LOCAL CLIMATE CHANGE AND WIND GUSTS IN UTQIAGVIK, ALASKA: AN ANALYSIS OF WIND SPEED, TEMPERATURE, AND VARIABILITY

By

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For all the scientists who do what they do because they believe a better world is possible.

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CHAPTER 1

Introduction

As global climate change accelerates, the temperatures in the Arctic have risen much faster in comparison than temperatures in the mid- and lower-latitudes. From 1971 to 2019, average temperatures in the Arctic have risen 3.1°C, while the rest of the world has gotten only 1°C warmer on average (Monitoring and Programme). This phenomenon, known as Arctic amplification, describes the observed disproportionate warming trend in the Arctic (Monitoring and Programme; 21). Over the past few decades, communities all over the world have demonstrated increased awareness and concern over global climate change. Arctic climate change is also of increasing concern to local Arctic communities, especially rural populations, because it directly threatens local infrastructure, exacerbates food insecurity, and causes coastline erosion, among other issues (20).

There are many factors that contribute to the Arctic's accelerated warming, and though the relative contributions of those factors is still a topic of debate, albedo feedback and temperature feedbacks (surface warming feedbacks and atmospheric warming feedbacks) are typically named as the strongest (21; 19). Other important feedbacks include water vapor feedback, which affects downwelling radiation, sea ice feedback, which describes the progressive thinning of sea ice as temperatures warm and causes it to melt more readily, and permafrost feedback, in which carbon is released from previously frozen soil to become greenhouse gases (GHGs), although the release of GHGs from permafrost may cause more widespread warming across the Northern hemisphere rather than just in the Arctic (21). Arctic amplification from recent years is strongly correlated with the decrease in the surface area of sea ice and glaciers (21). Sea ice and glaciers have high albedo and reflect a large percentage of incoming solar radiation. However, as they become unstable and melt due to rising temperatures, the overall albedo of the Arctic region decreases from darker ocean or land becoming exposed by the melting reflective ice. This leads to the surface absorbing solar radiation and warming in a location that would have been previously reflected back if the surface was covered by ice, thereby exacerbating the rising temperatures in a positive feedback loop (21). Though many studies have credited albedo feedback as the main cause of Arctic amplification, the Arctic still warms disproportionately in simulations without albedo changes, which suggests that decreasing albedo may be a secondary factor; some recent studies have suggested temperature feedbacks such as Planck feedbacks and lapse-rate feedbacks may be the main drivers (19). The Planck feedback describes the "vertically uniform warming of the surface and troposphere;" because longwave radiation (R) and temperature (T) have a direct relationship according to the Stefan-Boltzmann equation, $R = \varepsilon\sigma T^4$, increases in emitted radiation cause "a larger temperature increase at colder background temperatures" (19). Thus, the Planck feedback contributes to Arctic amplification because the poles are colder than the tropics and a greater temperature increase would be needed in the Arctic to balance the same forcing (19). The lapse-rate feedback has a cooling effect towards the equator and a warming effect in the Arctic, because in the Arctic ”cold dense air close to the surface is hardly mixed with the lighter air aloft,” so ”a larger increase in surface temperatures is required to offset a given TOA imbalance,” and thereby exacerbates the effects of Arctic amplification (19). Other causes of Arctic amplification include “atmospheric and oceanic heat transports,” “impacts of cloud cover and water vapor,” and “increasing concentrations of black carbon aerosols in the Arctic,” among others (21).

Wind patterns are driven by temperature and pressure gradients, and the Arctic is home to major atmospheric currents that shape the global climate system (Monitoring and Programme). However, the effects of climate change on these wind patterns, and especially the impact of rising temperatures related to Arctic amplification, have not been widely studied. Thus, there is no general consensus about how rising temperatures will affect the frequency or intensity of wind gusts in the Arctic, or what other factors beyond climate change will influence wind gusts (21). However, evidence is emerging that smoother surface roughness, changes in atmospheric stability, and sea ice loss increase near-surface winds (8).

One community directly impacted by climate change is Utqiagvik, Alaska, the northernmost city in the United States. Bowhead whale hunting continues to be an important source of food, especially because transporting food to Utqiagvik is extremely expensive (20). Here, more frequent wind storms have begun to threaten the traditional hunting practices of Iñupiaq inhabitants (20). The threshold for safe boating conditions during whale hunting season is considered to be 6 m/s, and wind speeds above 10 m/s have the potential to cause infrastructure damage (9). The increasing severity of wind storms and resulting wave action has also contributed to coastline erosion in Alaska, and thus exacerbated community vulnerability to coastal flooding (14). Studying the impacts of Arctic amplification on wind gusts can help contribute to a wider understanding of how our planet responds to rising temperatures, as well as the potential to directly help Arctic communities adapt to climate change. Researching wind patterns in the Arctic, and especially how they respond to climate change, can also provide insight into impacts on other Arctic communities as well as Arctic navigation waters (10).

To estimate the effects of Arctic amplification on wind patterns in the Arctic, my project evaluates the variability of wind gusts between 1994 and 2022 in Utqiagvik, Alaska and assesses the various parameters that influence wind conditions. With these data I can determine what, if any, effect warming has already had on winds, and the causes of any observed wind changes. I am particularly interested in exploring how both the variability of short-term wind gusts has changed and how average wind speeds may have changed in Utqiagvik. In this thesis, I answer the following research questions:

- How has the variability of wind speeds in Utqiagvik, Alaska changed over the past 30 years, if at all?
- If the variability of wind speeds is influenced by multiple factors, which factor influences variability most strongly? What are the effects of temperature changes, especially, on wind variability in the Arctic?
- Do different seasons (e.g. winter vs. summer) experience different magnitudes of change in wind variability? If so, how do seasonal differences in wind variability compare with seasonal differences in rising temperatures?

Given that we know many of the meteorological parameters that influence wind conditions in the Arctic are changing with the climate, especially an increase in temperature, this project aims to uncover how the variability of wind speeds is responding in turn.

I also developed a preliminary predictive model that I will refine and use in further research to predict the variability of wind speed, which we define as the standard deviation from the hourly mean wind speed, given values of temperature and wind speed within a particular hour.

Key terminology used in this study will be defined below.

- *t_2m*: The temperature recorded at 2 meters above the ground level, reported in °C.
- *wind_spd*: In the minute dataset, the minute average of the recorded wind speed in m/s. In the hourly dataset, the hourly average of the recorded wind speed in m/s.
- *t_difference*: The difference between the temperature at 10 meters above ground level and the temperature at 2 meters above ground level, reported in °C.
- *wind_sd*: The hourly standard deviation of wind speed, reported in m/s. The standard deviation was calculated for each hourly period from the minute-averaged wind speeds during each period.
- *High wind gust*: An occurrence where *wind_sd* is equal to or exceeds 2 m/s.
- Temperature exceedances: The number of hours above a threshold of -1.8°C, the temperature at which sea ice begins to melt.

CHAPTER 2

Review of the Literature

2.1 Effects of Climate Change in the Arctic

Because of Arctic amplification, the northern high latitudes have experienced warming about two to three times greater than the midlatitudes and tropics; one study shows that ”the frequencies of winter air temperatures above -5°C have been increasing by 4.25 days per decade in the North Pole region and by 1.16 days per decade in the Pacific sector of the Arctic Ocean” (24). Arctic amplification is not a new phenomenon, as paleoclimate records suggest that the Arctic has warmed disproportionately to mid- and lower-latitudes during historical periods of natural warming (21). Climate indicators, which describe and quantify changes in weather patterns, that are used to measure trends in present Arctic climate change include temperature, pressure, sea ice extent, snow cover, and mass balance (6). Loss of sea ice, land ice, and permafrost is accelerating, which further amplifies the effects of Arctic amplification due to the decrease in regional albedo (16).

Increasing temperatures drive major changes to the Arctic climate system, but the rates of change in temperature are not equal throughout the year (6). Observed temperature trends show that the rate of increase of temperature is higher in winter than during the other seasons, and that temperature increases are smallest during the summer months (7). While ”Arctic annual average air temperatures 1971–2017 increased 2.7 °C, at 2.4 times the rate of the Northern Hemisphere average,” the cold season experienced warming ”2.8 times the rate of the Northern Hemisphere cold season average” and the warm season experienced warming ”1.7 times the rate of Northern Hemisphere summer” (6). Modern Arctic Amplification is also supported by trends shown in the polar cold air mass (PCAM) that indicate a faster loss of extremely cold air than moderately cold air (12). This is significant because the spatial patterns of the surface air temperature over the 60-year study period (1959-2018) suggests that the loss of sea ice is a driving factor of the variability of circulation in the Arctic atmosphere, especially when coupled with ice-albedo temperature feedbacks (12). Other prominent effects resulting from an increase in air temperature include an intensified hydrologic cycle, a decrease in sea-ice coverage, and warming of near-surface permafrost (6).

Historically, the ice-freeze season in Utqiagvik has begun in October, and the ice-melt season has lasted between April and August (21). However, compared to sea ice data 40 years ago, Arctic sea ice now refreezes a full month later each autumn due to warming temperatures, and if these trends continue then the Arctic is expected to have completely ice-free summers by 2070 (11). The interactions between sea ice and the atmosphere have exacerbated the variability of rare weather events in the Arctic, including permafrost thawing and wildfire outbreaks in the Arctic Circle (18).

Downscaled GCM projections simulating future Arctic Amplification informed by archival analysis of weather records suggest a decline in the frequency of low-temperature days through the 2040s as well as changes in extreme snowfall events and high-speed wind events (13). The most heavily impacted parameters are expected to be temperature and sea ice (24). While temperature variations consistent with Arctic amplification do show a positive trend over the past century, and projections show this warming trend to continue, variations in precipitation show no clear pattern, which is interesting because temperature and precipitation extremes are driven by temperature and moisture advection (5). Since projections of atmospheric circulation changes "are less robust than the projected thermodynamic changes," the effects of Arctic amplification on wind in the Arctic are much more uncertain (5). Thus, projected effects of Arctic amplification on bowhead whales and bowhead whale hunting remain unclear (17).

2.2 Impacts of Climate Change on Alaskan Coastal Communities

The native Iñupiat of Utqiagvik have continued to maintain their traditional hunting methods, including seal hunting in winter and bowhead whale hunting in spring and fall (20). Consistent wind speeds below 6 m/s are critical for safety during bowhead whale hunting because stronger winds can cause larger waves that make hunting in boats unsafe. In recent decades, increases in wind speeds correlated with rising Arctic temperatures and changes in sea ice breakups have made "the increases in both total number of open water days and unboatable days... statistically significant" and as a result impacted local hunting practices (20). Both qualitative reports from rural Alaskans and quantitative data from wind speed measurements in Utqiagvik suggest that there has been a decrease in the number of suitable hunting days, up to 7 days fewer per year since 1971 (9). Whale hunting is important both for cultural reasons and for food security. Because of the high costs associated with transporting food to Utqiagvik, Arctic amplification and impacts on hunting opportunities directly impacts food security for indigenous residents who rely on subsistence hunting methods to obtain a stable food supply (20; 9).

Humans have dealt with climate change in the Arctic using short-term strategies, such as adapting to new hunting conditions, as well as long-term strategies, such as intercommunity trade, which has historically been "a means of addressing regional differences in resource availability" but will likely become increasingly important as the future of Arctic resources becomes more uncertain with rising temperatures (4).

The northern coast of Utqiagvik has experienced a threefold increase in high-speed wind events capable of causing coastline erosion between 1979 and 2014 (20). Additionally, there are two key wind speed values with regional importance for Alaskan coastal communities: 6 m/s, above which wind speeds are considered unsafe for bowhead whale hunting, and 10 m/s, above which sustained winds have the potential to cause damage to infrastructure and wildlife habitats (20; 9). However, the variability of wind speeds garners less attention in research than identifying threshold exceedances. Even if the average wind speed for a particular day or hour is below the threshold for safe boating conditions, a short but sudden wind gust above that threshold still has the potential to endanger hunters (9).

2.3 Wind Gusts in the Arctic

Researchers typically develop their own definitions of what constitutes ”gusty” conditions based on their specific scientific questions, and may use many various parameters to define gusts (3). Many researchers studying high-speed wind conditions represent its properties using the gust factor, typically a ”ratio between the maximum and average wind speed,” but this variable has no strict mathematical definition (3). Other ways researchers have measured and/or characterized wind gusts have included turbulence regimes (1), specifying the consecutive duration thresholds of winds above a certain speed (13; 2), frequency of exceedances of a value (24), and advection types (23).

Periods of turbulence in the stable Atmospheric Surface Layer (ASL) are characterized by velocity dipoles and heat transfer (1). During more turbulent vertical fluctuations, the dipoles are stronger but confined to the first 6m of the ASL; during transitional periods the dipoles are weaker but spread across a greater vertical profile and heat transfer is increased (1). Turbulence may also be explained by turbulent pressure transport (1).

2.4 Effects of Arctic Amplification on Arctic Wind Patterns

Since it is well understood that the Arctic has experienced faster warming rates than the rest of the globe, studies suggest that rising temperatures in the Arctic will increase the variability in wind gusts (7; 24). However, there is no widely accepted projection as to how strongly the changing temperatures will influence wind patterns in the Arctic. Most research teams agree that the strengthening of Arctic amplification is linked to changes in atmospheric circulation, but there is disagreement about which changes are causes versus effects, and what changes are most likely to be observed in coming decades (21).

Arctic amplification influences, and is influenced by, many atmospheric processes, including the polar jet stream, ”changes in atmospheric and oceanic heat flux convergence, and changes in cloud cover and water vapor content that affect... atmospheric energy flux convergence” (21). The Arctic’s rising temperatures especially affect heat fluxes during the autumn freeze-up because of ocean-atmosphere heat exchange in areas where ice has melted to uncover newly open water (11). This leads to feedback within the air-ice-ocean system whereby the ” clear linkages between the loss of ice and the large-scale atmospheric patterns” enable ”the atmosphere to continue to enhance delays in autumn freeze-up" (11). While the ice-melt season typically lasts between April and August, delays in autumn refreezing "can intensify storm systems over the Arctic" due to the increase in vertical instability over water that had previously been frozen over (7). This finding provides support for my hypothesis that a lengthening ice-melt season leads to gustier conditions in Utqiagvik, with a particular increase in wind storms during the months bordering the historical ice-melt season.

CHAPTER 3

Datasets and Methods

3.1 Dataset

All measurements used for the relevant datasets were obtained from the Barrow Atmospheric Baseline Observatory, part of the Earth Systems Research Laboratory (ESRL) Global Monitoring Laboratory, located in Utqiagvik, Alaska. The datasets used were obtained from this location's continuous in situ meteorology measurements between 1994 and 2022; this project's study period began in April of 1994 when the ESRL began to collect data on the minute-level frequency as well as hourly averages. The meteorology datasets include measurements of the following variables: wind speed and direction, wind steadiness factor, pressure, temperature at 2 meters above ground level, temperature at 10 meters above ground level, temperature at the top of the instrument tower (27 meters above sea level), relative humidity, and precipitation intensity. Of these variables, only wind speed (*wind_spd*) and temperature at 2 meters (*t_2m*) were used in this study. The temporal resolutions used were the minute data and hourly data. The dataset was filtered to include only minutes with measurements for both parameters.

The primary output variable that was analyzed is *wind_sd* on an hourly basis, which we calculated as the standard deviation of wind speeds within an hour-long period. While there is no universally agreed-upon method to measure or define gusts, we chose to represent wind gusts using the standard deviation of hourly wind speed because it is a clearly defined variable. The hourly mean wind speed, expressed as "*wind_spd*" in meters per second, and *t_2m*, temperature in Celsius 2 meters above ground level, were chosen as input variables for the predictive models.

3.2 Research Methodology

All data processing and analysis in this thesis use the R version 4.2.2 software package. From the minute scale meteorology ESRL datasets, I created "*combined_cc*," an hourly dataset with: mean wind speed, wind speed variability, maximum wind speed in that hour, and minimum wind speed in that hour.

To remove data artifacts, I set mean wind speed limits between 0 m/s and 25 m/s, and set a maximum wind speed limit at 35 m/s. Then, I manually checked for lingering equipment malfunctions in the dataset by cross-validating measured data points that had especially low or high *wind_sd* values or measured wind speeds with other records of Utqiagvik's weather from that day. For example, there were about a dozen days that had consistent wind speeds all day except for a few hours that suddenly dropped to 0 m/s, then resumed measuring a few hours later at around the same wind speed from before; such instances were likely equipment malfunction, or the instrument may have stopped measuring because it had frozen over. Further data filtering removed all cases where *wind_sd* >5 to remove outliers. After artifact removal, I saved my final working dataset as "*new_combined_cc*."

Other values that I calculated to update the "*combined_cc*" dataset later on were $t\_difference$, which reports the difference between the temperatures 10 meters and 2 meters above ground level, and the bulk Richardson number. I considered trying to estimate the effect of atmospheric turbulence generated by mechanical shear using the bulk Richardson number (Rb). The bulk Richardson number was calculated, but was not a statistically significant predictor of wind variability.

3.3 Pilot Testing

Before attempting to make predictions, I visualized the raw data in R to evaluate the relationship between different meteorological variables and *wind_sd*, and looked at each parameter individually as it related to *wind_sd* before attempting to create a model that put them together. I used two different functions in R, quap and ulam, to model the relationships between my input and output variables. The *wind_spd* data and *t_2m* data was binned into 20 bins to visualize the relationships between each input variable with *wind_sd*, the output variable, and density plots of each were made.

I created two predictive models to evaluate how well my input variables could predict *wind_sd* values: $linear\_model$ and $mgustyMR\_predicteddraws$. The predictive linear model, "$linear\_model$," was calculated with the lm function in R, which is simply a linear regression model. Model "$mgustyMR\_predicteddraws$" is a predictive Bayesian multiple regression model that adds input terms and estimates the output using a Markov chain Monte Carlo technique, which allows sampling directly from the posterior distribution. Running the multiple regression model as a polynomial was attempted, but the resulting R-hat value (which reports the chain calibration for the model parameters) was outside the acceptable value range of 1.00 to 1.05. For $mgustyMR\_predicteddraws$, I used 4 chains, 4 cores, and 1000 iterations using Monte Carlo analysis with the ulam() function in R. After testing many different priors, the variable *wind_sd* was calculated as *wind_sd* $\sim$ *Normal*(α, σ) whereas the priors, taken from the input values, were $\alpha \sim$ *Normal(0.5, 0.5);* $\beta_1 \sim$ *Normal(0, 0.02),* $\beta_2 \sim$ *Normal(0, 0.05);* $\sigma \sim$ *Exponential(2).* Alpha (prior α) is a normally distributed prior centered on 0.5, based on an average *wind_sd* of 0.5. The β_1 and β_2 priors are the range of slopes of *t_2m* and *wind_spd*, respectively. Sigma squared represents the variance of the residuals.

After both predictive models ran successfully, I used them both to plot the actual *wind_sd* values from my original dataset vs. the *wind_sd* values that the models predicted. Visualizing this drew my attention to possible outliers that remained in my dataset, so I manually looked at each remaining data point where *wind_sd* > 2 by returning to the minute data to see if any reportedly high *wind_sd* values were the result of equipment malfunctions or if the values could be explained by a weather pattern reflected by other parameters in the same dataset, like a temperature or pressure change, or change in wind direction. I also cross-checked data from my dataset with online weather records, and further removed outliers where there were discrepancies. The correlation coefficient was calculated for both models using the cor() function in R.

I also experimented with adding interactions between the input variables and adding bulk Richardson number as a predictor variable, but adjusting the model in this way did not offer any significant improvement in the correlation coefficient; in fact, in some cases, the correlation became slightly worse.

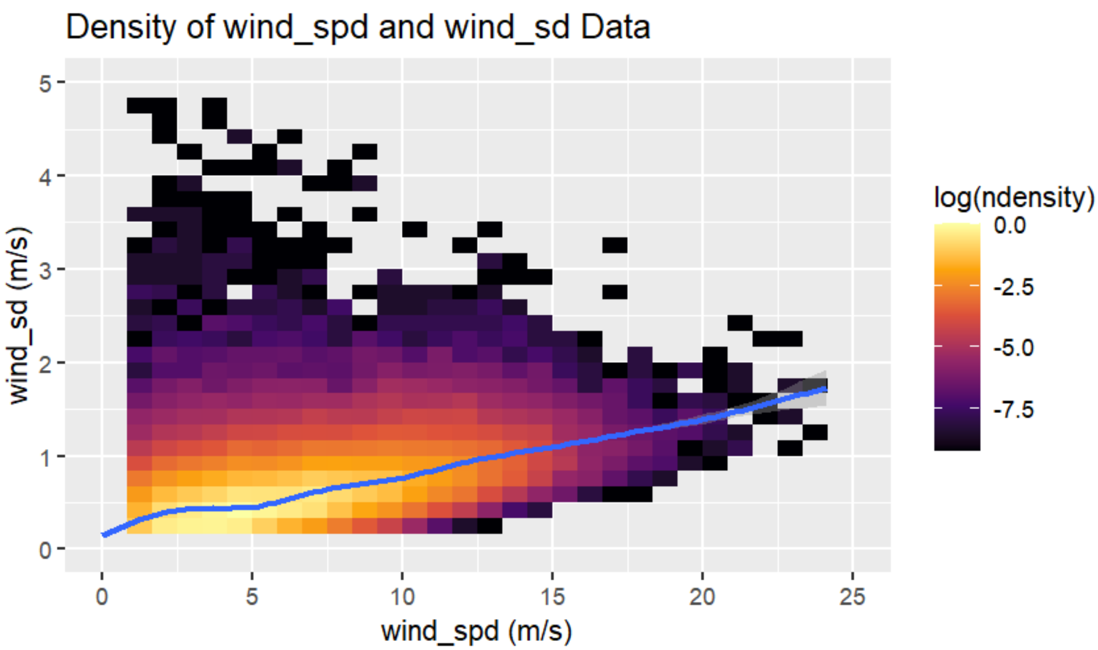
To examine whether the frequency of sudden high-variability wind gusts has changed over the study period, cases in the month datasets where *wind_sd* $>$ 2 m/s were isolated into new, separate datasets called "$Month(\#)$_*high*." Then, the total number of hours that contained values of *wind_sd* $>$ 2 m/s were tallied within each year for each month's dataset into datasets called "$Month(\#)$_*count*" and missing years with values of count = 0 were added. This gave datasets for each month that reported how many hours within each month and year exceeded *wind_sd* measurements of 2 m/s.

CHAPTER 4

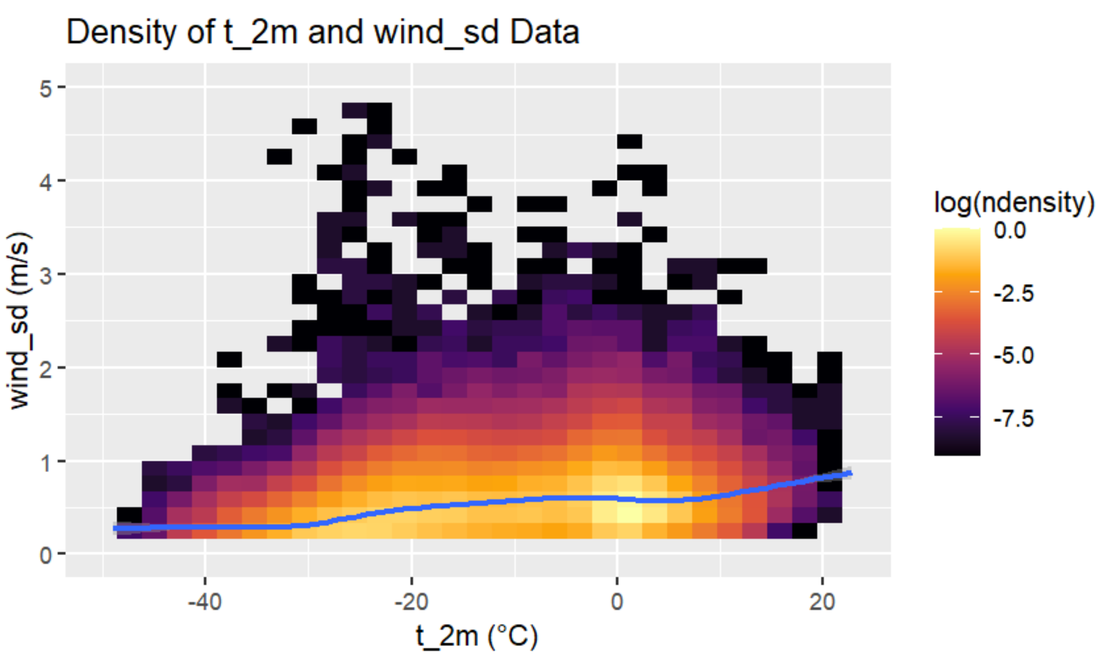
Results and Discussion of Findings

After comparing variables and their correlation with *wind_sd*, only two variables from the ESRL's raw meteorological data showed a strong enough correlation with *wind_sd* to be useful predictors: *wind_spd*, the hourly mean wind speed, and *t_2m*, the temperature 2 meters above ground level. The *wind_spd* and *wind_sd* have a strong positive relationship; generally, *wind_sd* increases with increasing *wind_spd*, which indicates that as the mean wind increases so does the variability, or gustiness. Values with a *wind_sd* above $\sim$ 1.2 m/s show much higher standard error than values below it because there aren't as many observations of associated wind speeds above about 17 m/s. The relationship between *wind_spd* and *wind_sd* over all months and years is shown in Figure 1A; the black lines in each box show the mean *wind_sd* associated with the wind speed in that bin. The relationship between *t_2m* and *wind_sd* is also generally positive, shown in Figure 1B. The bins with the hot colors such as yellow and orange have much more data than the bins with the cool colors.

I also looked at the relationship between *t_difference* and *wind_sd*, and planned to use the vertical temperature gradient to estimate the buoyancy production of kinetic energy so that I could measure turbulence. However, the temperature difference between 10 meters and 2 meters above ground level is so small that the correlation was not strong enough to consider using it as an input variable for my predictive models. The Bulk Richardson number was also considered as a predictor variable, but adding it to my predictive model did not have a significant effect on the predictability of *wind_sd*, so it was not used.



(a)



(b)

Figure 4.1: (a) Smooth line trend and data density plot of the observed relationship between *wind_spd* and *wind_sd* using only the raw data during the sample period (1994-2022). (b) Smooth line trend and data density plot of the observed relationship between *t_2m* and *wind_sd* using only the raw data during the sample period (1994-2022). The horizontal axes report (a) *wind_spd* in m/s, (b) *t_2m* in degrees C, and the vertical axes report *wind_sd* in the of standard deviations from the mean *wind_spd* (in m/s) observed in the hour.

After removing outliers, both models were rerun based on the filtered dataset. The plots of the actual *wind_sd* values vs. the predicted *wind_sd* values for both models appear below in Figure 2.

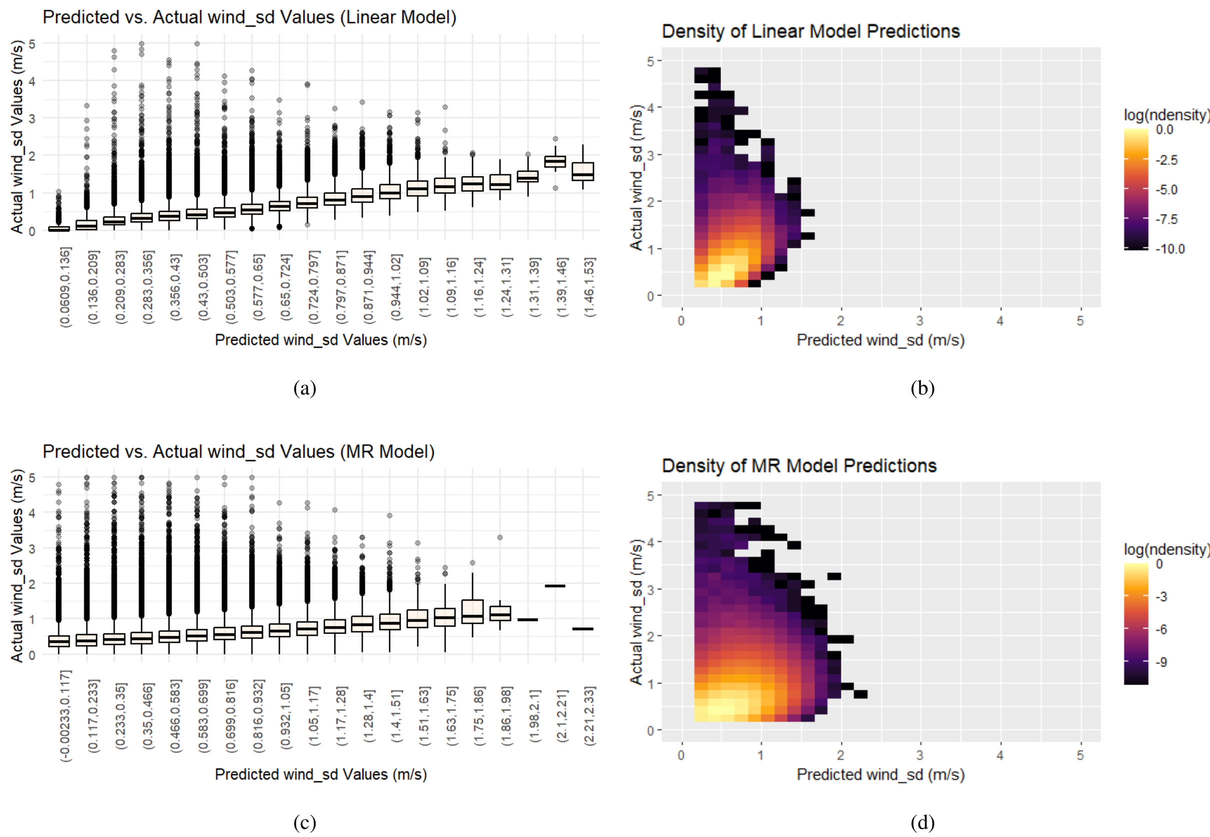


Figure 4.2: Predicted fit for *wind_sd* output using the linear model (a and b, R = 0.569) and the Bayesian multiple regression model (c and d, R = 0.358). The predicted *wind_sd* values were calculated using linear and Bayesian methods, respectively, as a function of *t_2m* and *wind_spd* collected from the data between 1994 and 2022.

The linear model has a correlation coefficient of 0.588, and the Bayesian multiple regression model has a correlation coefficient of 0.347. Though the linear model shows a correlation closer to 1 and predicts *wind_sd* values more accurately, only the multiple regression model was reliably able to predict *wind_sd* values more than 1.5 standard deviations from the mean. The linear regression model predicted only two *wind_sd* values beyond 1.5 standard deviations out of 232,726 data points, 2,392 of which had actual *wind_sd* values above 1.5. Since I am particularly interested in higher variability wind gusts, I will need to improve the accuracy of the linear regression model before I will use its predictive data.

Analysis of wind speed data in Utqiagvik indicates that both the input variables of *wind_spd* and *t_2m*, when analyzed separately from each other, are strongly correlated with *wind_sd*. Both *wind_spd* and *t_2m* show a positive trend whereby the variability of wind speed as measured by *wind_sd* increases with higher temperatures and higher hourly average wind speeds. Thus, gustier conditions are associated with warmer temperatures and higher mean wind speeds. In Figure 1A, the blue line shows an exponential increase of *wind_sd* up to *wind_spd* values of about 3 m/s, plateaus between approximately 3 and 4.5 m/s, then demonstrates a fairly linear increase up to 20 m/s. Above *wind_spd* values of approximately 17 m/s, the standard error increases because there are many fewer data points that measure such a high magnitude of *wind_spd*. The trendline in Figure 1B shows that *wind_sd* generally increases with temperature, though between about -4°C and 5°C there is a minimal decrease. This indicates that as the surface temperatures warm, even though they remain below freezing, there is likely more turbulence that causes increases in wind gusts. When the surface temperature approaches the melting point (0°C) the gustiness decreases for unknown reasons.

For the linear predictive model and the Bayesian multiple regression predictive model, obtaining a correlation of R^2 = 1 between observed and predicted values will not likely be possible. However, the models still fail to predict *wind_sd* values above 2. In the original dataset, the datapoints with *wind_sd* above 3 but < 5 are explainable, but rarer cases with *wind_spd*s averaging between 3 and 6 m/s during the hour but a few minutes of very high wind speeds during that hour bring the *wind_sd* up. Further work will need to be done to be able to predict occurrences with higher *wind_sd*.

Next, I considered how each variable changed over time by separating the data over all years by month and season. For example, the respective dataset for August contained all data points collected during August 1994 and each subsequent August through August 2021. Time series plots of each variable were made for each month to visualize how *wind_sd*, *wind_spd*, and *t_2m* have changed over the past three decades in different parts of the year, and the rate of change was calculated for each using the slope. To verify the reliability of observed trends, a regression slope test was performed for each monthly dataset at the 95% confidence level. The resulting slopes of high gust frequency, *t_2m*, *wind_spd*, and *wind_sd*, as well as their standard errors, for each month were summarized in a dataframe "*slopes_df*."

4.1 Temperature

Plotting the slope of *t_2m*, the rate of change of the average temperature between 1994 and 2022, separated by each month reveals some interesting trends. Over the study period, the average temperature increased in each month, but different months demonstrate very different rates of increase. The months that showed statistically significant temperature increases were January, May, October, November, and December. The relationship of temperature increases to the season will be discussed later in this thesis. The months that did not pass the regression test show a lot of scatter in temperature fluctuations over the years, but nevertheless, each month separately has a positive trend that shows average temperatures are increasing. Figure 3 plots the rate of change of temperature increase for each month. Figure 8 is located in the Appendix and shows the breakdown of each year and month's mean temperature.

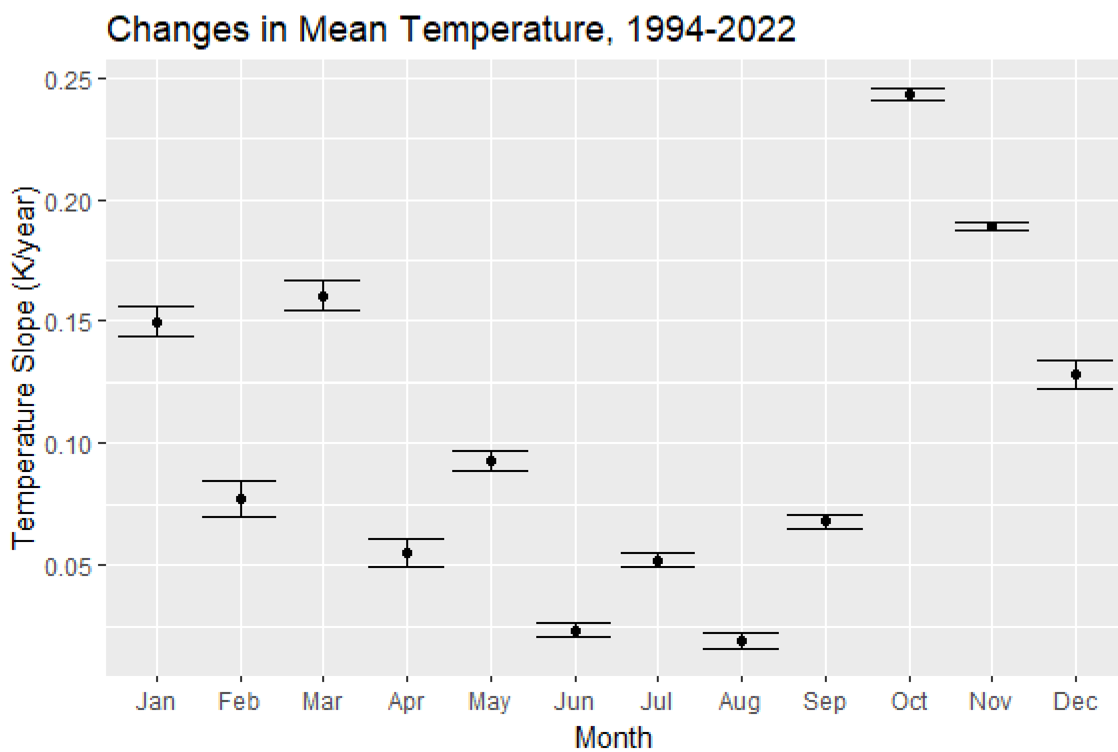


Figure 4.3: Whisker plot of average temperature change within each month from 1994 to 2022. The dots correspond to the slope of the average temperature change for each month between 1994 and 2022, and whiskers correspond to the standard error.

Significance test:

Month	Temperature slope (K/year)	p-value
January	**0.1497**	**0.0226**
February	0.0778	0.3324
March	0.1603	0.0559
April	0.0552	0.3055
May	**0.0926**	**0.0367**
June	0.0233	0.2888
July	0.0520	0.0659
August	0.0188	0.6073
September	0.0678	0.0707
October	**0.2429**	**0.0001**
November	**0.1890**	**0.0123**
December	**0.1285**	**0.0450**

Table 1. Student-t significance test for the rate of change of t_2m (K per year) and associated p-values, rounded to 4 digits. The trend is considered significant if $p < 0.05$; months with values significant at the 95% confidence level are bolded.

Temperature has increased much more strongly between October and March (fall and winter), especially during October through January, compared to April through September (spring and summer). October showed the most positive slope of all months, and has experienced temperature increases of 2.43°C per decade. The average temperature during the winter months increased 1.07°C per decade, whereas the summer months only saw an average warming of 0.36°C per decade. The seasonal disparity between rates of temperature increase are in line with previous studies of Arctic amplification that have found overwhelming evidence for winter temperatures increasing more rapidly than summer temperatures in the Arctic (23; 6).

One notable observation for the month of January was that temperatures at or below -40°C occurred, though rarely, at the beginning of the study period. Of 11770 measurements taken between 1995 and 2011 during the month of January, 235 hours (0.02%) had a mean temperature at or below -40°C. However, temperatures below -40°C have not occurred at all in January in the past decade, and last occurred on 24 January 2011 between 0:00 and 0:59.

At the beginning of the study period, the average temperature in September was below freezing; the year 1994 had a mean t_2m of -2.77°C. However, in more recent years towards the end of the study period, average temperatures have risen above freezing. This is significant because September has historically been the start of the ice-freezing season; however, atmospheric temperatures are rising and may not be cold enough to allow freeze-up. The month of September is now warm enough on average in Utqiagvik that the duration of the melt season may have lengthened by up to a month; mean temperatures do not drop below freezing until October in more recent years. Figure 8 in the appendix displays the mean temperatures over the study period for each individual month. This finding supports the trends observed by Thomson et al., 2022 that Arctic sea ice refreezes up to a full month later than it did 40 years ago due to rising temperatures.

4.2 Mean Wind Speeds

Calculating the rate of change of mean wind speed for each month over the study period and performing a regression test did not reveal any strong evidence for an overall trend in mean wind speed. A two-sided student's t-test was used to determine statistical significance of the mean *wind_spd* trend over the study period. Since only one month (June) had a p-value of < 0.05, the data does not provide enough evidence to assume a significant change in the mean wind speed at this location according to the student's t-test. Figure 4 shows the slope of the change in mean wind speed per year during each month, and associated p-values are reported in Table 2.

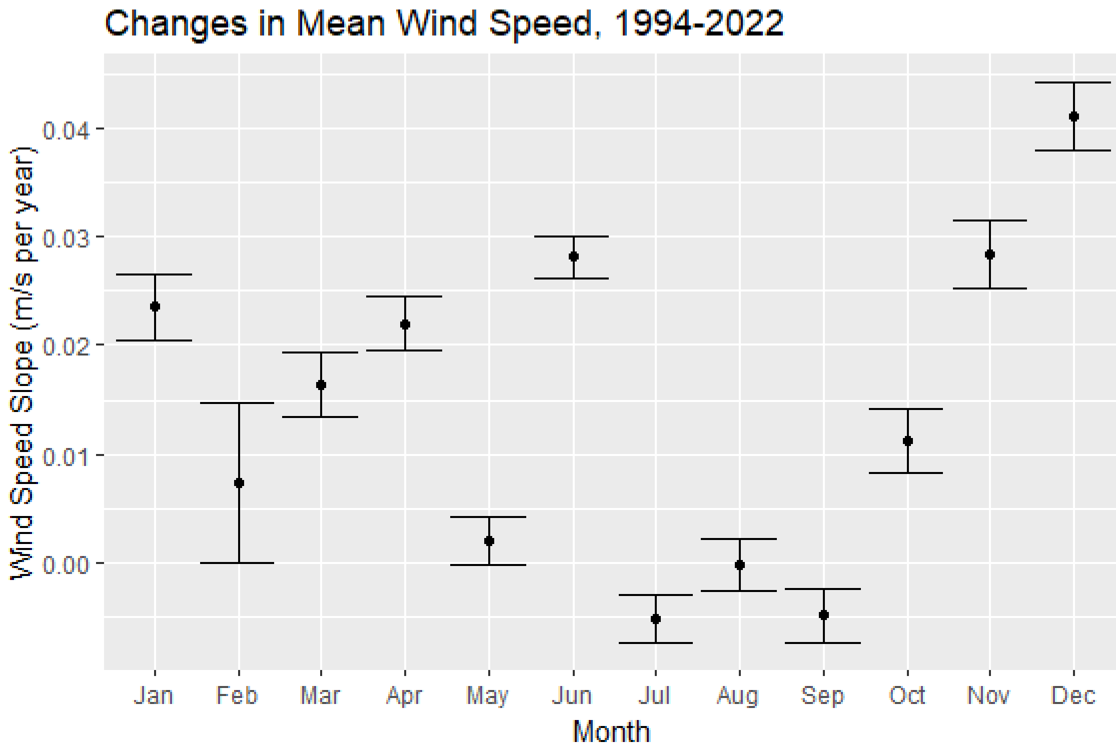


Figure 4.4: Whisker plot of average wind speed change within each month from 1994 to 2022. The dots correspond to the slope of the average wind speed change for each month between 1994 and 2022, and error bars correspond to the standard error.

Significance test:

Month	*wind* slope (m/s per year)	p-value
January	0.0235	0.5007
February	0.0073	0.8272
March	0.0164	0.4828
April	0.0220	0.1297
May	0.0019	0.9655
June	**0.0282**	**0.0452**
July	-0.0052	0.3357
August	-0.0002	0.9737
September	-0.0049	0.7591
October	0.0113	0.4765
November	0.0284	0.3675
December	0.0411	0.1800

Table 2. Student-t significance test for the rate of change of *wind_spd* (m/s per year) and associated p-values, rounded to 4 digits. The trend is considered significant if $p < 0.05$; because none of the associated p-values from the student's t-test were below that, it is reasonable to conclude that changes in wind speed were not significant.

4.3 Mean *wind_sd*

Using similar methods as before, the rate of change of *wind_sd* over time was calculated for each month as a slope. According to the student's t-test significance test, there is enough evidence to conclude that all months except September, which has a p-value > 0.05, show a significant trend in mean *wind_sd*. The mean *wind_sd* has been increasing for all months of the year, and each month except September showed a statistically significant increase. Therefore, it is reasonable to conclude that the variability of wind speeds has increased over the study period.

Figure 5 below shows the different rates of change for *wind_sd* during each month, and Table 3 shows associated p-values. "Mean *wind_sd*" refers not to the mean standard deviation for the entire month, but to the average value of all *wind_sd* values recorded within that month. The individual breakdown of yearly mean *wind_sd* values for each month is shown in Figure 10, located in the appendix.

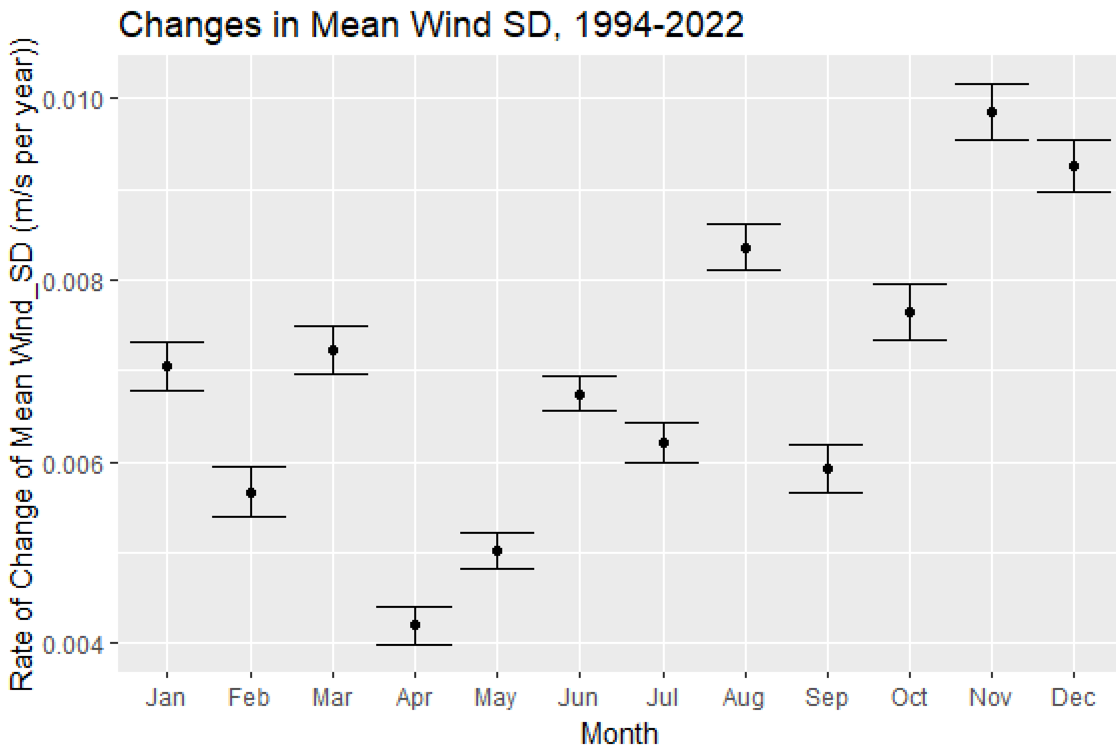


Figure 4.5: For each month, the slope of change in the mean standard deviation of wind speed between 1994 and 2022.

Significance test:

Month	mean *wind* slope (m/s per year)	p-value
January	**0.0071**	**0.0191**
February	**0.0057**	**0.0136**
March	**0.0072**	**0.0034**
April	**0.0042**	**0.0007**
May	**0.0050**	**0.0027**
June	**0.0067**	**0.000**
July	**0.0062**	**0.0012**
August	**0.0084**	**0.0090**
September	0.0059	0.0584
October	**0.0076**	**0.0384**
November	**0.0098**	**0.0092**
December	**0.0093**	**0.0085**

Table 3. The mean *wind_sd* slope for each month and associated p-values obtained from the student's t-test.

Bolded values have a p-value < 0.05 and are significant at the 95% confidence level.

October through December as well as August are the months experiencing the most rapid increase in mean *wind_sd*. The seasonal changes in mean *wind_sd* parallel the seasonal changes in *t_2m*; the winter and fall months experience greater changes in both *wind_sd* and *t_2m* on average than the spring and summer months.

4.4 High Gust Frequency

The rate of change in occurrences of high gusts for each month was calculated as a slope. Figure 6 shows the rate of change in the frequency of these high gusts over the study period, separated by month.

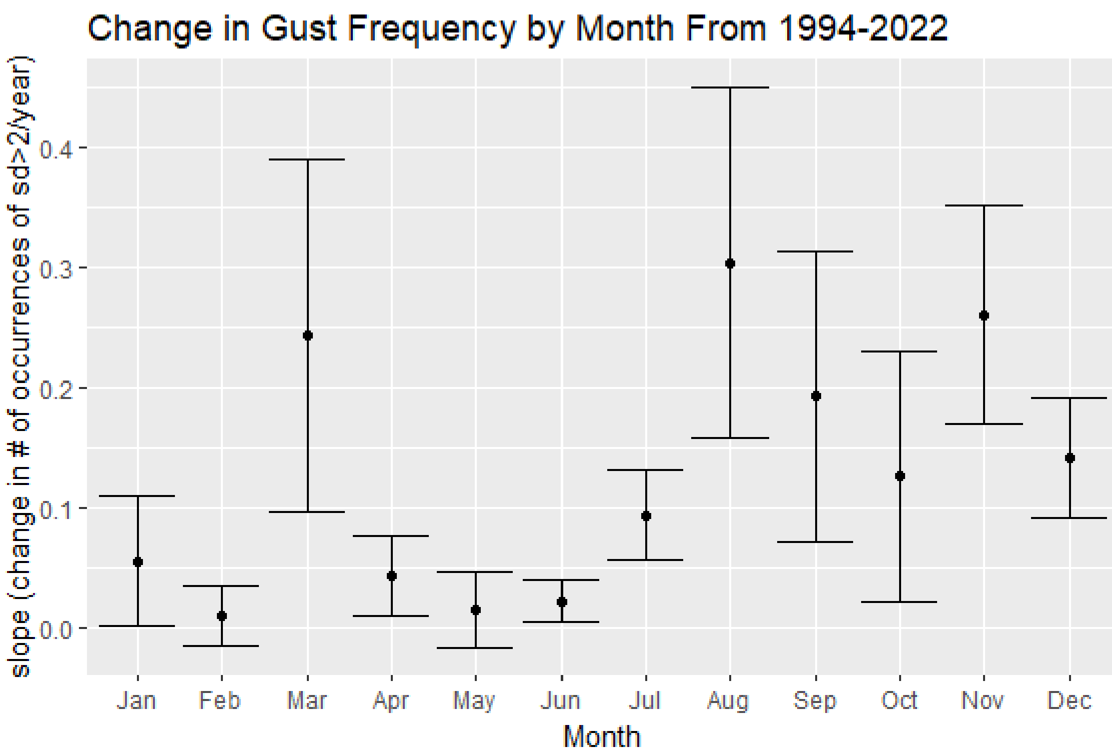


Figure 4.6: Change in the frequency of the occurrences of hours with high wind gusts (*wind_sd* > 2) between 1994 and 2022 for each month out of the year.

Significance values:

Month	Rate of change of gust frequency (# of occurrences of *wind_sd* > 2/year)	p-values
January	0.0547	0.3242
February	0.0094	0.7064
March	0.2429	0.0921
April	0.0429	0.1349
May	0.0143	0.4649
June	0.0217	0.2288
July	**0.0933**	**0.0195**
August	**0.3035**	**0.0486**
September	0.1924	0.1244
October	0.1253	0.2420
November	**0.2597**	**0.0008**
December	**0.1407**	**0.0121**

Table 4. The rate of change of gust frequency for each month and associated p-values obtained from the student's t-test. Bolded values have a p-value < 0.05 and are significant at the 95% confidence level.

Each month has experienced an increase in the frequency of high wind gusts between 1994 and 2022. The months that experience the greatest overall increases in *wind_sd* are not the same months that experience a greater frequency of high wind gusts. The months with the greatest increase of occurrences of high gusts are March and August, which border the historical ice-melt season, September, which has warmed enough in recent years to potentially become part of the new ice-melt season, and November, which is a month shown to have the second-highest temperature increase and the highest *wind_sd* increase.

In terms of the raw number of high gust occurrences, winter (December through March) is the season that showed the most frequent instances of high wind gusts; 55% of all hours with *wind_sd* > 2 occurred during the winter months. This lines up with the stormy season, when "winter extratropical cyclones" are more frequent in the Arctic (14). Extending this range to October through April, the ice-freeze season, sees 78% of all high gusts occur between these months. Not only do the summer months experience only a very slight increase in the frequency of high gust events, they also do not have many occurrences of high gusts to begin with. The mean wind speeds of each month, shown in the Appendix Figure 12, do not show a strong seasonality difference, and do not parallel these high gust months.

Of particular interest is that March and August, the border months of the ice-melt season, experience some of the most sharp increases in the frequency of high gusts. The ice-melt season is lengthening due to temperatures rising above freezing more frequently earlier in the winter so that sea ice begins to melt earlier, and temperatures dropping below freezing again later in the year so that sea ice begins to refreeze later. Studies have found an inverse relationship between sea ice cover and wind speed, and Earth system model projections show that winds are likely to strengthen in the future with further sea ice loss (8); since the relationship between wind speed and *wind_sd* is direct, the changes in the ice-melt season are also likely to reflect an increase in high gust frequency as sea ice cover decreases. High gusts may be occurring more frequently in recent years during these months because of increased turbulent heat fluxes between the ocean and atmosphere over newly open waters. Changes in sea ice drive changes in wind, but changes in near-surface winds do not impact sea ice loss (8); therefore, as sea ice has decreased and the ice-melt season has lengthened, the frequency of high wind gusts has increased in turn.

4.5 Temperature Exceedances

Each month was also evaluated for the "thawcount" frequency of temperature exceedances, or the number of hours in a month during which the mean temperature reaches above the -1.8°C threshold at which sea ice starts to melt. Figure 7 shows each separate month's rate of change of temperature exceedances.

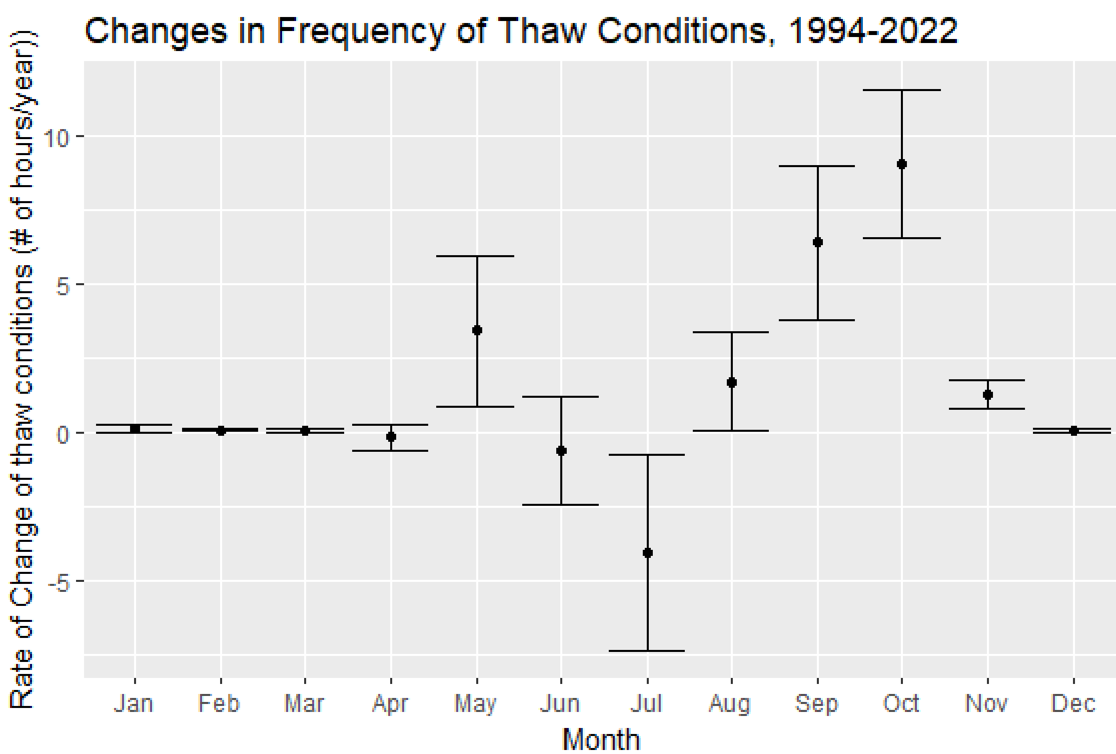


Figure 4.7: For each month, the slope of change in the number of hours that exceed -1.8°C between 1994 and 2022.

Significance test:

Month	Rate of change of thaw conditions	p-values
January	0.1297	0.2356
February	0.0952	0.1101
March	0.0712	0.2790
April	-0.1702	0.7029
May	3.4150	0.1871
June	-0.6286	0.7321
July	-4.0450	0.2320
August	1.7190	0.3000
September	**6.3970**	**0.00210**
October	**9.0560**	**0.0011**
November	**1.2556**	**0.0149**
December	0.0572	0.3750

Table 5. The rate of change of thaw condition frequency for each month and associated p-values obtained from the student's t-test. Bolded values have a p-value < 0.05 and are significant at the 95% confidence level.

April, June, and July have all experienced fewer occurrences of temperature exceedances towards the end of the study period than at the beginning of the study period. Most other months show an increase in the frequency of temperature exceedances, most notably between August and November. Existing research has demonstrated that global climate change has caused summer temperatures to increase less rapidly than winter temperatures (6), so this data is in line with existing observed trends. However, it is still unclear why June and July would have relatively fewer hours per year in recent years, though July seems to have a couple of recent outlier years significantly below the trendline that may have skewed the representation of the data. Further analysis will need to be performed with "thawcount" trends to ascertain why the observed trends occur. Figure 11, which shows the thawcount for each monthly dataset by individual year, is located in the Appendix.

4.6 Discussion of Findings

Comparing the trends observed for each variable reveals some perplexing findings. Notably, performing a statistical significance test for the analyzed variables shows that even though there has been no significant change in hourly mean wind speeds (except in June, which had a p-value just below < 0.05), the *wind_sd* has significantly increased for every month except September; even though hourly mean wind speeds have not changed in Utqiagvik, the variability of the wind speeds that occur within those hourly time periods has significantly increased. The causes and implications of this are still unclear, but there are two potential influencing factors I plan to explore to continue this research.

One potential cause for the disparity between variability of wind speeds and mean wind speeds is changing patterns in sea ice. The ice-freeze season in the northern coast of Alaska has been determined to have shortened up to 4 days per year between 1979/80 and 2010/11 due to warming temperatures (22); ice-freeze periods are shorter and the temperatures that exceed the ice-melt threshold have become more frequent. In Utqiagvik, the ice-freeze season has experienced an average temperature increase of 3.6°C from 1994-2022, whereas the melt season has experienced an average temperature increase of only 1.2°C. High wind gusts are reported to occur less frequently during the ice-melt season on average, and most high wind gusts occur during the autumn sea ice freeze-up period. However, two of the three months that demonstrate the greatest increase in high gust frequency are March and August, the months that currently bookend the ice growth period. March and August may be experiencing an increase in the occurrences of high gust events because of ocean-atmosphere heat exchanges over newly open water where sea ice has historically been frozen, reflecting the lengthening open-water season. Another potential link between more frequent high gusts and ice loss could be due to changes near surface static stability or atmospheric static stability and decreasing surface roughness due to sea ice loss (8).

Another potential explanation is the weakening of the polar jet stream, a result of rising temperatures (21). The polar jet stream has taken on a more meandering pattern, which contributes to greater heat and moisture exchange between the poles and mid-latitudes and causes displacements in the polar vortex (24). Since the jet stream has become more variable and changed atmospheric dynamics in the Arctic, this may have created a thermodynamic response that results in greater variability of wind speeds. Both hypotheses provide a link between Arctic amplification and the increasing variability of wind speeds observed in Utqiagvik. A similar ongoing topic of research includes potential changes in the frequency or intensity of Arctic storms, which may similarly influence the variability of wind speeds.

The months that show the higher rates of change in high gust frequency are not necessarily the months that show higher rates of change in mean *wind_sd*. For example, June has experienced a high gust frequency increase of only 0.022 occurrences per year, compared to March which experienced a high gust frequency increase of 0.243 occurrences per year. However, June has experienced a 0.0067 m/s per year increase in *wind_sd*, comparable to the 0.0072 m/s per year *wind_sd* increase in March.

The months that experience higher rates of temperature increase also tend to have higher rates of *wind_sd* increase. The months with the highest rate of increase of mean temperature are October, November, March, January, and December, respectively, which are five of the six months that also experience the highest increase in *wind_sd*. Between the two observed variables that influence *wind_sd* (mean wind speed and mean temperature), only temperature seems to have a significant influence on the variability of wind; mean *wind_sd* has experienced significant increase in all but one month and *t_2m* has increased in all months as well, but wind speed has had no significant trend over the course of the study period.

The *t_2m* rates of change over time in the summer months, unlike the comparatively more positive *t_2m* rates of change over time during the winter months, do not have statistical significance as calculated by the student-t-test regression analysis. Therefore, the seasonal differences in temperature trends from Utqiagvik reveal that winter temperatures have been rising significantly in comparison to summer temperatures, which have not experienced enough of an increase to determine whether the temperature rise is significant. This finding does support the hypothesis that Utqiagvik has experienced more severe warming in winter than in summer, which is consistent across the Arctic, but even though *t_2m* has been increasing, the lack of statistical significance for the trend in *t_2m* during the summer months means that summer temperature increases are likely not sufficient to explain the observed increase in *wind_sd* during the summer months.

Further research will bring together a wider contextual understanding of other potential physical explanations for the *wind_sd* increase during the summer months. One possibility is that the change in the mean temperatures in the summer is relatively small but that the number of outliers on the high end is increasing; there may be a change in the frequency of hotter days that is not strongly reflected in the mean value. Quantifying how much of a temperature increase must occur to have a significant effect on *wind_sd* is also critical for understanding how wind patterns have evolved in Utqiagvik.

In the predictive model, both *t_2m* and *wind_spd* were used as predictor variables for *wind_sd*; of the two, *t_2m* appears to have the stronger influence on the output. Because *wind_sd* has experienced significant increases in eleven of twelve months of the year, and wind speed has not had any significant change, the change in *wind_sd* can be attributed at least partially to temperature increases. Both temperature and *wind_sd* have distinctly positive trends overall during the study period, and their correlation does support existing findings from the literature that suggests a relationship between rising temperatures and increased wind variability, but rising temperatures alone likely cannot explain the observed increase in *wind_sd*, especially for elevated *wind_sd* values during the summer months. Because temperature increases drive sea ice loss, which in turn has increased mean wind speeds (8), monitoring *wind_sd* appears to be a potentially useful climate signal. If rising temperatures do indeed lead to increased *wind_sd*, wind speeds in Utqiagvik will become more variable in the future as well. This has the potential to increase the impact of wind storms on bowhead whale hunting and make hunters more vulnerable to more severe wind speeds.

Future work for this project will focus on improving the basic predictive models I have already developed so that they can estimate *wind_sd*, and use them to estimate how the variability of wind speeds in Utqiagvik may change, especially taking future climate projections into account to see how projected warming in the Arctic may influence *wind_sd*. Eventually, my final goal is to create a projected time series of what future *wind_sd* conditions may look like in Utqiagvik according to different warming scenarios using a Bayesian statistical model. At present, the most prominent shortcoming of the predictive models is that they fail to predict *wind_sd* values higher than 2, which is a particular area of interest because they're anomalous. I plan to improve my predictive models by selecting one of my two predictive models (linear vs. Bayesian multiple regression), leaving out about 20% of the data to test the model performance, and fitting the remaining 80% using cross-validation to assess the skill of the model I have built based on how well it predicts the 20% of data that has been left out, and adjusting the model accordingly. One additional predictive method that I would be interested in trying is a random forest model, a method that uses multiple decision trees. Future work will also focus on developing a more in-depth explanation about why *wind_sd* is changing, and characterizing a physical explanation for why changes in *t_2m* are the primary influence for changes in *wind_sd*– or, if there is an additional input factor that I have missed, why *wind_sd* is changing due to a combination of input factors. The remainder of this project is expected to take three years.

This thesis has a couple limitations. The scope of the study is limited to meteorological data obtained between 1994 and 2022 (29 years), the range when data was collected at the minute level. For climate purposes, the dataset I am working with is relatively short; studying climate change and being able to track meaningful changes usually requires a minimum time window of thirty years. Additionally, measuring wind variability using standard deviation instead of the number of exceedances above a particular wind speed threshold doesn't catch outliers as well as if we looked at the statistics of extremes. Therefore, the relatively narrow scope of study and the limitations of measurable variables may have influenced the reliability of my results.

Another limitation of this study is that data is only from one location - Utqiagvik, Alaska – and therefore is not appropriate for evaluating patterns of wind variability across the Arctic as a region. Thus, the conclusions drawn from this study should be interpreted as an evaluation of the local climate change, and should not be used to make broad conclusions about climate change in the whole Arctic or on the global scale unless this study is evaluated alongside other research studies. This study is also limited to considering the changes in mean wind speed, standard deviation of wind speed, air temperature 2 meters above the surface, the frequency of gusts with a high standard deviation value, and frequency of exceeding sea-ice thaw temperatures.

CHAPTER 5

Conclusions

Overall, the findings of this project reveal three primary conclusions:

1. Winter temperatures in Utqiagvik have increased more rapidly than summer temperatures since 1994. This underscores a seasonal disparity in regional warming that is supported by previous studies.

2. Mean wind speeds in Utqiagvik have not experienced any statistically significant change over the past 30 years; however, the variability of wind speeds has increased significantly.

3. The primary influence on $wind\_sd$ is t_2m, but changes in t_2m alone cannot fully explain why $wind\_sd$ has increased. The months that experience higher temperature increases tend to have higher increases in $wind_sd$ as well, but the t_2m increase observed in the summer months is not strong enough to have statistical significance whereas $wind_sd$ is.

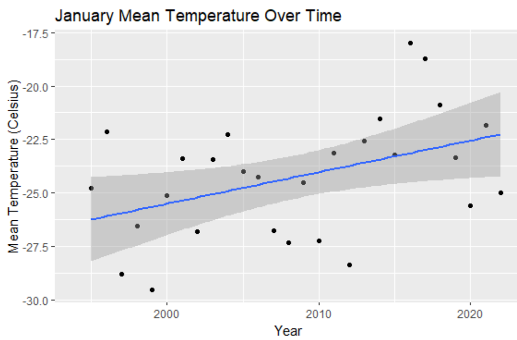
Climate change-induced warming in the Arctic might further increase the variability of wind speeds in the future. To forecast what future wind conditions may be like in Utqiagvik, the next step of this research will be to enhance the predictive model, and subsequently create a time series of estimations of future $wind\_sd$ values. While mean wind speeds and temperature are the strongest influences on $wind\_sd$, there may be other factors that need to be accounted for before this model can be developed.

5.0.1 Ethical Considerations

This project was done with regards to research integrity and accuracy, and proper credit was given to all studies referenced in this thesis. Methods and results were written as factually and thoroughly as possible to avoid falsification. None of the following research results have been previously published, and the role of everyone involved in the research has been appropriately referenced.

Appendix A

Additional Figures



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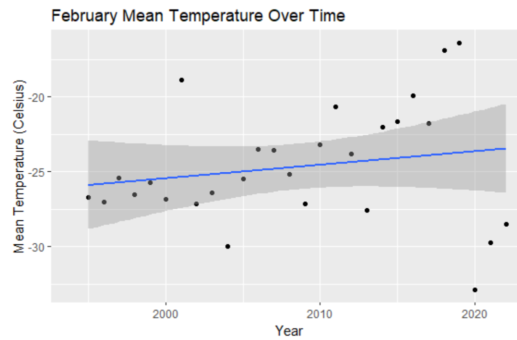

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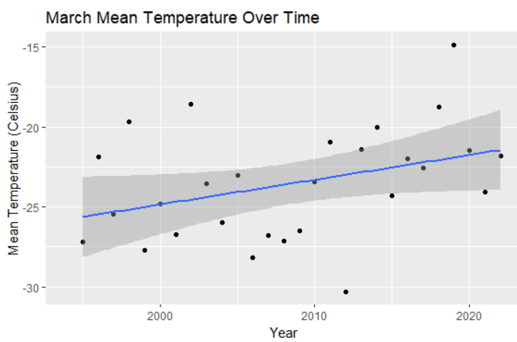

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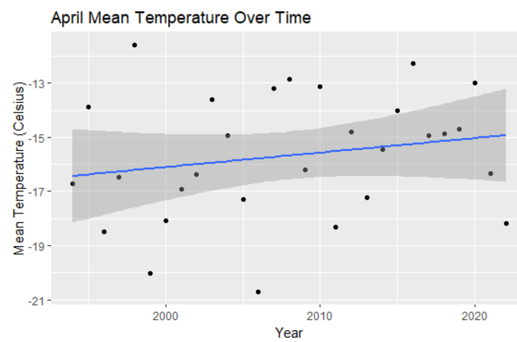

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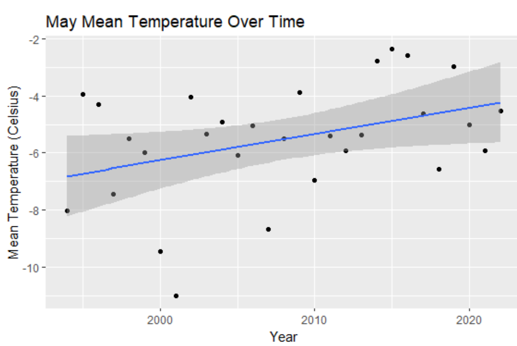

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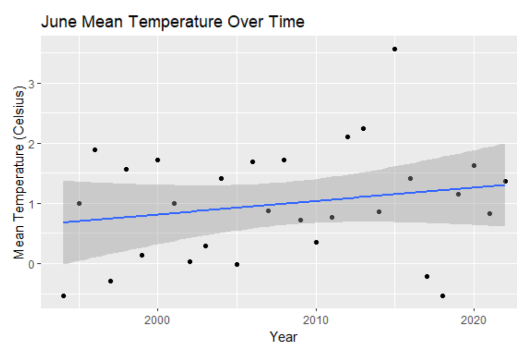

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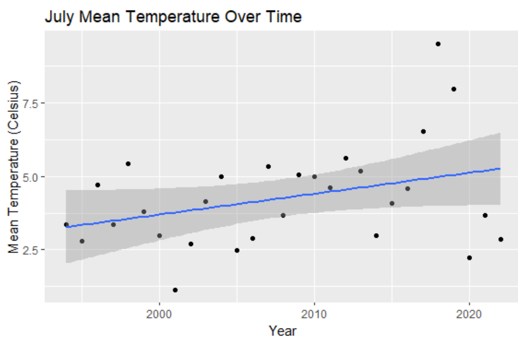

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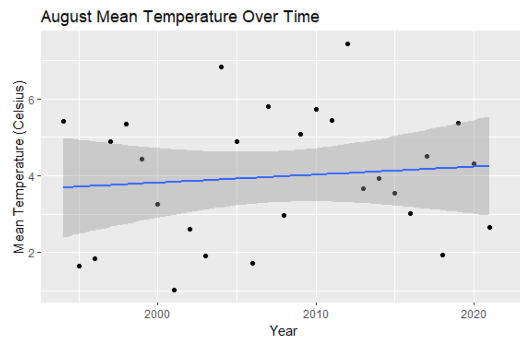

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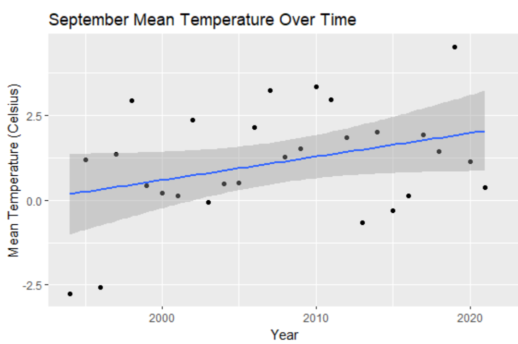

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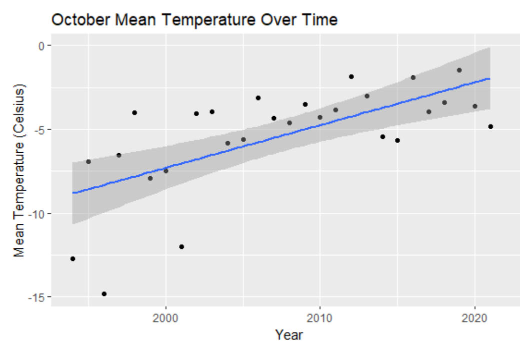

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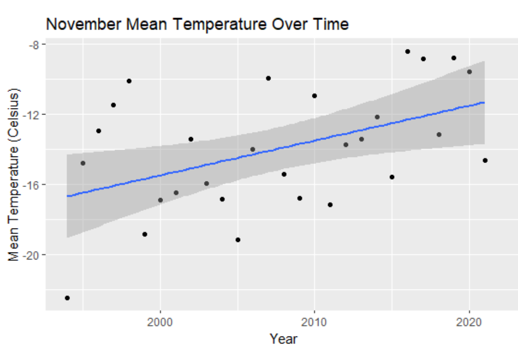

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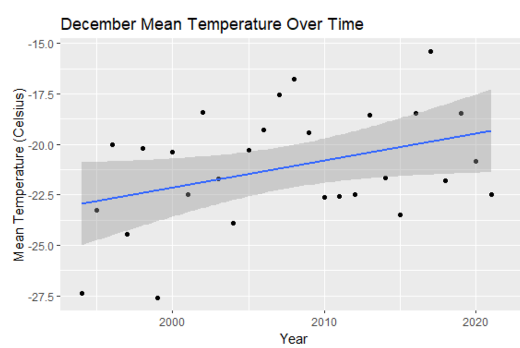

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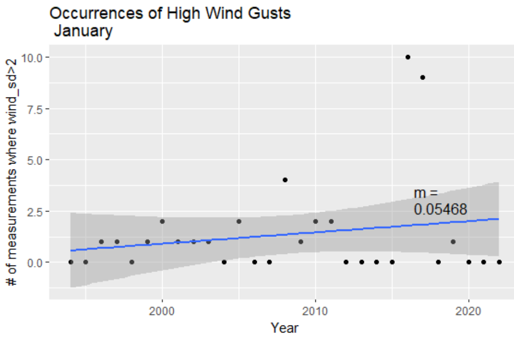
Figure 8: Mean temperature for each individual month between 1994 and 2022. The trendlines (blue) show the rate of change of the temperature over time, the gray shading shows the standard error, and the black dots show the mean temperature for a particular month and year.


Occurrences of High Wind Gusts
January
# of measurements where wind_sd>2
Year
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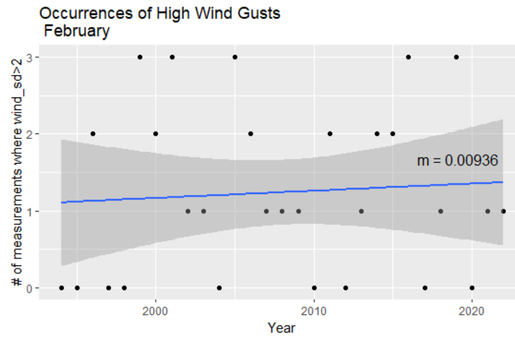
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Year
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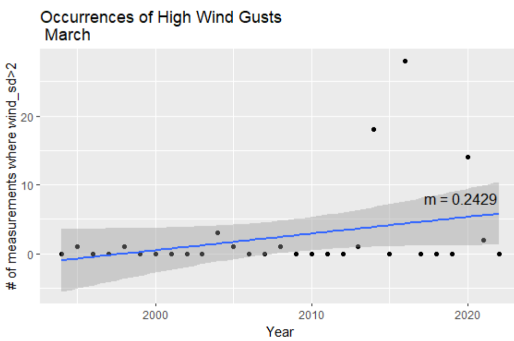
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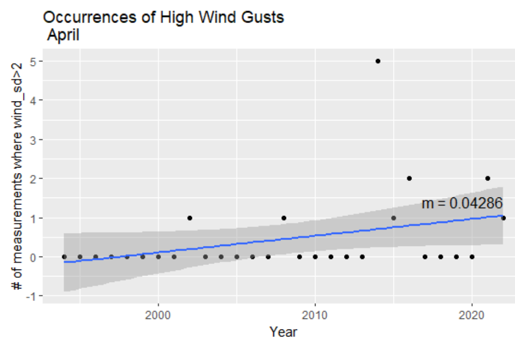
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Year
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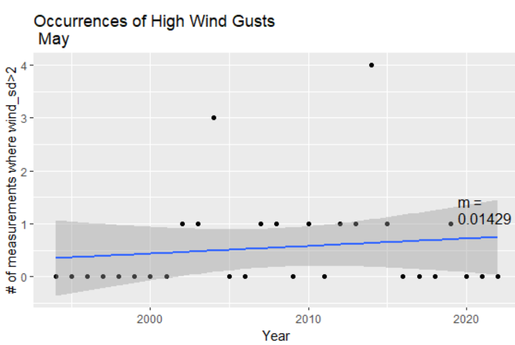
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# of measurements where wind_sd>2
Year
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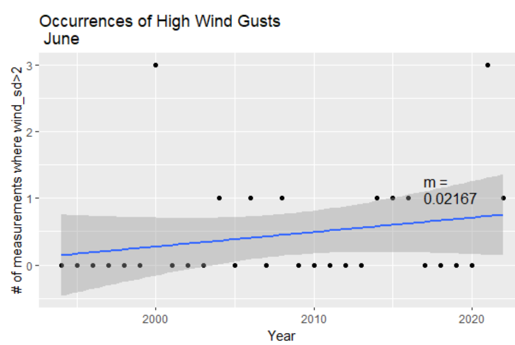
Occurrences of High Wind Gusts
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# of measurements where wind_sd>2
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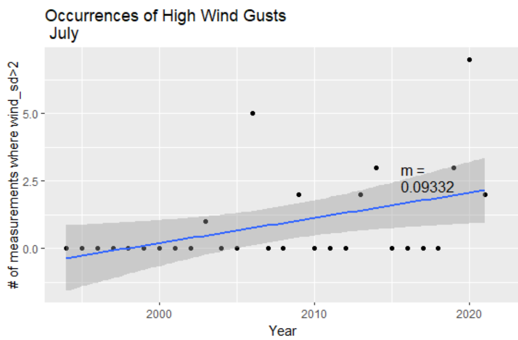
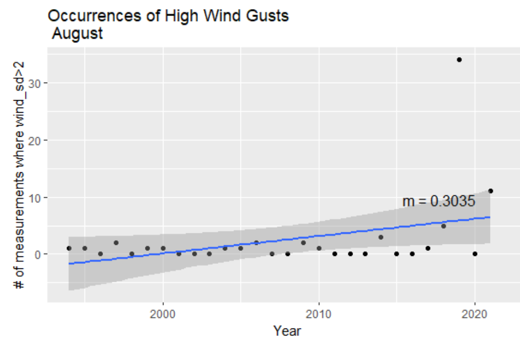
0.02167

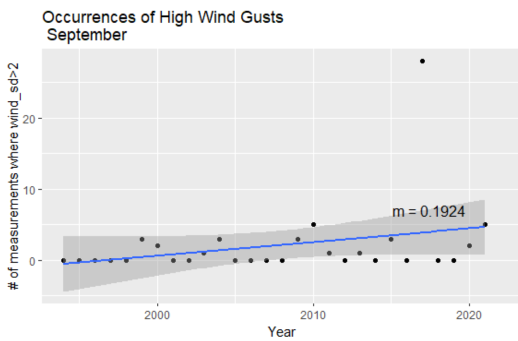
(f)



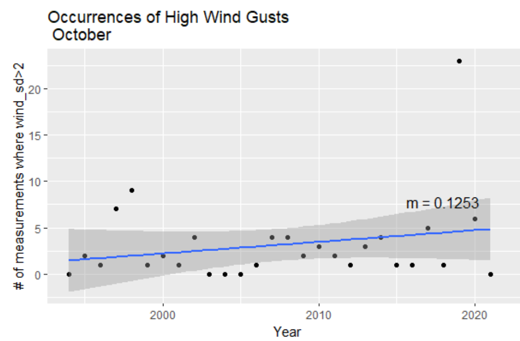
(g)



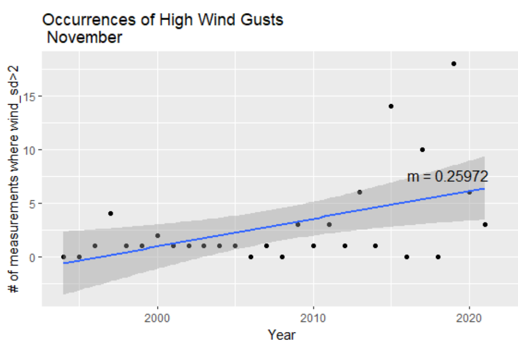
(h)



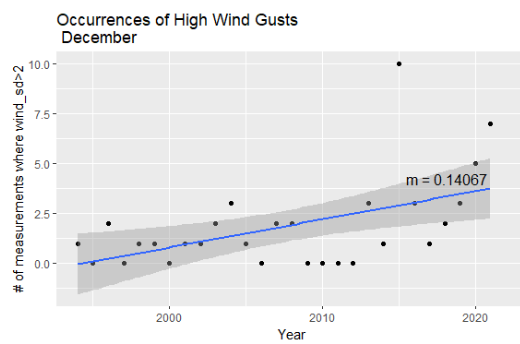
(i)



(j)

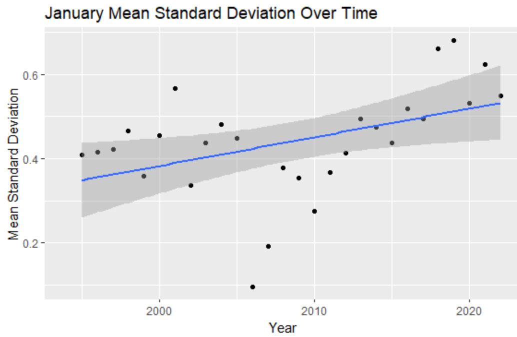


(k)

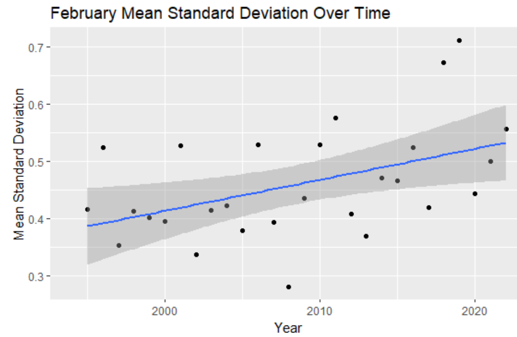


(l)

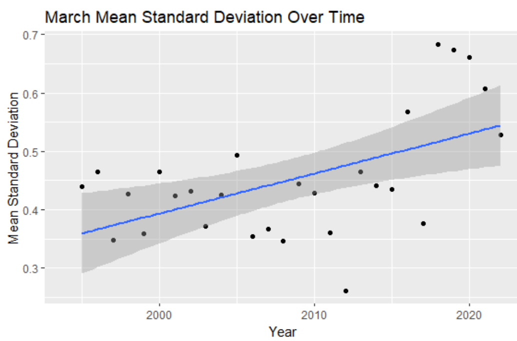
Figure 9: Occurrences of hours with high wind gusts (*wind_sd* > 2) for each individual month between 1994 and 2022. The trendlines (blue) show the rate of change of the frequency of high gusts over time, the grey shading shows the standard error, and the black dots show the total number of measured hours where *wind_sd* >2 for a particular month and year.


January Mean Standard Deviation Over Time
Mean Standard Deviation
0.2
0.4
0.6
2000
2010
2020
Year

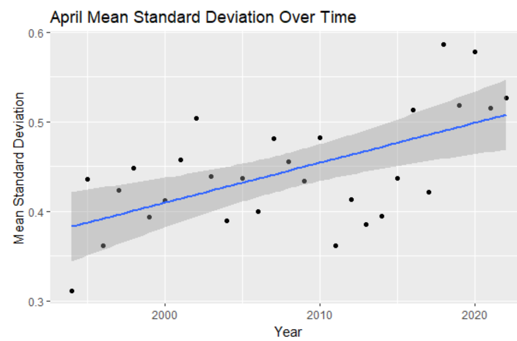
(a)


February Mean Standard Deviation Over Time
Mean Standard Deviation
0.3
0.4
0.5
0.6
0.7
2000
2010
2020
Year

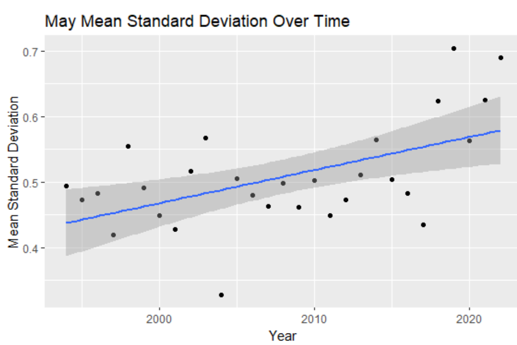
(b)


March Mean Standard Deviation Over Time
Mean Standard Deviation
0.3
0.4
0.5
0.6
0.7
2000
2010
2020
Year

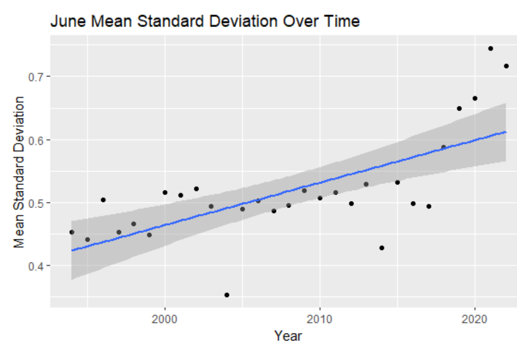
(c)


April Mean Standard Deviation Over Time
Mean Standard Deviation
0.3
0.4
0.5
0.6
2000
2010
2020
Year

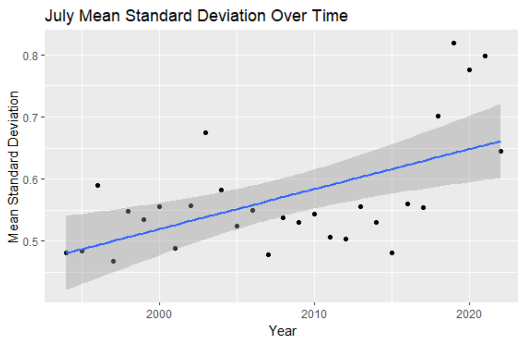
(d)


May Mean Standard Deviation Over Time
Mean Standard Deviation
0.4
0.5
0.6
0.7
2000
2010
2020
Year

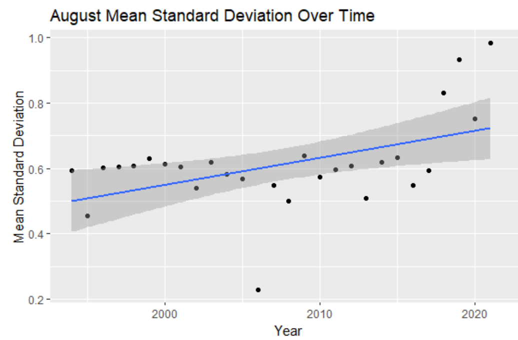
(e)


June Mean Standard Deviation Over Time
Mean Standard Deviation
0.4
0.5
0.6
0.7
2000
2010
2020
Year

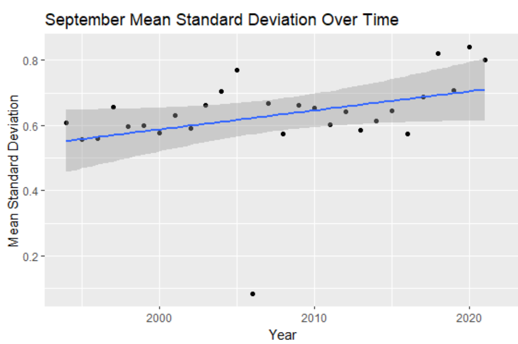
(f)



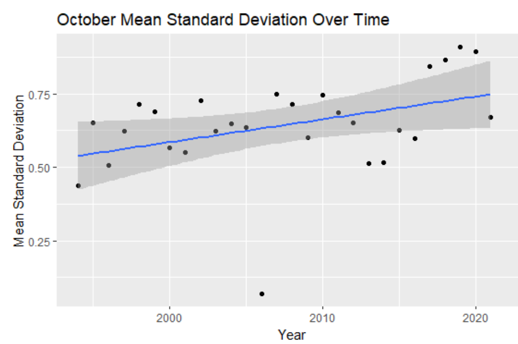
(g)



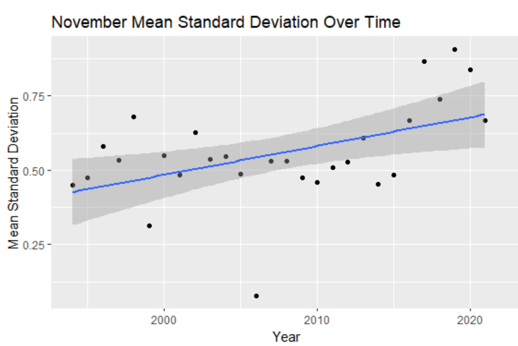
(h)



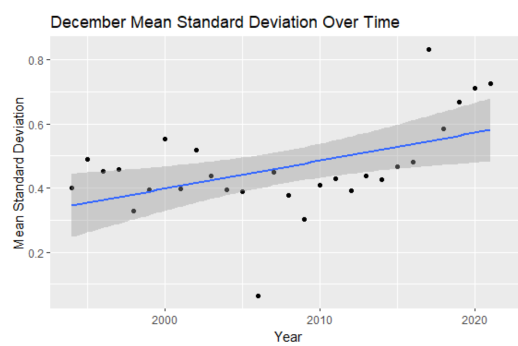
(i)



(j)

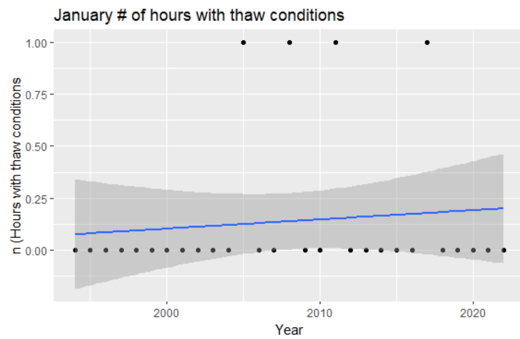


(k)

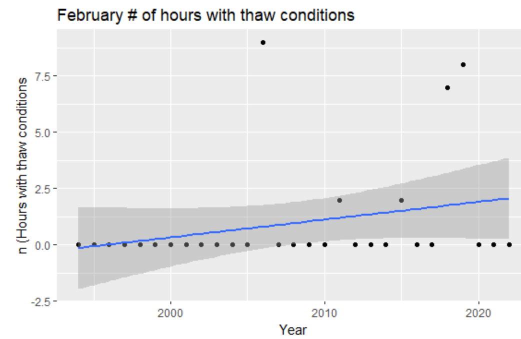


(l)

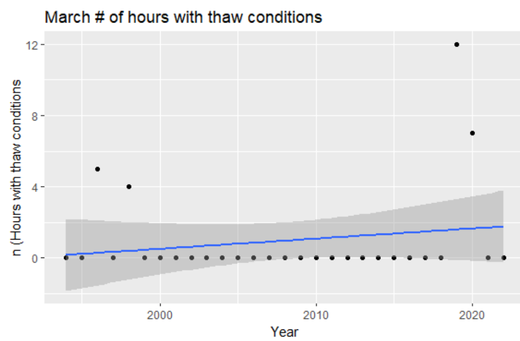
Figure 10: Mean *wind_sd* (standard deviation of wind speed) for each individual month between 1994 and 2022. The trendlines (blue) show the rate of change of the standard deviation over time, the grey shading shows the standard error, and the black dots show the mean standard deviation for a particular month and year.


January # of hours with thaw conditions
n (Hours with thaw conditions
1.00
0.75
0.50
0.25
0.00
2000
2010
2020
Year

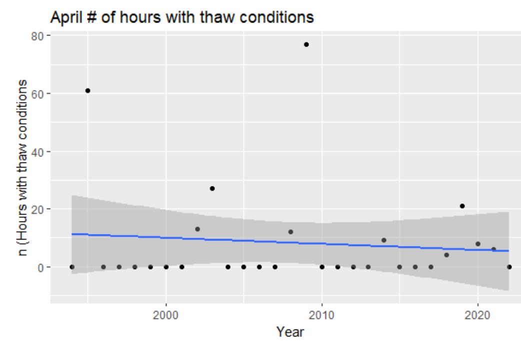
(a)


February # of hours with thaw conditions
n (Hours with thaw conditions
7.5
5.0
2.5
0.0
-2.5
2000
2010
2020
Year

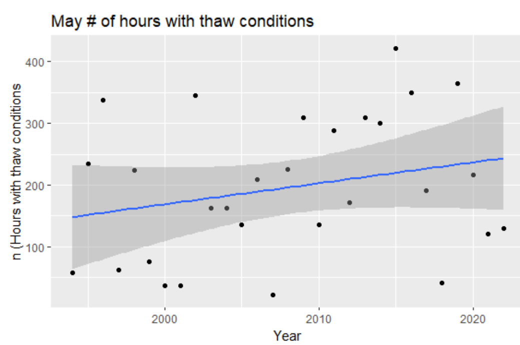
(b)


March # of hours with thaw conditions
n (Hours with thaw conditions
12
8
4
0
2000
2010
2020
Year

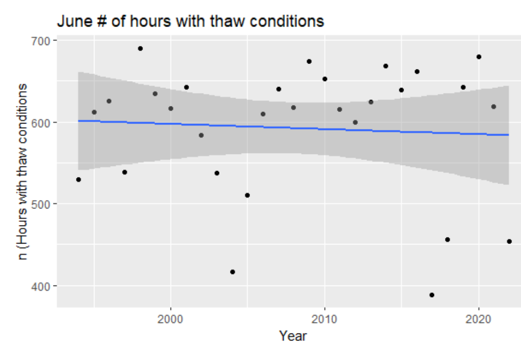
(c)


April # of hours with thaw conditions
n (Hours with thaw conditions
80
60
40
20
0
2000
2010
2020
Year

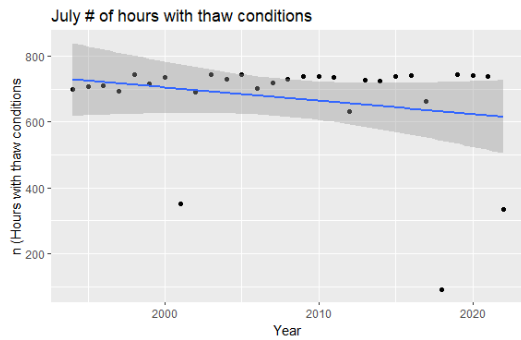
(d)


May # of hours with thaw conditions
n (Hours with thaw conditions
400
300
200
100
2000
2010
2020
Year

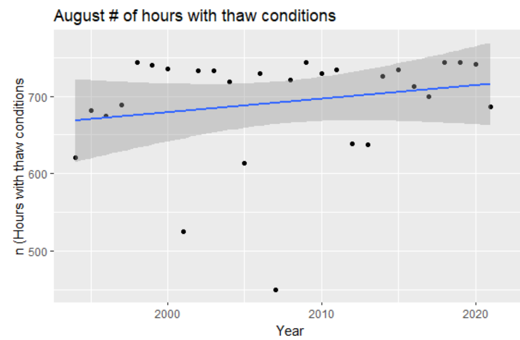
(e)


June # of hours with thaw conditions
n (Hours with thaw conditions
700
600
500
400
2000
2010
2020
Year

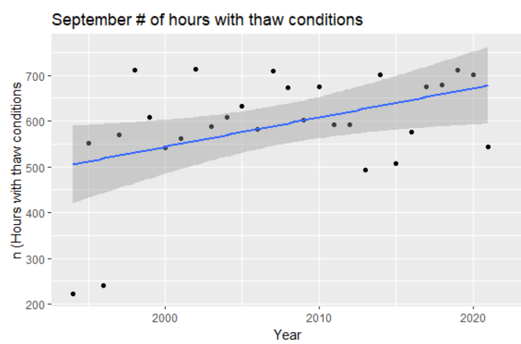
(f)



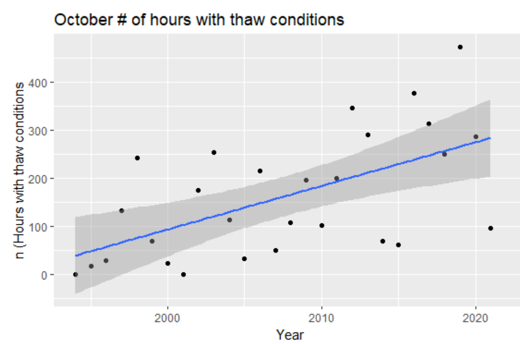
(g)



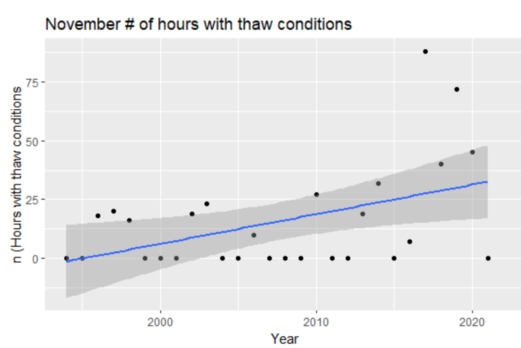
(h)



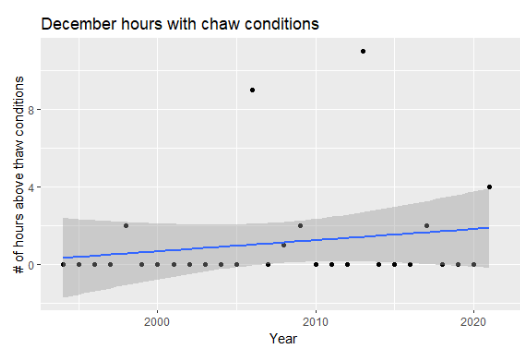
(i)



(j)

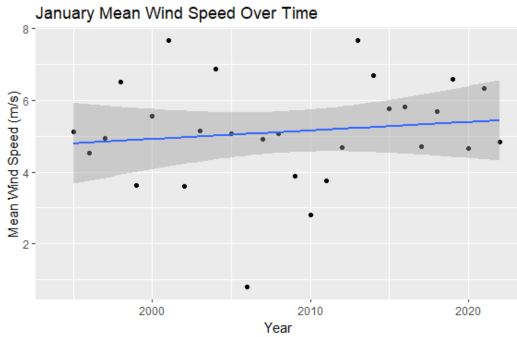


(k)

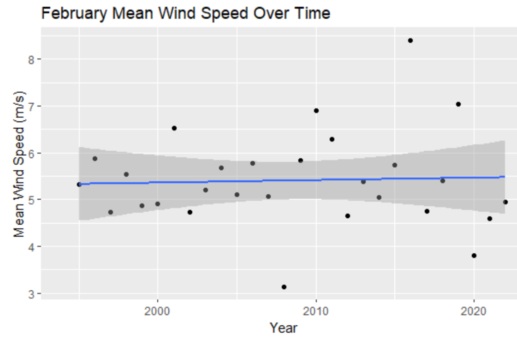


(l)

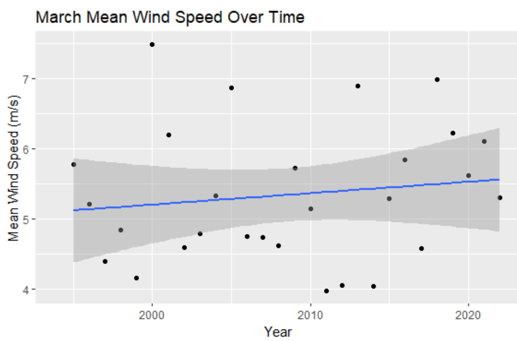
Figure 11: Occurrences of hours with thaw conditions (t_2m > -1.8) for each individual month between 1994 and 2022. The trendlines (blue) show the rate of change of the frequency of high gusts over time, the grey shading shows the standard error, and the black dots show the total number of measured hours where t_2m > -1.8 for a particular month and year.


January Mean Wind Speed Over Time
Mean Wind Speed (m/s)
2
4
6
8
2000
2010
2020
Year

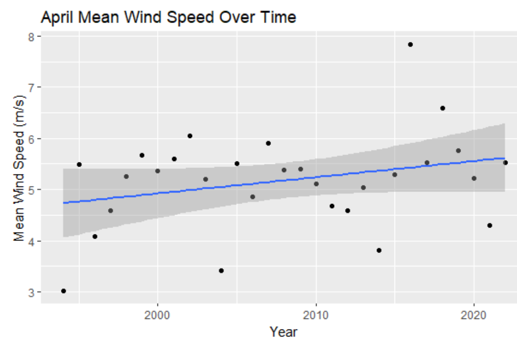
(a)


February Mean Wind Speed Over Time
Mean Wind Speed (m/s)
3
4
5
6
7
8
2000
2010
2020
Year

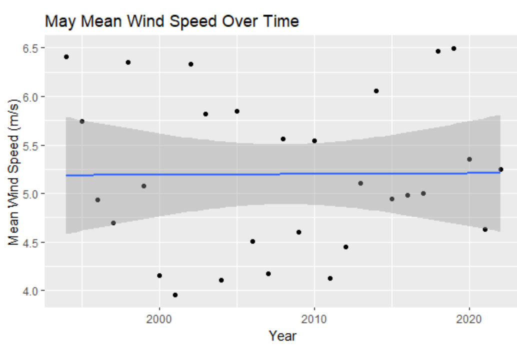
(b)


March Mean Wind Speed Over Time
Mean Wind Speed (m/s)
4
5
6
7
2000
2010
2020
Year

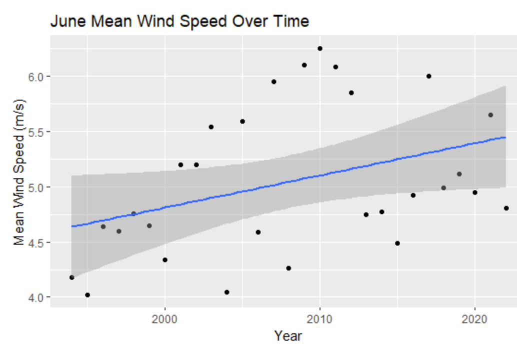
(c)


April Mean Wind Speed Over Time
Mean Wind Speed (m/s)
3
4
5
6
7
8
2000
2010
2020
Year

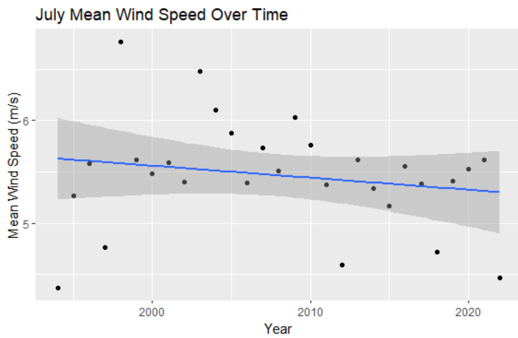
(d)


May Mean Wind Speed Over Time
Mean Wind Speed (m/s)
4.0
4.5
5.0
5.5
6.0
6.5
2000
2010
2020
Year

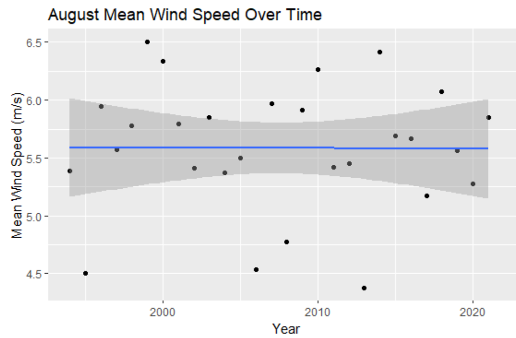
(e)


June Mean Wind Speed Over Time
Mean Wind Speed (m/s)
4.0
4.5
5.0
5.5
6.0
2000
2010
2020
Year

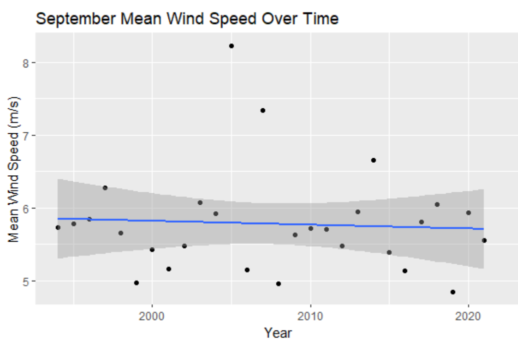
(f)



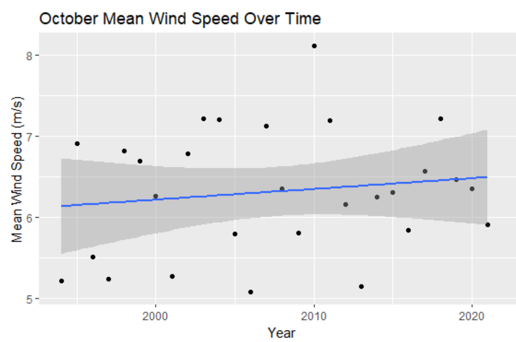
(g)



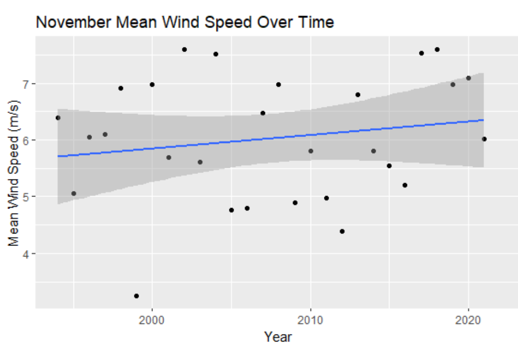
(h)



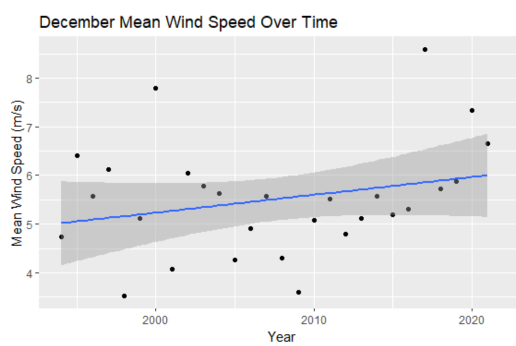
(i)



(j)



(k)



(l)

Figure 12: The mean wind speed in m/s for each individual month between 1994 and 2022. The trendlines (blue) show the rate of change of the mean wind speed over time, the grey shading shows the standard error, and the black dots show the mean wind speed in m/s for a particular month and year.

References

[1] Allouche, M., Bou-Zeid, E., Ansorge, C., Katul, G. G., Chamecki, M., Acevedo, O., Thanekar, S., and Fuentes, J. D. (2022). The detection, genesis, and modeling of turbulence intermittency in the stable atmospheric surface layer. *Journal of the Atmospheric Sciences*, 79:1171–1190.

[2] Atkinson, D. E. (2005). Observed storminess patterns and trends in the circum-arctic coastal regime. *Geo-Marine Letters*, 25:98–109.

[3] Bardal, L. M. and Sætran, L. R. (2016). Wind gust factors in a coastal wind climate. volume 94, pages 417–424. Elsevier Ltd.

[4] Berkes, F. and Jolly, D. (2001). Adapting to climate change: Social-ecological resilience in a canadian western arctic community.

[5] Bieniek, P. A. and Walsh, J. E. (2017). Atmospheric circulation patterns associated with monthly and daily temperature and precipitation extremes in alaska. *International Journal of Climatology*, 37:208–217.

[6] Box, J. E., Colgan, W. T., Christensen, T. R., Schmidt, N. M., Lund, M., Parmentier, F. J. W., Brown, R., Bhatt, U. S., Euskirchen, E. S., Romanovsky, V. E., Walsh, J. E., Overland, J. E., Wang, M., Corell, R. W., Meier, W. N., Wouters, B., Mernild, S., Mård, J., Pawlak, J., and Olsen, M. S. (2019). Key indicators of arctic climate change: 1971-2017.

[7] Cohen, J., Zhang, X., Francis, J., Jung, T., Kwok, R., Overland, J., Ballinger, T. J., Bhatt, U. S., Chen, H. W., Coumou, D., Feldstein, S., Gu, H., Handorf, D., Henderson, G., Ionita, M., Kretschmer, M., Laliberte, F., Lee, S., Linderholm, H. W., Maslowski, W., Peings, Y., Pfeiffer, K., Rigor, I., Semmler, T., Stroeve, J., Taylor, P. C., Vavrus, S., Vihma, T., Wang, S., Wendisch, M., Wu, Y., and Yoon, J. (2020). Divergent consensuses on arctic amplification influence on midlatitude severe winter weather.

[8] DuVivier, A. K., Vavrus, S. J., Holland, M. M., Landrum, L., Shields, C. A., and Thaker, R. (2023). Investigating future arctic sea ice loss and near-surface wind speed changes related to surface roughness using the community earth system model. *Journal of Geophysical Research: Atmospheres*, 128.

[9] Hansen, W. D., Brinkman, T. J., Leonawicz, M., Chapin, F. S., and Kofinas, G. P. (2013). Changing daily wind speeds on alaska's north slope: Implications for rural hunting opportunities.

[10] Heij, C. and Knapp, S. (2015). Effects of wind strength and wave height on ship incident risk: Regional trends and seasonality. *Transportation Research Part D: Transport and Environment*, 37:29–39.

[11] Jim Thomson — Applied Physics Lab, University of Washington, S. W. U., Maddie Smith — Applied Physics Lab, University of Washington, S. W. U., Kyla Drushka — Applied Physics Lab, University of Washington, S. W. U., and Craig Lee — Applied Physics Lab, University of Washington, S. W. U. (2022). Air-ice-ocean interactions and the delay of autumn freeze-up in the western arctic ocean. *Oceanography*. Arctic sea ice is becoming a more seasonal phenomenon as a direct result of global warming. Across the Arctic, the refreezing of the ocean surface each autumn now occurs a full month later than it did just 40 years ago. In the western Arctic (Canada Basin), the delay is related to an increase in the seasonal heat stored in surface waters; cooling to the freezing point requires more heat loss to the atmosphere in autumn. In the marginal ice zone, the cooling and freezing process is mediated by ocean mixing and by the presence of remnant sea ice, which may precondition the ocean surface for refreezing. The delay in refreezing has many impacts, including increased open ocean exposure to autumn storms, additional wave energy incident to Arctic coasts, shifts in animal migration patterns, and extension of the time window for transit by commercial ships along the Northern Sea Route. This article reviews the observed trends in the western Arctic and the processes responsible for these trends, and provides brief in situ observations from the Beaufort Sea that illustrate some of these processes.

[12] Kanno, Y., Walsh, J. E., Abdillah, M. R., Yamaguchi, J., and Iwasaki, T. (2019). Indicators and trends of polar cold airmass. *Environmental Research Letters*, 14.

[13] Kettle, N. P., Walsh, J. E., Heaney, L., Thoman, R. L., Redilla, K., and Carroll, L. (2020). Integrating archival analysis, observational data, and climate projections to assess extreme event impacts in alaska. *Climatic Change*, 163:669–687.

[14] Lynch, A., Curry, J., Brunner, R., and Maslanik, J. (2004). Toward an integrated assessment of the impacts of extreme wind events on barrow, alaska. *Bulletin of the American Meteorological Society*, 85:209 – 221.

[Monitoring and Programme] Monitoring, A. and Programme, A. Arctic climate change update 2021: Key trends and impacts.

[16] Moon, T. A., Overeem, I., Druckenmiller, M., Holland, M., Huntington, H., Kling, G., Lovecraft, A. L., Miller, G., Scambos, T., Schädel, C., Schuur, E. A., Trochim, E., Wiese, F., Williams, D., and Wong, G. (2019). The expanding footprint of rapid arctic change.

[17] Moore, S. E. and Huntington, H. P. (2008). Arctic marine mammals and climate change: Impacts and resilience.

[18] Overland, J. E. (2021). Rare events in the arctic. *Climatic Change*, 168.

[19] Pithan, F. and Mauritsen, T. (2014). Arctic amplification dominated by temperature feedbacks in contemporary climate models. *Nature Geoscience*, 7:181–184.

[20] Rolph, R. J., Mahoney, A. R., Walsh, J., and Loring, P. A. (2018). Impacts of a lengthening open water season on alaskan coastal communities: Deriving locally relevant indices from large-scale datasets and community observations. *Cryosphere*, 12:1779–1790.

[21] Serreze, M. C. and Barry, R. G. (2011). Processes and impacts of arctic amplification: A research synthesis. *Global and Planetary Change*, 77:85–96.

[22] Stammerjohn, S., Massom, R., Rind, D., and Martinson, D. (2012). Regions of rapid sea ice change: An inter-hemispheric seasonal comparison. *Geophysical Research Letters*, 39(6).

[23] Sulikowska, A., Walawender, J. P., and Walawender, E. (2019). Temperature extremes in alaska: temporal variability and circulation background. *Theoretical and Applied Climatology*, 136:955–970.

[24] Walsh, J. E., Ballinger, T. J., Euskirchen, E. S., Hanna, E., Mård, J., Overland, J. E., Tangen, H., and Vihma, T. (2020). Extreme weather and climate events in northern areas: A review. *Earth-Science Reviews*, 209:103324.