT-ST) ² /LT	Chi-Square
N	598	530	7.672	113.06
NNE	454	460	0.092	$\chi^2_{0.95}(16) = 26.30$
NE	266	291	2.385	Reject H₀
ENE	188	226	7.543	p-value = 0.000
E	148	191	12.264	Min Count = 8
ESE	179	171	0.371	Phi-value = 0.11
SE	327	217	36.836	Adj: Do Not Reject
SSE	833	716	16.629	
S	1047	1181	17.081	
SSW	705	711	0.060	
SW	724	698	0.930	
WSW	590	571	0.596	
W	456	517	8.184	
WNW	530	523	0.084	
NW	795	795	0.000	
NNW	912	951	1.723	
Calm	8	10	0.615	

Table 3 – χ^2 Test for Smaller Scaling Factor

Wind Directions - Eagle Butte LT/ST Frequency x 2,000				
Direction	15Yr WD	4Yr WD	(LT-ST) ² /LT	Chi-Square
N	136	121	1.752	25.81
NNE	104	105	0.021	$\chi^2_{0.95}(16) = 26.30$
NE	61	66	0.544	Can't reject H₀
ENE	43	52	1.722	p-value = 0.057
E	34	44	2.800	Min Count = 2
ESE	41	39	0.085	Phi-value = 0.11
SE	75	50	8.410	Confirm
SSE	190	163	3.797	
S	239	270	3.900	
SSW	161	162	0.014	
SW	165	159	0.212	
WSW	135	130	0.136	
W	104	118	1.869	
WNW	121	119	0.019	
NW	182	182	0.000	
NNW	208	217	0.393	
Calm	2	2	0.140	

Table 4 shows the χ^2 test for short and long-term atmospheric stability class distributions. The χ^2 statistic on the left, based on conversion of relative frequencies to percentages, indicates non-rejection of H₀. On the right, after converting frequencies to annual hours the χ^2 statistic indicates

rejection of H_0 . But when adjusted for the larger sample size the phi coefficient of 0.11 is less than 0.20 and therefore shows the distributions to be similar. Once again, the phi coefficient is independent of the choice of sample size and therefore offers a more reliable measure of similarity.

Table 4 – χ^2 Test for Stability Class Distributions at EBM

Convert Relative Frequencies to Percent					Convert Relative Frequencies to Annual Hours				
Class	15YR	4YR	$(ST-LT)^2/LT$	Chi-Square	Class	15YR	4YR	$(ST-LT)^2/LT$	Chi-Square
A	3.99	4.84	0.18	0.97	A	350	424	15.70	84.60
B	3.08	3.58	0.08	$\chi^2_{0.95}(5) = 11.07$	B	270	313	7.04	$\chi^2_{0.95}(5) = 11.07$
C	5.55	6.50	0.16	Can't Reject H_0	C	486	569	14.14	Reject H_0
D	69.41	65.51	0.22	p-value = 0.965	D	6081	5739	19.20	p-value = 0.000
E	12.82	14.78	0.30	Min Count = 3	E	1123	1295	26.37	Min Count = 2
F	5.14	4.79	0.02	Phi-value = 0.10	F	450	419	2.14	Phi-value = 0.10

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

Application of the Student's T-Test

The two-sample t-test can be used to assess similarity between two frequency distributions, if those distributions are expanded to form year-to-year frequencies within each individual data category. Appendix B eliminates two-sample t-tests conducted in the manner of the χ^2 test discussed above. Such a test evaluates differences between two complete frequency distributions, but in this application the short and long-term frequencies will always have the same mean ($1/C$, where each of the paired distributions has C categories). Under these circumstances the t-test will always show equivalence.

The two-sample t-test is therefore applied separately to each wind speed, wind direction, and stability class. This scenario requires 7 t-tests for wind speeds (6 speed classes plus a “calm” class), 17 t-tests for wind directions (16 directions plus “calm”), and 6 t-tests for stability classes. A demonstration of representativeness between frequency distributions will be made if each of the 30 tests fails to reject the null hypothesis that the short and long-term data populations are different. For any given category, the first sample in each test consists of annual frequencies over the long term (15 frequencies). The second sample consists of annual frequencies for the same category over the short term (4 frequencies).

There are 17 degrees of freedom in each comparison ($15 + 4 - 2$). The critical value $T_{(0.95,17)}$ is 2.11. This forms the 95% confidence level in a two-tailed t-test, that the short-term sample comes from a different population than the long-term sample (i.e., it is not representative). Any t-statistic between negative 2.11 and positive 2.11 (or p-value > 0.05) signifies that insufficient evidence exists, at the 95% confidence level, to justify a conclusion that the two samples are statistically different.

Table 5 presents the results of individual t-tests performed on wind speed categories at Eagle Butte, using a pooled standard deviation S_p . The long-term wind data span 15 years, from 1995 through 2009. The baseline period spans 4 years, from 2010 through 2013. The p-values for each wind speed

class are much greater than 0.05, indicating insufficient evidence to conclude a difference between the short-term and long-term wind speed data.

Table 5 – EBM 15-Yr vs. 4-Yr Relative Wind Speed Frequencies and t-test Results

Speed (mph)	15YR Mean	15YR Stdev	4YR Mean	4YR Stdev	Stdev-Pooled	T-Statistic	P-Value
0 - 3	0.0456	0.0058	0.0451	0.0035	0.0055	0.14	0.887
4 - 7	0.2187	0.0137	0.2131	0.0206	0.0152	0.65	0.522
8 - 12	0.2923	0.0125	0.2994	0.0050	0.0115	-1.10	0.287
13 - 18	0.2431	0.0087	0.2458	0.0143	0.0099	-0.50	0.624
19 - 24	0.1137	0.0088	0.1127	0.0050	0.0083	0.21	0.836
> 24	0.0858	0.0108	0.0826	0.0074	0.0103	0.55	0.593
Calm	0.0009	0.0006	0.0011	0.0012	0.0008	-0.58	0.572

Table 6 presents the results of individual t-tests performed on wind direction categories for the same periods at Eagle Butte, using a pooled standard deviation S_p . Again, the p-values for each wind direction class are much greater than 0.05, indicating insufficient evidence to conclude a difference between the short-term and long-term wind direction data.

Table 6 – EBM 15-Yr vs. 4-Yr Relative Wind Direction Frequencies and t-test Results

Wind Direction	15YR Mean	15YR Stdev	4YR Mean	4YR Stdev	Stdev-Pooled	T-Statistic	P-Value
N	0.0682	0.0125	0.0605	0.0101	0.0121	1.13	0.274
NNE	0.0518	0.0201	0.0526	0.0047	0.0184	-0.07	0.944
NE	0.0303	0.0111	0.0332	0.0019	0.0101	-0.51	0.619
ENE	0.0215	0.0086	0.0258	0.0098	0.0089	-0.86	0.401
E	0.0169	0.0047	0.0218	0.0129	0.0069	-1.26	0.227
ESE	0.0204	0.0097	0.0195	0.0065	0.0092	0.18	0.859
SE	0.0373	0.0191	0.0248	0.0060	0.0175	1.27	0.222
SSE	0.0951	0.0375	0.0817	0.0183	0.0348	0.69	0.503
S	0.1196	0.0399	0.1348	0.0170	0.0369	-0.74	0.473
SSW	0.0804	0.0158	0.0812	0.0095	0.0149	-0.09	0.931
SW	0.0827	0.0151	0.0797	0.0122	0.0147	0.36	0.724
WSW	0.0674	0.0098	0.0652	0.0098	0.0098	0.39	0.704
W	0.0521	0.0093	0.0590	0.0044	0.0087	-1.43	0.172
WNW	0.0605	0.0100	0.0597	0.0045	0.0092	0.15	0.885
NW	0.0908	0.0166	0.0908	0.0076	0.0154	0.00	0.997
NNW	0.1041	0.0221	0.1086	0.0235	0.0223	-0.36	0.724
Calm	0.0009	0.0006	0.0011	0.0012	0.0008	-0.58	0.572

The use of a pooled standard deviation assumes the unknown variances of the two populations are equal. This assumption can be supported or refuted by Levene's test performed for each two-sample t-test. If the p-value for Levene's test is less than 0.05, we conclude that the variances are unequal and repeat the t-test based on unequal variance. If the p-value is greater than 0.05, we preserve the t-test results based on the pooled estimate of the standard deviation.

Table 7 lists the p-values from Levene's test applied to the short and long-term wind speed frequencies for each class. Since all of the p-values are greater than 0.05, the test confirms the assumption of equal variances among relative frequencies for each wind speed, and thereby validates the t-test results in Table 5.

Table 7 – Levene's Test for Equal Variance Among Wind Speed Frequencies at EBM

Wind Speed (mph)	Levene's p-value
0 - 3	0.181
4 - 7	0.969
8 - 12	0.087
13 - 18	0.712
19 - 24	0.361
> 24	0.460
Calm	0.483

Table 8 lists the p-values from Levene's test applied to wind direction frequencies. Since all p-values are greater than 0.05, the test confirms the assumption of equal variances among relative frequencies for each wind direction, and thereby validates the t-test results in Table 6.

Table 8 – Levene's Test for Equal Variance Among Wind Direction Frequencies at EBM

Wind Direction	Levene's p-value
N	0.869
NNE	0.377
NE	0.358
ENE	0.821
E	0.215
ESE	0.672
SE	0.243
SSE	0.115
S	0.242
SSW	0.406
SW	0.977
WSW	0.899
W	0.549
WNW	0.643
NW	0.483
NNW	0.891
Calm	0.483

Appendix A illustrates how inter-site comparisons using the class-wise, two-sample t-test can show significant differences for a majority of the wind speed and direction categories. It also cites support for the t-test performed on wind frequency distributions in the literature of meteorological statistics.

Brooks and Carruthers (Brooks 1978, p. 66) offer an example that seeks to determine whether the frequency of occurrence of gale-force winds over a 3-year period is the same as the frequency of gale-force winds over a previous 9-year period. A two-sample t-test is used to demonstrate a significant difference between the two frequencies. This approach is equivalent to the above analysis, except that Brooks and Carruthers applied it to only one wind speed category.

Evaluation of the Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov (K-S) test is a nonparametric test for the equality of continuous, one-dimensional probability distributions that can be used to compare two samples without many of the assumptions required for other statistical methods. In exchange for this broad applicability, the K-S test sacrifices statistical efficiency. The case study in Appendix A shows that all inter-site comparisons using the K-S test result in the false conclusion that the wind speed and wind direction distributions are statistically no different. The respective wind roses, the χ^2 test, and the t-test all contradict this result. While its consistent finding of insignificant differences superficially supports the case for representativeness, the inability of the K-S test to distinguish between clearly dissimilar wind patterns eliminates this method as an appropriate alternative.

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). Appendix A offers an in-depth analysis of linear correlation and regression in the context of meteorological frequency distributions.

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.

Appendix A notes several refinements to the regression analyses in previous submittals to NRC:

1. Adopting the convention of assigning long-term frequencies to the independent variable
2. Using non-overlapping short-term and long-term periods to enforce sample independence
3. 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

Figure 6 illustrates the linear association between short and long-term wind speed frequencies at Eagle Butte. The hourly data for each distribution fall into one of 7 categories. The graph illustrates the degree to which the 4-year frequencies match the 15-year frequencies. The R^2 value of 0.999 confirms a very strong linear relationship, and the slope of 1.005 indicates substantial equivalence between short and long-term frequencies. A p-value of zero leaves little doubt that this relationship is significant.

Figure 6 – EBM Short and Long-Term Wind Speed Frequency Distributions

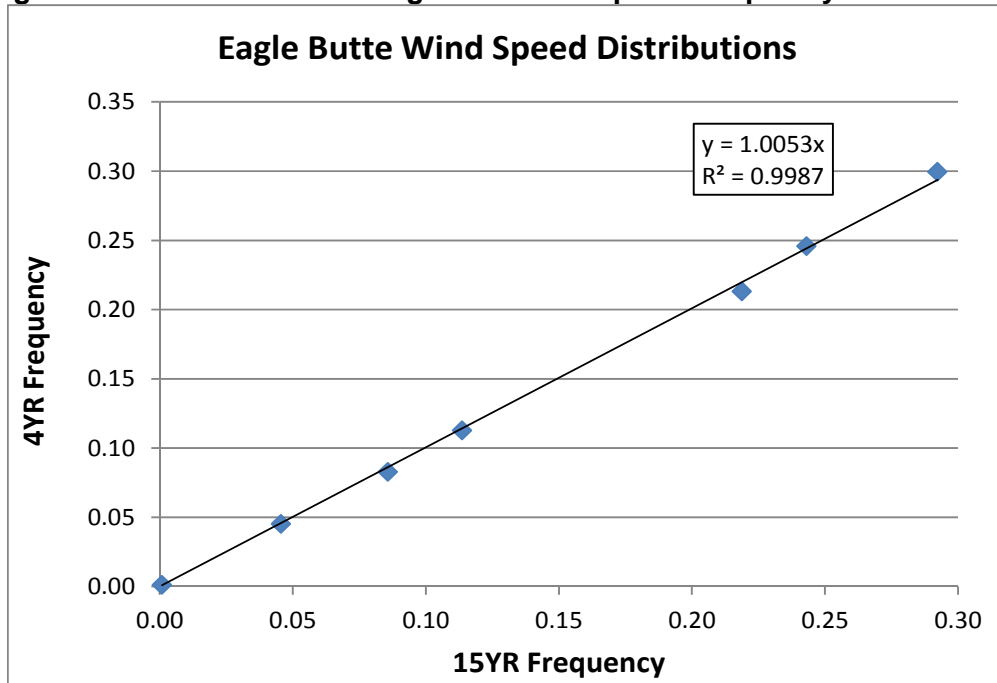
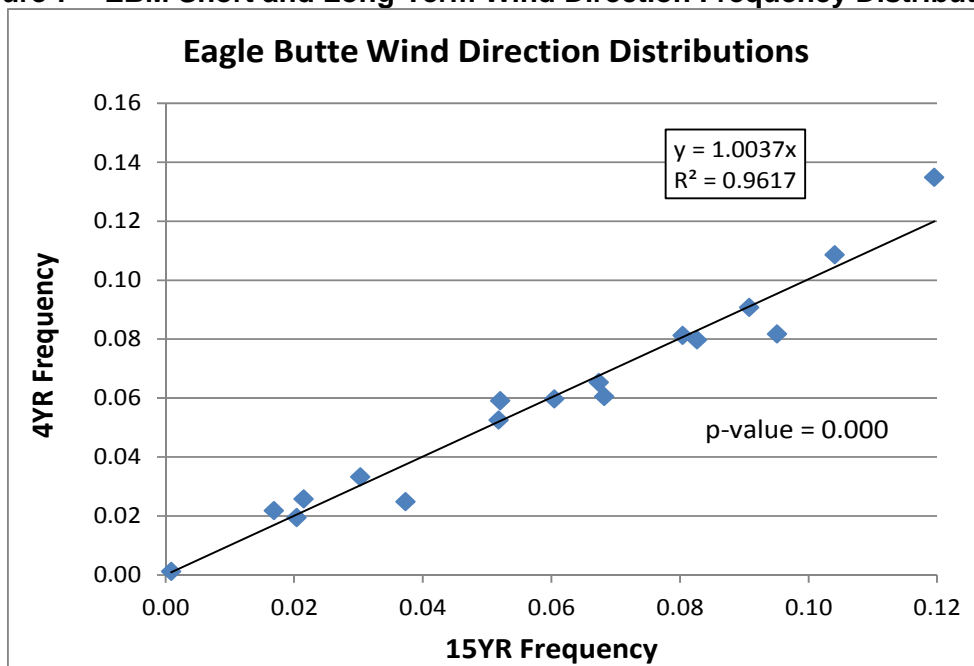


Figure 7 illustrates the linear association between short and long-term wind direction frequencies at Eagle Butte. The hourly data for each distribution fall into one of 17 categories. The graph illustrates the degree to which the 4-year frequencies match the 15-year frequencies. The R^2 value of 0.962 confirms a strong linear relationship, and the slope of 1.004 indicates substantial equivalence between short and long-term frequencies. A p-value of zero leaves little doubt that this relationship is significant.

Figure 7 – EBM Short and Long-Term Wind Direction Frequency Distributions



The MILDOS model accepts meteorological inputs in the form of joint wind speed, wind direction and stability class frequency distributions, also known as STAR distributions. An important subset of the STAR distribution is the two-way wind classification, which 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 $5 \cdot \log_{10}(N)$, 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.

Joint wind speed and direction distributions are amenable to linear regression or correlation. Analyzing 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. This comparison also offers the best quantitative measure of the similarity between the associated wind roses (see Figure 2 and Figure 4).

Figure 8 shows the linear relationship between short and long-term joint frequencies at Eagle Butte. The hourly data for each distribution fall into one of 97 categories. The graph illustrates the degree to which the 4-year joint frequencies match the 15-year frequencies. The R^2 value of 0.951 confirms a strong linear relationship, and the slope of 1.015 indicates substantial equivalence between short and long-term frequencies. A p-value of zero leaves little doubt that this relationship is significant.

Figure 9 graphs the short-term joint frequency distribution from the Dry Form Mine against the long-term joint frequency distribution from Eagle Butte. The contrast to Figure 8 illustrates how effectively linear regression discriminates between similar and dissimilar wind regimes. Since Dry Fork is less than five miles east of Eagle Butte, Figure 9 also illustrates how sensitive wind patterns are to local terrain.

Linear regression isolates the sources of variation among category frequencies. When multiplied by 100, R^2 signifies the percent of variation from a mean frequency that is common to both short and long-term distributions. In Figure 8, for example, 95% of the variation among 4-year joint frequencies can be predicted based on measured long-term frequencies, while only 5% is attributed to random, year-to-year fluctuations and/or measurement error. In Figure 9, 50% of the variation at Eagle Butte cannot be explained by the observed wind patterns at Dry Fork.

Linear correlation produces Pearson's correlation coefficient R , based on the assumption of normally distributed data. This assumption can be relaxed by ranking the data and computing Spearman's correlation coefficient, a method commonly applied to nonparametric data. Appendix A shows that the Spearman's and Pearson's coefficients are very similar for wind frequency distributions.

Figure 8 – EBM Short and Long-Term Joint Frequency Distributions

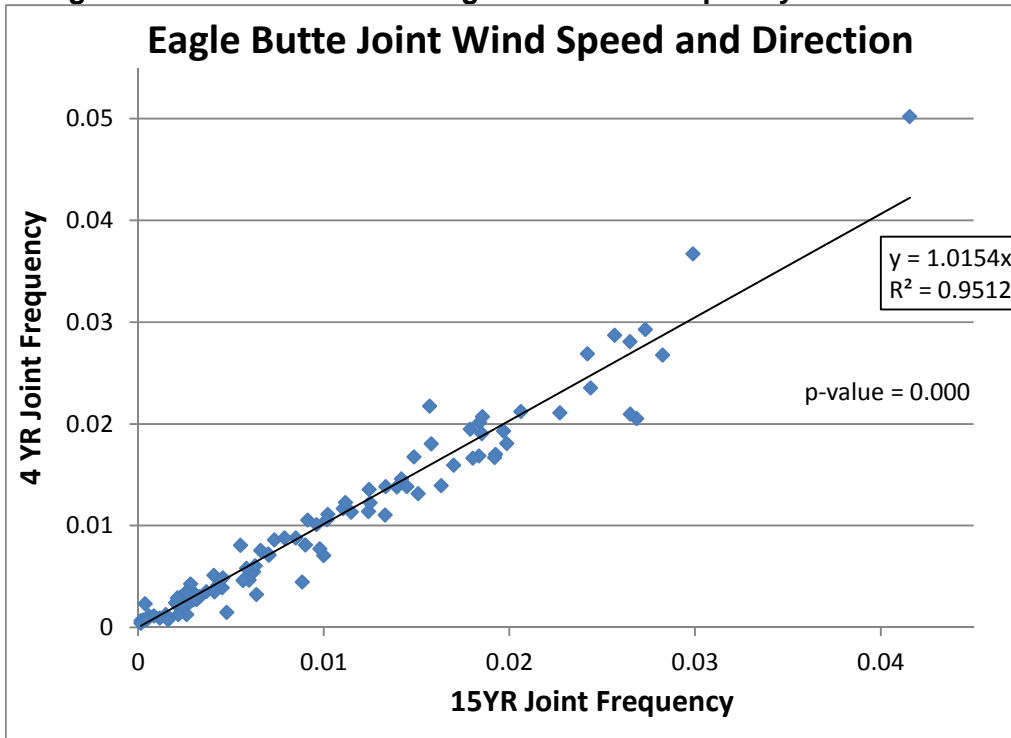
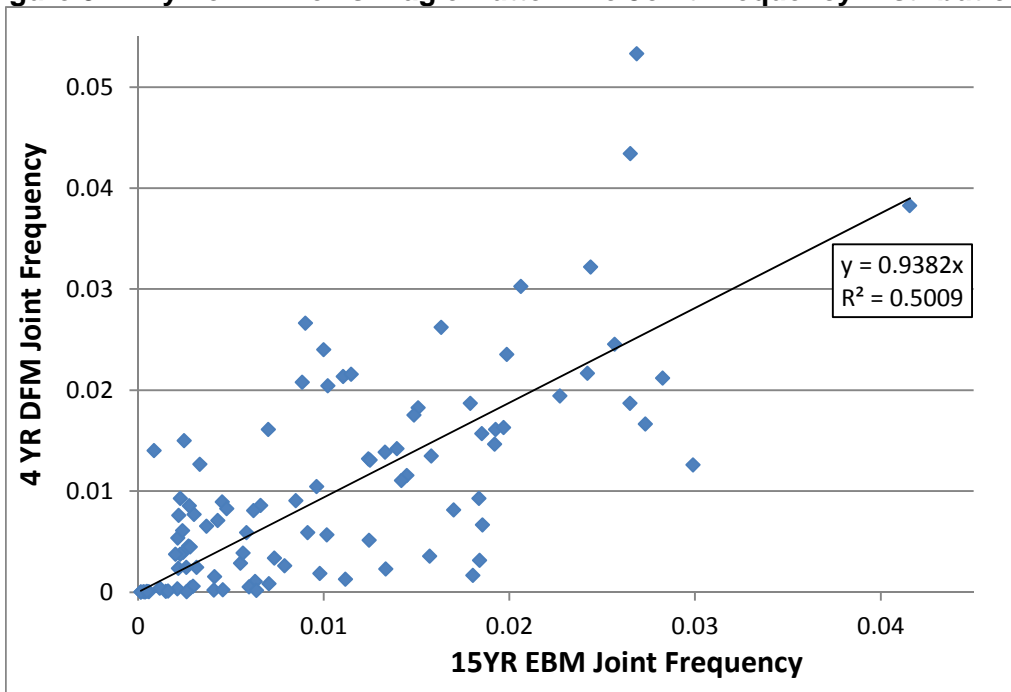


Figure 9 – Dry Fork Mine vs. Eagle Butte Mine Joint Frequency Distributions



Conclusion

In fulfillment of NRC guidelines, the combination of visual evidence, linear correlation and hypothesis testing provides a comprehensive demonstration of long-term representativeness of baseline meteorological data at the Ross ISR Project. For the Eagle Butte Mine site, the most recent 4 years of hourly wind data are statistically no different than the previously recorded 15 years of data. This conclusion is supported by graphical analyses and by three 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. The Student's t-test
3. Linear correlation coefficient R (or coefficient of determination R^2)

Table 9 summarizes the test results for the Eagle Butte site. For wind speed, wind direction, joint frequency and stability class distributions, all relevant statistical tests infer the absence of a significant difference between short and long term data.

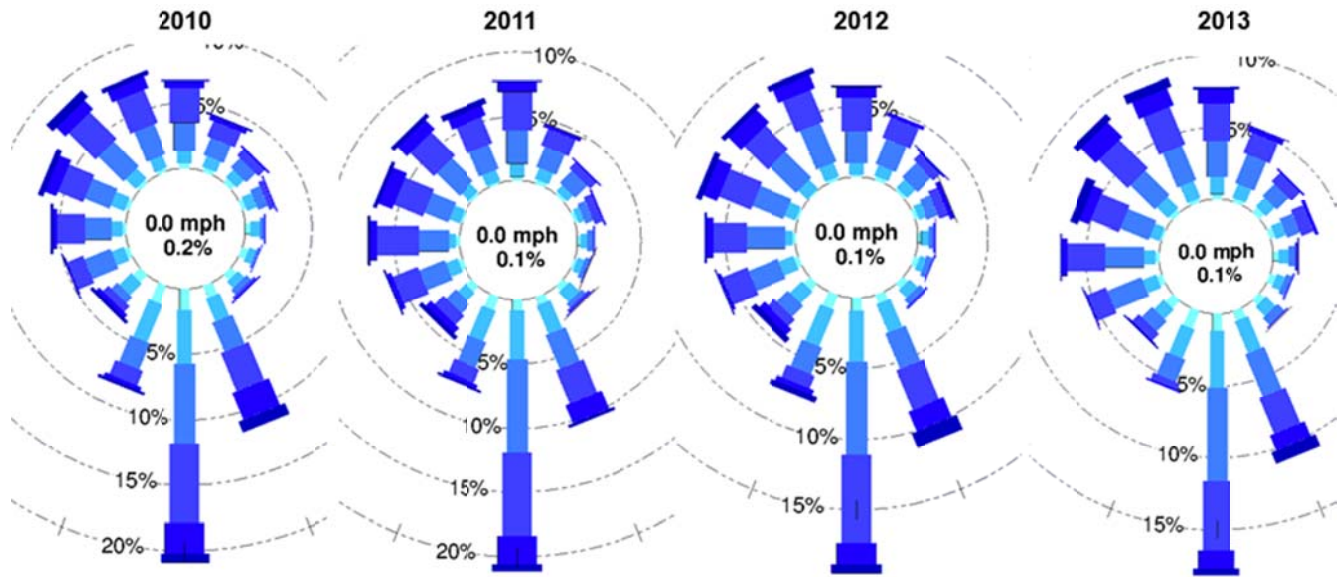
Table 9 – Summary of Statistical Analysis of Frequency Distributions at EBM

15-Yr vs. 4-Yr Frequency Distributions	Statistical Method							Overall Conclusion
	χ^2 at 8,760 hrs.	ϕ -Coeff.	Adjusted χ^2 Result	t-test min. p-value	t-test Result	Linear Regress. R^2	p-value for R^2	
Wind Speed	4.8	0.11	Similarity	0.287	No statistical difference	0.999	0.000	No statistical difference
Wind Direction	113	0.02	Similarity	0.172	No statistical difference	0.962	0.000	No statistical difference
Joint Wind Speed and Wind Direction	N/A	N/A	N/A	N/A	N/A	0.951	0.000	No statistical difference
Atmospheric Stability Class	84.6	0.10	Similarity	N/A	N/A	0.999	0.000	No statistical difference

That the methods summarized in Table 9 yield similar results is no coincidence. All of these methods deal with differences between measurement frequencies over two different time periods. Such differences are manifest as $(O - E)^2/E$ for the χ^2 test, as $(\bar{X}_1 - \bar{X}_2)$ with S_p for the two-sample t-test, and as the distance from the fitted line for linear regression. The χ^2 test and the t-test give a yes/no answer: either they result in 95% confidence in a significant difference, or they do not. Among the three methods considered, linear regression supplies the best measure of the degree of similarity between wind speed, wind direction and stability class distributions. It is the only one applicable to joint wind speed and direction frequencies due to the large number of categories.

Eagle Butte is considered representative of the Ross site due to its proximity, similar elevation, comparable terrain, and susceptibility to the same regional climatological factors. With four years of hourly data now available from the Ross site, it is also possible to examine on-site temporal trends in wind data. Figure 10 compares the annual wind roses at Ross for these four years.

Figure 10 – Ross Yearly Wind Roses



While the wind roses show small variations from year to year, the dominant wind pattern has persisted throughout the monitoring period. Table 10 corroborates Figure 10 by applying the χ^2 test to the 2010 (ST) and 2011-2013 (LT) data from Ross. The 2010 wind data were used for the original MILDOS modeling. For both wind speed and wind direction distributions, the phi coefficients in Table 10 adjust the χ^2 values and point to similarity between 1-year and 3-year frequency distributions.

Table 10 – Chi-Square Test for Ross Wind Frequency Distributions

Wind Directions - Ross LT/ST Annual Frequency				Wind Speeds - Ross LT/ST Annual Frequency			
3Yr WD	1Yr WD	$(LT-ST)^2/LT$	Chi-Square	3Yr WS	1Yr WS	$(LT-ST)^2/LT$	Chi-Square
562	560	0.011	202.76	489	492	0.023	22.31
277	290	0.600	$\chi^2_{0.95}(16) = 26.30$	1627	1638	0.072	$\chi^2_{0.95}(6) = 12.59$
188	194	0.234	Reject H_0	2320	2271	1.013	Reject H_0
131	176	15.813	p-value = 0.000	2198	2164	0.529	p-value = 0.001
156	198	11.131	Min Count = 122	702	681	0.622	Min Count = 444
122	132	0.726	Phi-value = 0.15	444	539	20.022	Phi-value = 0.05
253	242	0.546	Adj: Do Not Reject	981	976	0.025	Adj: Do Not Reject
685	551	25.944					
1057	910	20.510					
436	372	9.180					
697	536	37.416					
384	424	4.260					
686	721	1.751					
537	525	0.271					
817	999	40.669					
791	954	33.668					
981	976	0.025					

Given this on-site evidence of temporal uniformity and the preceding demonstration of 4-year/15-year equivalence at a surrogate site (EBM), it is reasonable to conclude that the four years of data collected at the Ross site are representative of the long term.

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.
- IML 2014a, Meteorological Monitoring Database for Ross ISR Project, IML Air Science, Period Of Record 2010-2014.
- IML 2014b, Meteorological Monitoring Database for Eagle Butte Mine, IML Air Science, Period Of Record 1995-2014.
- 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.
- NRC 2011, NU-REG 1475, Revision 1, Applying Statistics, March 2011.
- NRC 2014, Supplemental Safety Evaluation Report for the Strata Energy, Inc. Ross ISR Project, Crook County, Wyoming, Materials License No. SUA-1601, ML14083A240, April 2014.