Incorporating Climate Variability into Cover System Design

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ABSTRACT

Climate is the ultimate determinant of cover system performance. Typical cover system design efforts apply average climate values as model inputs, resulting in an over-simplification of what is inherently a very complex system. The purpose of this work was to demonstrate a novel technique for separating the inherent scales of variability within a given climate signal. Long term air temperature and precipitation data from Fort McMurray, Canada were used. Air temperature averaged 0.3 °C, while the long term average precipitation was 412 mm. A moving average was used to reveal a long-term warming trend of 0.03 °C yr^{-1}. Determination of the cumulative departure from the mean for precipitation showed qualitatively periods where the annual average values departed substantially from the mean, suggesting the presence of wet and dry climate cycles. Unfortunately both techniques still operate under the assumption of data stationarity, or the assumption of a constant mean and variance, which by definition does not incorporate small scale cycles and long-term trends. Empirical mode decomposition (EMD) was used as a means of dealing with a non-linear, non-stationary dataset. The EMD technique works directly in the time domain to separate out the scales of variability inherent in the input signal, as well as to determine the contribution to the total measurement variance of each inherent scale. Air temperature was found to be dominated by the annual scale of variation, accounting for 76% of the total variance; a finding that is not surprising. However, the EMD technique was also able to demonstrate the long-term warming trend, while also uncovering high frequency variations from five to seventeen days. Precipitation had a more even contribution of high, medium, and low frequency cycles of variation. A major contribution to the total variance of the precipitation signal was at the 3 and 7 year scales, which are postulated to correspond to El Niño / La Niña cycles, and the Pacific Decadal Oscillation, respectively.

Keywords: Climate, cycles, variability, cover system

INTRODUCTION

Climate is the primary determinant governing cover system performance (MEND or INAP reference). The climate at a mine site will set the basic performance constraints, within which the cover system designer must work to achieve the design outcomes. Expected precipitation volumes and the evaporative capacity of a given location are two major design considerations that will ultimately dictate the success or failure of the entire closure landform. Given the risks involved should a closure landform not perform as designed, it is not surprising that climate data represents a critical model input during early design efforts.

Typical design approaches supply a long-term average precipitation value as a modelling input to predict future performance. However, using a single average value does not account for changing mean and variance in a climate dataset. Furthermore, applying a single average value does not allow for changes in antecedent conditions within the cover system. All periodic processes will have a range of scales of variation, from small, high-frequency changes on the order of minutes to hours, to large, low-frequency trends that can take decades to move through a single cycle. Failing to account for the many scales of variation in a climate dataset will ensure that the underlying complexities of the interactions at the soil atmosphere interface are not fully understood.

There are a number of methods for describing a climate dataset that range from very basic to extremely sophisticated. At its most basic, a characterization of the mean and variance will begin to describe the inherent qualities of the climate dataset. However, measurements of the central tendency and data dispersion soon become inadequate to properly characterize the variability of the climate model inputs. Geostatistical techniques are often employed to better understand the natural cycles of variability contained within a climate data time series. In addition, to the mean and variance, geostatistics only requires the probability distribution and the similarity between values at different temporal scales to be determined.

Geostatistics operate under the fundamental assumption that measurements made close together in time (space) tend to be more similar than those made further apart (Goovaerts, 1997). Geostatistics are used to analyze the distribution of data in a time series, and help to quantify patterns and structures within the dataset by describing the relationship between two points in time. The temporal (or spatial) structure, or the covariance, as a function of the separation, or the scale, helps to identify patterns in the dataset and major repeating processes (Si et al., 2007). Having an understanding of the structure of spatial or temporal variability in a dataset allows for better design of monitoring networks, proper data interpretation, and better assessments of simulation and uncertainty analyses (Si et al., 2008).

Whereas many common geostatistical techniques take advantage of the similarity of adjacent data points, spectral analysis transforms values from the spatial or temporal domain to the frequency domain. The result of analyzing data in the frequency domain is that the data are now partitioned wherein the total variation of the data are separated into different frequency scales. Spectral techniques then make it easy to identify dominant processes at discrete temporal or spatial scales, by simply identifying prominent spikes in frequency.

A drawback of spectral methods is that the mean and variance of the dataset do not change over time; a condition known as stationarity. For the cover system designer analyzing a climate dataset, this is problematic. Not only is it the cycles of variation within the dataset, it is the overall trend that in climate that can be of major concern. Using a single mean value for precipitation or temperature ignores the implications of climate change in the cover system design. Spectral methods such as wavelet analysis (Torrance and Compo, 1998), Hilbert spectral analysis (Biswas et al., 2013), including empirical mode decomposition (Biswas et al. 2009) are methods that can account for nonstationary datasets. Thus, the methods are ideally suited for analyzing climate datasets when designing soil cover systems. Not only do the methods analyze high frequency, small scale climate cycles, but can also account for long term trends that span the entire dataset.

Application of geostatistics and spectral analysis to the investigation and design of unsaturated soil cover systems represents an excellent potential opportunity to define the dominant controls on performance. Too often the analysis of climate data inputs is reduced to using one mean value for the entire duration of the simulations, without consideration of the wider context of shorter term climate cycles and longer term trends. The objective of this manuscript is to demonstrate the utility of analyzing climate data inputs using geostatistical techniques.

METHODOLOGY

Dataset

The climate dataset in this analysis is the long-term Environment Canada data recorded at Fort McMurray, in the Athabasca region of Alberta, Canada. Records of precipitation extend from 1908 to 2012, while air temperature records begin in 1924 and continue to 2012. The Environment Canada data are freely available at http://climate.weather.gc.ca/. Data were initially analyzed by calculating the mean, variance, and standard deviation. Further analysis involved estimation of a 365 day moving average, and a cumulative departure from the mean (CDM). The CDM is simply calculated by summing the cumulative difference between the average value for a year, and the average value for the entire dataset.

Empirical Mode Decomposition

Geostatistical analysis was performed using empirical mode decomposition (EMD). The EMD method separates the variation in the temporal series into discrete component characteristic scales. The EMD method works directly with the dataset, rather than transforming the data into the spectral domain, as is the case with wavelet analysis. The method assumes that the temporal signal is composed of multiple components, all varying at their own specific scales of variability. The sum of all the components is equal to the dataset itself. Empirical mode decomposition is then used to sift out the component scales of variation into intrinsic mode functions (IMF) and determine their overall contribution to the total variance (Biswas et al., 2009).

The EMD method is adaptive and works directly with the data, without the need to rely on a mathematical function to transform the data, as is the case with wavelet analysis (Biswas and Si, 2011). For a complete treatment of the EMD process used to separate out the component IMFs the reader is referred to the examples shown by others (Huang et al., 1998; Biswas and Si, 2011; and Sang et al., 2012). In the present analysis, we are most concerned with the contribution of a particular temporal scale to the overall variance of the dataset.

$$\%Contribution = \left(\frac{Variance\ of\ IMF_i}{\sum Variance\ of\ all\ IMFs}\right) \times 100 \tag{1}$$

Examination of the amount of contribution of a particular IMF to the total variance allows for an estimation of the relative dominance of a particular spatial scale. The average scale of an IMF is calculated by counting the number of oscillations present in the IMF in question. For example, if over the 105 year dataset a particular IMF exhibits 5 oscillations, then the average scale of that IMF will be 105 / 5 = 21 years. This was the method used for reporting average temporal scales in the subsequent analysis. Oscillations of the IMFs can vary locally, and as such, reporting of temporal scales represents an average range for the particular scale. Therefore, the temporal scales of each IMF will be reported as a range, rather than a discrete value.

RESULTS AND DISCUSSION

Initial Data Analysis

Air temperature at Fort McMurray over the entire study period averaged 0.3 °C with a standard deviation of 1.4 °C (Figure 1). Precipitation averaged 412 mm with a standard deviation of 116 mm (Figure 2). Note that precipitation data are missing for 1911 through 1913, as well as 1947.

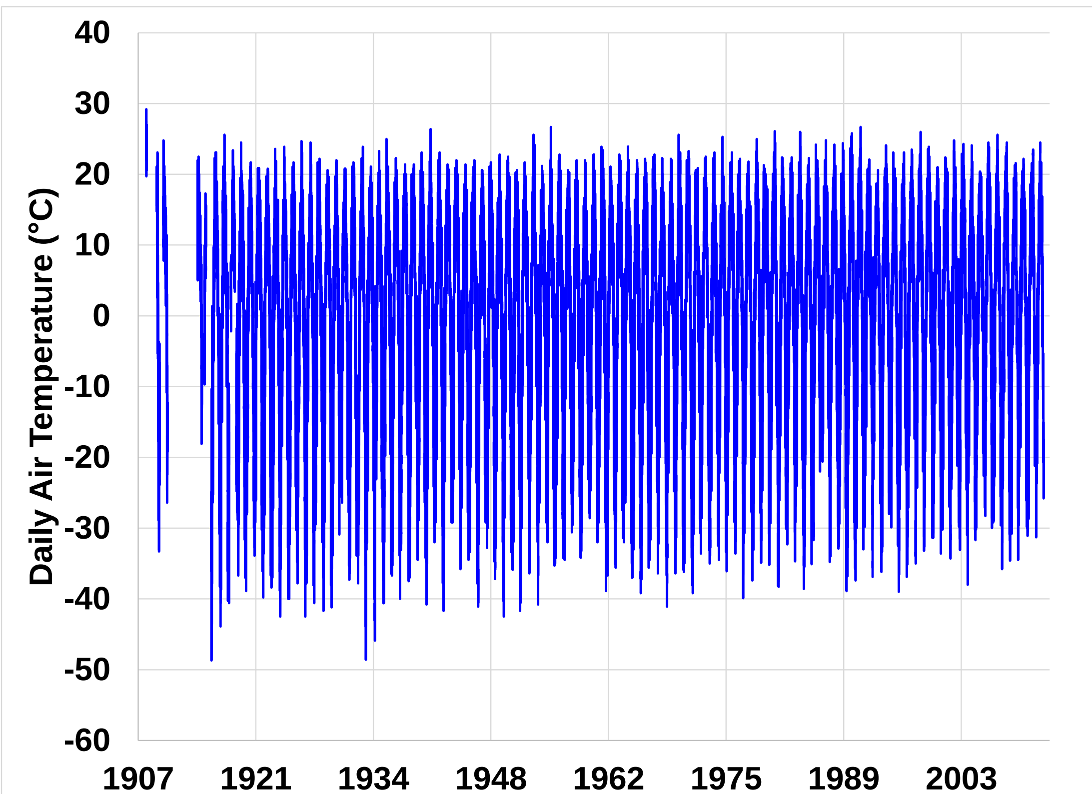

Figure 1 Average annual air temperature at Fort McMurray, 1908 to 2012.

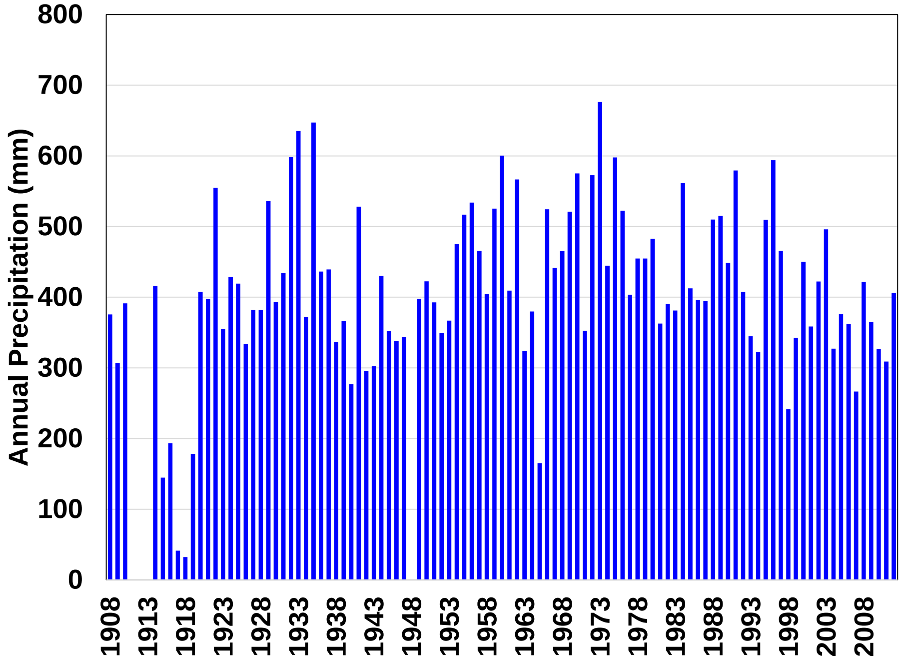

Figure 2 Average annual precipitation at Fort McMurray

Trends and cycles in the air temperature and precipitation data are not readily apparent from Figures 1 and 2. Without further investigation, the cover system designer could be satisfied that there a general annual average value for both air temperature and precipitation would be sufficient for use in modelling analyses. As will be further explored, the assumption of stationarity (constant mean and variance) may not be applicable.

A simple calculation of the average annual air temperature begins to suggest an overall trend in long term average air temperature (Figure 3). While it appears that temperatures have climbed above the mean value of 0.3 °C after 1970, the values are still within two standard deviations of the mean (± 2.8 °C).

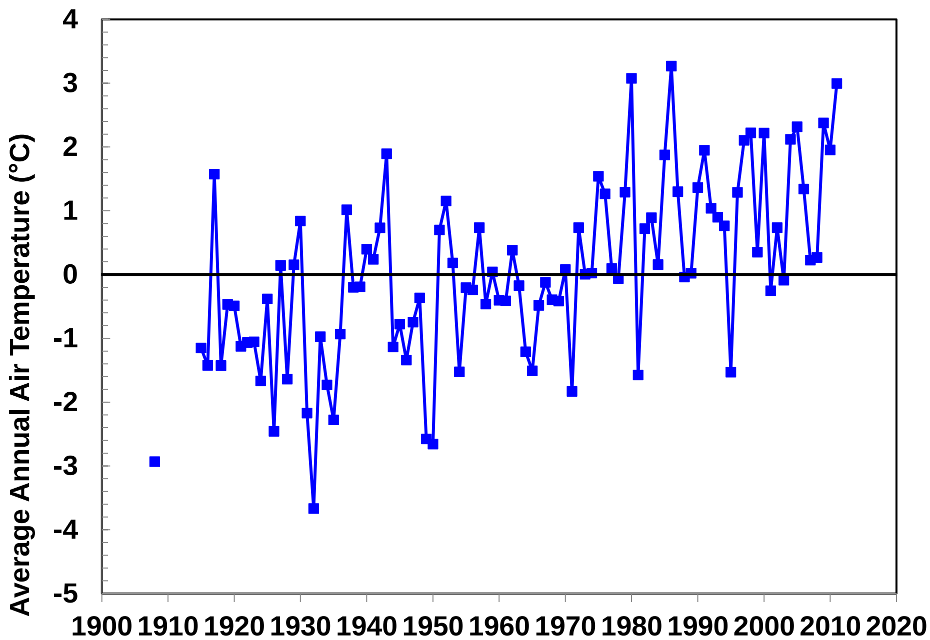

Figure 3. Average annual air temperature recorded at Fort McMuray, 1908 to 2012.

Moving Average

A common method to visualize long term trends in a dataset is to calculate a long term moving average. Three hundred sixty five day moving averages were calculated for air temperature (Figure 4).

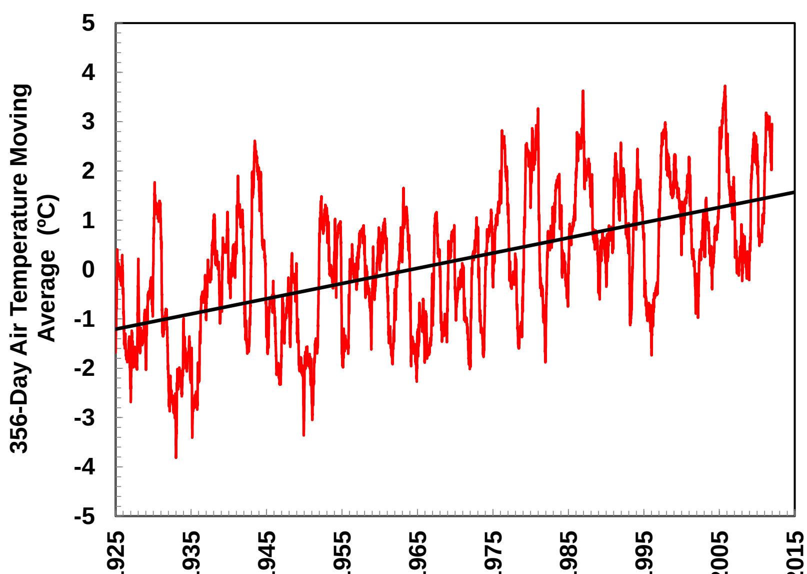

Figure 4 One year air temperature moving average.

A trend of increasing temperature is clearly evident from Figure 4. The slope of the trend line indicates a warming rate of 0.03 °C yr^{-1}. While the long term trend of the data is important, calculation of a moving average does not provide any additional information about the higher frequency, shorter duration cycles of variability within the dataset.

Cumulative Departure from the Mean

The cumulative departure from the mean of non-frozen precipitation (April through October) was calculated to demonstrate the variability of the precipitation dataset (Figure 5).

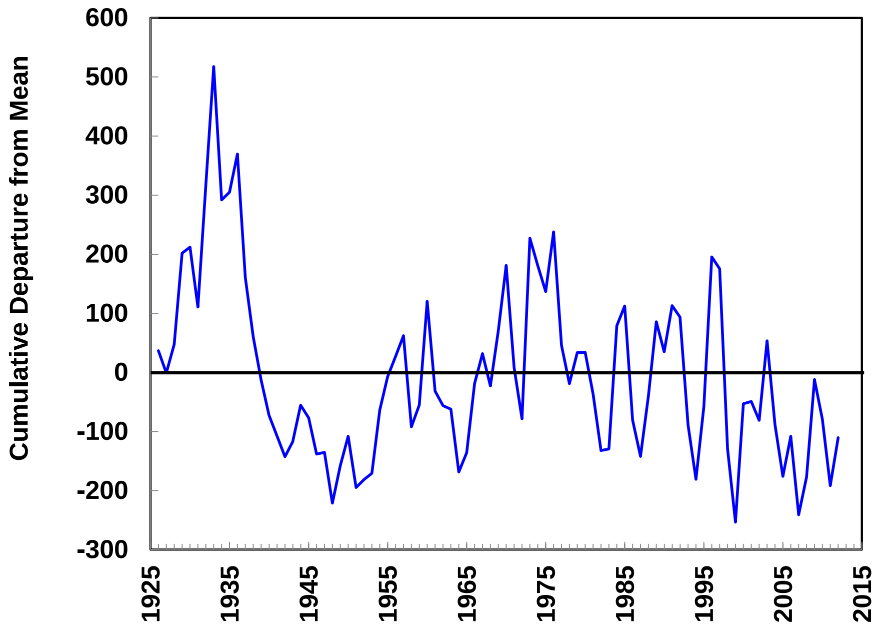

Figure 5 Cumulative departure from the mean for non-frozen precipitation.

The CDM technique is useful for demonstrating variability in a general sense. However, the technique still suffers from an assumption of data stationarity, in that the data are always compared to a single mean value. Furthermore, there is no means by which internal cycles of variability within the dataset can be elucidated.

Empirical Mode Decomposition

Empirical mode decomposition (EMD) works directly within the time domain to separate out scales of variation. The method results in a series of intrinsic mode frequencies that identify the scales of temporal variation buried within the data, as well as that scale's contribution to the total variance. Thus, an intuitive means of examining both low and high frequency variations results. Temporal variations of air temperature are dominated by the annual temperature signal (Figure 6).

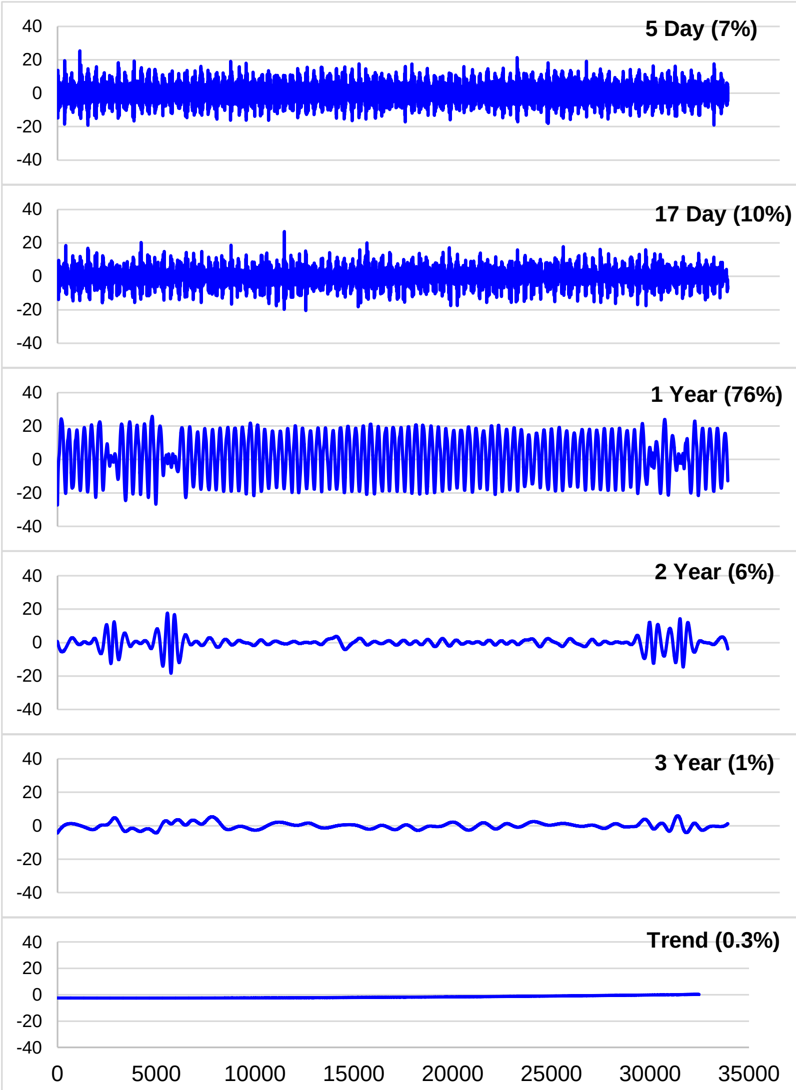

Figure 6. Temporal scales of variation intrinsic within the 1924 to 2012 Fort McMurray air temperature record.

It is clear from Figure 6 that temporal variations in air temperature are dominated by the annual signal and higher frequency signals between five and seventeen days. Also of note is the long term trend. Although the overall trend contributes very little to the total variance (0.3%), the trend is nonetheless present, thus verifying the trend that was identified earlier in the analysis. In fact, the overall trend increases at a rate of 0.03 °C yr^{-1}, providing further credence to the method.

Precipitation exhibits a more even distribution of scale contribution, relative to air temperature (Figure 7). Roughly a third of the scale dominance is contributed by the three year scale, suggesting that high frequency cycles of alternating wet and dry are to be expected in the region. It is possible that the three year cycles of variability could correspond to alternating El Niño / La Niña events.

Another major contributor to the total variance is the 7 year scale. It is interesting to note that the 7 year scale may roughly correspond to the Pacific Decadal Oscillation, another major determinant of Western Canadian weather patterns. Finally trend towards decreasing precipitation accounts for 23% of the total variance. While the EMD technique does not forecast into the future, it does elucidate the dominant cycles of variation over the timespan of the dataset. In the case of Fort McMurray for more than 100 years, the trend has been towards decreasing precipitation.

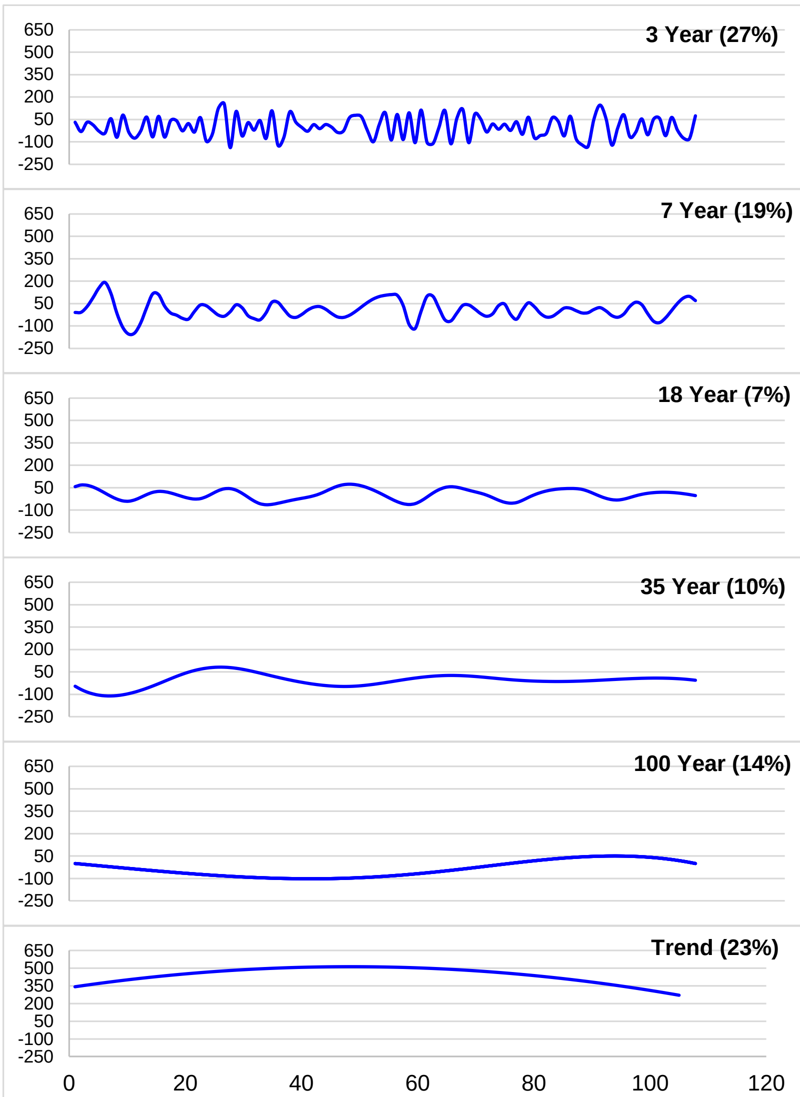

Figure 7. Temporal scales of variation intrinsic within the 1908 to 2012 Fort McMurray precipitation record.

CONCLUSION

Climate is the ultimate governor of cover system performance at a mine site. While certain cover system design parameters can be adjusted to certain degrees, the climate at a site cannot be controlled. Therefore, it is imperative that the designer understands the dominant climate at a site to the fullest extent possible. However, all too often a simple average of climate parameters is used as an input into the models used during the cover system design process. Not only does an average value of precipitation or air temperature result in an unrealistic generalization of site conditions, it fails to account for the cycles of variation that are inherent within all climate signals. Failure to examine the scales of variability within a climate dataset necessarily results in a spurious simplification of what is a very complex system.

The examples used in this manuscript demonstrate the need to have a greater understanding of the cycles of variability within a climate dataset, when designing a cover system. Long term temperature signals are not surprisingly dominated by the annual signal, but also contain a long term trend that indicates consistently rising temperatures. While the trend was not dominant, it explains why the recognition of changing temperatures is difficult to perceive. The signal of the warming trend is buried within more dominant, smaller scale / higher frequency signals.

Precipitation demonstrated that a number of scales of variation contribute to the total variance of the system. While no one signal was dominant, it goes to demonstrate that the cover system designer must be aware of all of the cycles of variation when designing the system. Determination of the cycles of variability underscores the importance of understanding where in a wet / dry cycle the system is being designed. If an average precipitation value is used from a dataset that doesn't capture the dominant scales of variability, the design of the cover system cannot be fully optimized. For instance, if a ten year average precipitation value is used to determine the optimal cover system thickness for supporting vegetation, and the average was taken from a wet cycle, the system may not be able to support vegetation throughout the entire life of the cover system. Conversely, when designing upland / wetland reclamation systems, it is critical to have a good understanding of long term climate in order to ensure that the watershed will have sufficient water supply to support wetland functions. If the watershed designer does not incorporate an analysis of precipitation trends and cycles of variability, the system will be less likely to be resilient to the cyclical changes in water supply.

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