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Predicting Peak Wind Gusts During Specific Weather Types with the Meteorologically Stratified Gust Factor Model

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PREDICTING PEAK WIND GUSTS DURING SPECIFIC WEATHER TYPES WITH THE METEOROLOGICALLY STRATIFIED GUST FACTOR MODEL

by

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ABSTRACT

PREDICTING PEAK WIND GUSTS DURING SPECIFIC WEATHER TYPES WITH THE METEOROLOGICALLY STRATIFIED GUST FACTOR MODEL

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Peak wind gusts were estimated by the meteorologically stratified gust factor model at Milwaukee, WI (KMKE) for eight different weather types during 2010-2017. The gust factor model couples gust factors with wind speed and direction forecast guidance to produce peak gust forecasts. The model evaluated used two model output statistics (MOS) guidance products at lags ranging from 6-24 hr and was compared with peak gust forecasts provided by the Localized Aviation MOS Program (LAMP) as well as observed gusts reported by automated surface observing systems (ASOS).

Compared with climatology, the gust factor model showed skill when coupled with MOS in predicting peak gusts during most of the eight weather types at the analyzed lags of 06 hr, 12 hr, 18 hr, and 24 hr. The MOS products results performed similarly for each of the weather types. The gust factor model does not show skill during convective weather situations, in part because during these conditions the provided MOS wind speed and direction forecasts are less accurate. This is important for operational wind forecasting, because this method can be used for many non-convective gust-producing weather situations.

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LIST OF ABBREVIATIONS

ASOS	Automated Surface Observing System
GF	Gust Factor
MAE	Mean Absolute Error
MOS	Model Output Statistics
NWS	National Weather Service
PProg	Perfect Prognosis
GFS	Global Forecast System
NAM	North American Mesoscale
LAMP	Localized Aviation MOS Program

1 Introduction

Wind gusts are difficult to forecast. Gusts are a perturbation on the mean wind and are such a small-scale phenomenon that they are problematic to measure; there is simply not enough data. Gusts originate from the atmosphere above where the winds are stronger, so knowledge of the conditions in this part of the atmosphere is critical for forecasting gusts. These data are only routinely collected every 12 hours with radiosondes, however, so the knowledge is not always current.

In addition to limited upper atmospheric condition data, the U.S. National Weather Service Automated Surface Observing System (ASOS) criteria for reporting wind and gusts are constricting. For ASOS hourly reports, the reported wind speed is the two-minute average of the three-second wind measured during minutes 51 and 52 of the hour, and the gust observation is the highest three-second average wind recorded during the 10-minute period from minutes 43 to 52 of each hour (Harris & Kahl 2017). The criteria which must be satisfied for gusts to be reported are as follows: the wind must exceed two kts, the difference between the gust and wind must be greater than or equal to three kts, and the gust must exceed the minimum three-second wind speed by 10 kts (Harris & Kahl 2017). With these limiting criteria in place, most gusts are neither reported with the hourly data nor archived, thus creating verification issues. Rather than hourly resolution data, proper verification of wind and gust forecasts thus requires analysis of one-minute data.

1.1 Motivation

Developing an accurate method to forecast peak gusts is important. Wind gusts are a hazard to aviation and marine activities and pose a threat to the integrity of forests, bridges, tall buildings, powerlines and other electricity networks, personal property, semi-truck drivers, and the workers and equipment at construction sites (Harris & Kahl 2017). Sudden strong wind gusts during an otherwise calm day, because they are so unexpected, can sometimes be more dangerous than wind gusts that occur during severe storms or blizzards (Ashley & Black 2008). According to Della-Marta et al. (2010), wind events are the leading cause of property damage, which further motivates the desire for an accurate gust forecasting method. More so, the force exerted on an object by the wind is proportional to the square of the wind speed (Letson et al. 2017). If the hourly peak gust could be accurately forecasted, then measures could be taken to ensure safety and to design structures to withstand those gusts. Underestimates of gusts could lead to structural failures and overestimates could lead to unnecessary design expenses.

1.2 Previous Work

Previous attempts to forecast wind gusts include physical, statistical, and combined physical and statistical methods.

One physical method includes the estimation of the wind speed at the top of the planetary boundary layer with the assumption that the momentum can be transferred downward, but this method tends to overestimate gusts (Hart & Forbes 1999). Another physical method is based off of turbulence parameterization and the reasoning that gusts represent the amount of vertical mixing (Schreur & Geertsema 2008). A third method utilizes turbulent kinetic energy to make an estimation of the altitude at which the momentum is transferred down to the surface. This method also has the tendency to overestimate gusts (Brasseur 2001).

The model output statistics (MOS) model is a statistical method that uses regression-based techniques to downscale numerical weather prediction forecasts to particular locations. As predictor variables in its wind gust equations, this technique uses wind speeds at various heights, relative humidity, relative vorticity, turbulence, and the ratio between the 925 mb and 10 m wind speeds. While useful in short-term forecasting, the MOS approach is not reliable when it comes to making forecasts by 72 hours out (Rudack 2006). Most MOS products do not forecast gusts, however.

Another method is the Gust Factor (GF) model, an empirically derived statistical technique that is simple to use. The GF, defined by Sherlock in 1952, is the ratio of the observed wind gust to the observed wind speed. A known GF can thus be multiplied by the forecast wind speed to get the forecast gust. GF models are sensitive to different meteorological conditions, so the GF model has recently been climatologically stratified to consider details such as wind speed, wind direction, season, month, time of day, surface roughness, and atmospheric stability to try and produce the most accurate GF for each combination (Harris & Kahl 2017). Recently demonstrated meteorologically stratified GFs have shown potential in forecasting gusts.

More in-depth research has recently been done on forecasting peak gusts using meteorologically stratified GFs. Kahl (2020) tested the performance of the meteorologically stratified GF model at 15 sites around the United States during 2010-2017. According to this work, at 11 of the 15 sites the GF model showed skill in predicting peak gusts out to lags (forecast projections) of 72 hours, which indicates that this method can be used for forecasting at any location where meteorologically stratified GFs have been determined. However, the question remains open as to how well the model performs during different types of gust-producing weather phenomena (Kahl 2020). This is the question that this project endeavors to answer.

1.3 The Project

The meteorologically stratified GF model has demonstrated potential to forecast peak gusts when observed rather than forecast wind speed and direction is used (Harris & Kahl 2017) and has been successfully tested using wind forecast data at several sites (Kahl 2020). To examine the model's ability to predict peak gusts during different types of weather events, the following research questions are addressed. How well do the no-skill models, climatology and persistence, perform for different weather types? How well does the GF model predict peak wind gusts for different weather types when the wind speed and wind direction forecasts are perfect [the perfect prognosis (PProg) model]? How well does the GF model work when coupled with MOS wind forecasts? What is the effect of lag time on the GF model performance? What is the sensitivity of GF model performance on the types of MOS product? Finally, how well does the GF model perform compared to the peak wind gust forecasts provided by the Localized Aviation MOS Program (LAMP) system, one of the few MOS products offering wind gust guidance?

Milwaukee, WI (KMKE, latitude: 43.04°N, longitude: 87.91°W, altitude: 204 m msl) is the location from where wind data has been gathered and on which these analyses will be performed. Several weather types that are known to be associated with gusty winds will be considered to test the GF forecast skill coupled with the Global Forecast System (GFS) MOS and North American Mesoscale model (NAM) MOS at the lags of 06-h, 12-h, 18-h, and 24-h.

The upcoming chapters present the sources and methods used to collect the data used for analysis, the specification of the particular weather types and their criteria for identification, the application of these criteria to the gathered data and statistics performed on these data, a discussion of the results found for each weather type, conclusions, and suggestions for further research.

2 Data

2.1 Observed Wind and Gust Data

The wind dataset that was obtained for this project contains one-minute resolution ASOS wind and gust data for the 2010-2017 period at KMKE. There were roughly 4,000,000 observations during this time period. The publicly available data set (data set 6405, available at ftp.ncdc.noaa.gov/pub/data/asos-onemin) lacked sufficient quality control measures, so the wind and gust records were put through several other quality checks. The following quality control methods were used (Kahl 2020): the data were filtered for records that were repeated, out of chronological order, or not in a useable form, and then checks were made to exclude records that were illogical (e.g. negative wind speeds) or that lacked necessary data fields. The final quality control measure eliminated erroneously large winds and gusts. The surviving one-minute data were used to create an hourly dataset, with each hour comprised of at least 54 quality-controlled, one-minute records. This reduced the data set to 66,823 hourly records, 95.1% of the possible reporting hours during 2010-2017. The resulting dataset contained the year, month, day, hour, ASOS recorded mean wind speed, mean wind direction, peak wind gust for each hour, and gust factor ($GF = \frac{peak\ gust}{mean\ wind\ speed}$). This dataset will be referred to as the ASOS workbook.

2.2 Meteorologically Stratified Gust Factors

Harris & Kahl (2017) showed that the best performance in GF models was given by double stratification of gust factors by wind speed (0-5 kt, 5-10 kt, 10-15 kt, and >15 kt) and wind direction (30° bins). Figure 1 displays the stratified gust factors for KMKE in the form of a "gust web" diagram. The gust web shows that at KMKE, stronger winds above 10 kt (the outermost two rings) occur more frequently with wind directions from a broad sector extending from the south (180°) clockwise to the NNE (30°). The GFs associated with winds over 15 kt (the outermost ring) are largest from the in the WSW sector (GF=1.76) and smallest in the ENE sector (GF=1.50). This difference, due to the differences in surface roughness between the developed land to the west and Lake Michigan to the east, results in peak gusts associated with WSW winds being, on average, 19% stronger than those associated with NNE winds.

2.3 MOS Forecasts

MOS is a product that improves forecast model output via post-processing (Glahn & Lowry 1972). Wind speed and direction guidance from the GFS and NAM MOS text bulletins were obtained from the Iowa State University server (https://mesonet.agron.iastate.edu/mos/). The NAM MOS forecasts were initialized every 12 hours and the GFS MOS forecasts every 6 hours, and both products provide 6-60 hr forecasts at 3-hour intervals, as well as 66 hr and 72 hr forecasts. Only the lags out to 24 hr were utilized for the project. These data are used here with the intention of evaluating the performance of the GF model rather than evaluating the specific MOS products. In addition to the MOS forecasts, the GF model was also coupled with the no-skill climatology and persistence wind forecasts. Persistence forecasts were evaluated for lags 1-6 hr and climatology forecasts are stratified by hour and season. Figure 2 shows the KMKE hourly- and seasonally-stratified gust climatology for 2010-2017.

2.4 LAMP Forecasts

One operational method that is currently being used in gust forecasting is the LAMP system. LAMP is a combination of observations and GFS MOS forecasts (Glahn et al. 2017) and is operated by the National Weather Service; its forecasts are updated hourly (Ghirardelli & Glahn 2010).

LAMP is one of only a few MOS forecasting products that provides peak wind gust forecasts and these gusts are included in the LAMP bulletins when the gust forecast matches the ASOS gust reporting requirements (Nadolski 1998). LAMP forecasts are initialized every six hours and have hourly lags from one to 25 hours (Rudack & Ghirardelli 2010). It is interesting to note that LAMP forecasts predict the strongest wind gust during minutes 43–52 of the hour previous to the forecast hour (Ghirardelli 2005), while the GF model predicts the peak gust during the entire forecast hour (Kahl 2020). The LAMP forecasts are thus not entirely comparable to the GF model forecasts. They are nevertheless included here due to the possibility that some operational weather forecasters interpret LAMP gust forecasts as representing the peak gust during the entire forecast hour.

2.5 Weather Data Archive

The weather data archive used to identify the hours needed for each weather type being evaluated for the 2010-2017 time period at KMKE was retrieved from NOAA's National Centers for Environmental Information Local Climatological Data page (https://www.ncdc.noaa.gov/cdo-web/datatools/lcd). This data archive in the form of an Excel file included information such as hourly sea level pressure, weather type present, sky coverage, wind speed (in mph), and sunrise and sunset times. This dataset will be referred to as the Weather Data workbook.

3 Methods

3.1 Weather Type Identification

In order to determine which types of weather events to focus on for this project, an email survey was sent out to a group of professional, operational meteorologists. The survey contained a similar variation to the following two questions:

1. Under which situation(s) is gust forecasting the most difficult?
2. Under which situation(s) is gust forecasting the most important?

A total of 22 individuals or National Weather Service (NWS) offices were contacted and 14 people responded, often with the answers from multiple forecasters at the particular NWS office, a 64% response rate. Table 1 lists the locations from which the replies came. The range of answers was extensive, so Table 2 compiles the most frequent answers for each of the survey questions.

The responses to the survey questions helped inform the selection of weather types to include in the present analysis; some weather types, like high pressure, were added after the survey weather types were chosen since they are also conditions known to produce gusty winds. The weather types were selected as follows with the specified reasons:

- snowy conditions with winds greater than 17 kts to analyze winter storms and blizzard conditions. A wind speed of 17 kts was chosen because one qualification of a blizzard is a minimum sustained wind speed of 30.4 kts, but since winter storms were also being analyzed here, a slower wind was chosen that was still considered windy.
- snowy conditions with winds less than 17 kts as a comparison to the windier snowy conditions,
- convective systems to analyze low-pressure systems and thunderstorms
- non-convective rain to analyze gusts during rain showers,
- dry (no precipitation) nighttime conditions with clouds (specified reason in next weather type),
- dry nighttime conditions with no sky cover to see how well gusts are forecast during different nighttime mixing conditions, and
- high pressure systems, because fair weather that accompanies strong high pressure systems sometimes involves high wind gusts from converging winds above.

The Weather Data workbook was utilized to identify the dates and times during which the different weather types occurred. The selection criteria to identify which hours would be pulled from the weather data workbook for GF model analysis were the following:

- Windy snow: snowing with winds greater than or equal to 17 kts,
- Less windy snow: snowing with winds less than 17 kts,

- Convective systems: the weather condition "TS" (thunder) is present; this was done twice, the second time including both thunder and rain,
- Non-convective rain: rain is present, but no thunder is present,
- Overcast nighttime with no precipitation: night, no type of precipitation is present, and sky cover is "OVC" (overcast),
- Clear nighttime with no precipitation: night, no type of precipitation is present, and sky cover is "CLR" (clear),
- High Pressure: sea level pressure is greater than or equal to 1025 hPa.

After the hours for each weather type were identified, checked for accuracy and duplicate hours were deleted, these data were matched and merged with the corresponding ASOS wind and gust data and MOS data in the ASOS workbook to create a comprehensive dataset, which will be referred to as the Combined workbook. Table 3 shows the number of occurrences for each weather type. High pressure and dry nighttime conditions with clouds were the most abundant weather types, while windy snow and the convective situations occurred much less frequently.

Tables 4-11 show occurrence frequencies and wind/gust characteristics for each weather type. Windy snow is the least common weather type with only 192 occurrences, while high pressure is the most common with 8816 occurrences. Nighttime with clear and dry conditions had the smallest mean wind speed at 6 kt and smallest mean peak wind gust at 10.4 kt; windy snow had the highest mean wind speed at 20.2 kt and highest mean peak wind gust at 32.6 kt.

3.2 Model application and verification

The GF model for predicting peak wind gusts is

$$gust_{fcst} = GF * wspd_{fcst} \quad (1)$$

where $gust_{fcst}$ is the forecasted peak gust, $wspd_{fcst}$ is the forecasted wind speed for that hour, and GF is the gust factor. As described by Harris and Kahl (2017) and Kahl (2020), the GF is a site-specific, climatological representation of gustiness that is dependent on both wind speed and direction. In this project the wind speed and wind direction used to identify the appropriate gust factor were provided by the MOS forecasts. (The wind speed forecast $wspd_{fcst}$ is also used directly in Eq. 1.) Peak gust forecasts for KMKE at lead times ranging from 6-24 hr were calculated using wind speed and direction guidance provided by the GFS MOS and NAM MOS coupled with the meteorologically stratified GFs from the ASOS workbook.

Bias ($gust_{fcst} - gust_{obs}$), where $gust_{obs}$ is the hourly peak wind gust used for verification determined from the ASOS workbook observed data, and absolute error (|bias|) are two verification metrics that were used to evaluate model performance. These metrics were applied to the GF model, the peak gust forecasts produced by LAMP, and PProg model forecasts (using observed rather than forecast wind speed and direction in equation 1). Forecast verification was performed for all available hours during which the specified weather types occurred. Persistence (lags 1-6 hr only) and climatology, the no-skill models, were also verified. Table 12 provides the details for each model type used. Using the Combined workbook, the GF and LAMP models were evaluated using forecasts at lags of 06 hr, 12 hr, 18 hr, and 24 hr for this project.

3.3 Statistical Significance Testing

Statistical significance testing was performed on selected pairs of models using absolute error distributions via the sign test (Mendenhall et al. 1990). Differences were considered statistically significant when the null hypothesis, that there is no difference between the two distributions, was rejected at the 5% confidence level.

4 Results

4.1 No-skill models performance

How well do the no-skill models, climatology and persistence, forecasts perform for each weather type? Climatology and persistence forecasts are the no-skill models against which the GF models coupled with GFS and NAM MOS wind forecasts, and the LAMP model will be compared. These no-skill forecasts provide the benchmark against which the GF model must outperform in order to be considered skillful.

Persistence is a legitimate no-skill model for short-term lag times, but it is not a model that can be easily utilized by forecasters since the forecasts require the archival of gust observations free of the reporting protocols that accompany the hourly ASOS dataset (Harris & Kahl 2017). Figure 3 a-h shows the mean absolute errors (MAE) of the persistence and climatology forecasts of peak wind gusts for each weather type. Persistence forecasts, overall, performed better at shorter lags and decreased in accuracy with longer lags, and largely performed better than climatology. At shorter lags, persistence performed better for high pressure (Figure 3h) and nighttime with clear and dry conditions (Figure 3g); it performed considerably less well for both convective situations (Figures 3c and 3d).

Considering the 06-h lag persistence forecasts, it is interesting to note that MAEs were larger (7-8 kt) for the windy snow, convective with thunder, and convective with thunder and rain weather types, and smaller (4-6 kt) for the other weather types. This likely reflects the shorter lifetimes of the former weather types, and the longer lifetimes of the latter types.

Climatology only outperformed persistence for the 06-h lag of nighttime with clear and dry conditions (Figure 3g) and did a particularly poor job for the conditions that produce higher gusts, like windy snow (Figure 3a) and the convective situations (Figures 3c and 3d). The windy snow climatology MAEs were particularly large. This is likely because windy snow conditions only occur a small fraction of the time, so the climatology forecasts would not reflect these conditions.

Comparing the KMKE results with the persistence and climatology MAEs reported in Figure 5a of Kahl (2020) for the 2010-2017 time period at Providence, RI (KPVD), several of the models for various weather conditions performed similarly. The climatology MAE for KPVD was just under 5 kt, and less windy snow, both nighttime conditions, and high pressure were close to 5 kt, but the other types all had larger climatology MAEs. The only persistence models that performed worse than the MAEs reported in Kahl were both of the convective situations.

How well does the GF model predict peak wind gusts for different weather types when the wind speed and wind direction forecasts are perfect using the perfect prognosis (PProg) model? A smaller PProg MAE indicates that, on average, the GF model should work well if the wind speed and wind direction forecasts are of high quality. A larger PProg MAE means that the GF model would be expected to perform poorly even if the wind speed and direction forecasts were accurate. The PProg displayed small MAEs (between 1 and 2 kt) for all weather types except the two convective situations, which had MAEs around 4 kt. The PProg errors for the convective weather types are likely higher because convection produces gusts differently than most other weather types, so the surface roughness implied in the directional dependence of the GFs is less relevant in forecasting convective gusts. Convective situations only make up a small percentage of occurrences at KMKE, according to Table 3, at 1%. The small MAEs for the other weather types indicate the GF model can have skill if the wind speed and wind direction forecasts are of high quality.

4.2 GF and LAMP models performance

Figure 4 a-h shows each model's MAE within each weather type at lags of 06, 12, 18, and 24 hr.

How well does the GF model work when coupled with MOS wind forecasts? The 06 hr lag results for GFS MOS will be considered for this question. The MAEs of the 06 hr GFS model for all weather types were less than the climatology MAEs, and statistical significance testing shows that these differences were significant at a 5% confidence level for all weather types except the two convective types. This indicates that the GF model coupled with GFS MOS wind forecasts has skill in predicting peak gusts at 06 hr lags for all weather types studied except during convective situations. The MAEs range from 2.6 kt for high pressure to 6.4 kt for convective with thunder and rain. High pressure had the smallest 06 hr GFS MOS MAE even though it had the highest number of occurrences, so the GF model has notable skill during high pressure conditions. Less windy snow and both nighttime conditions all had MAEs around 3 kt as well with large numbers of occurrences, ranging from 2402 to 7192 occurrences (Table 3). By way of comparison, the MAE for GFS 06 hr at KPVD in Kahl (2020) was also 3 kt.

What is the effect of lag time on the GF model performance? The GFS MOS MAEs at the lags of 06 hr, 12 hr, 18 hr, and 24 hr will be compared for this question. According to Figure 4, the MAEs for each weather type do not have much variation as lag time increases from 06 to 24 hr. At these four lags, however, the GF model coupled with GFS MOS wind forecasts demonstrates skill, i.e., performs significantly better than climatology for all weather types except for the convective situations, which are not statistically significant at a 5% confidence level. It could be speculated that the MAEs would increase with longer lags up to 72 hours, because looking again at Kahl (2020), Figure 5c, the MAEs between lags 6 and 24 are approximately the same as they are for KMKE, but as the lag time gets longer, the MAEs start to get larger. The present results indicate that at KMKE, lag time does not have a large effect on the GF model for the shorter 06 – 24 hr lag times.

What is the effect of different MOS products on the GF model? GFS MOS and NAM MOS are compared against each other for all weather types at all lag times considered (Figure 4 a-h). The only weather type where NAM MOS outperforms GFS MOS for all lags is windy snow, and the largest variation between the two models is the 24 hr lag for windy snow, where NAM MOS does quite a bit better than GFS MOS. However, this difference is not statistically significant at a 5% confidence level. GFS MOS most commonly performs better for the 06 hr lag for all weather types, but beyond that, the performance quality for both models is very similar. Both GFS MOS and NAM MOS had difficulties forecasting for the convective types. Kahl (2020) shows in its Table 3 that at most of the sites included in that study, the GF model coupled with both GFS MOS and NAM MOS showed skill, i.e. statistically significant improvement over climatology, out to a lag of 72 hr.

Does the GF model perform worse during convection because the model itself does not perform well or does it not do as well because the wind speed and wind direction forecasts produced by the MOS models are not of good quality? Looking at Figure 5, the relationship is approximately linear between the gust bias and wind speed bias for the 24 hr lag of GFS MOS during both convective weather types. This shows that the GF model's failure to perform well is due, in part, to the GFS MOS's inability to accurately forecast wind speeds and directions during convection. When the wind speed forecast bias is small, between -2 kt and 2 kt for example, the peak wind gust bias ranges from -5 kt to 5 kt for both convective weather types. With larger wind speed forecast errors, the peak gust forecast errors are generally much larger. The GFS MOS peak gust forecast results for the two convective weather types were also examined for any dependence on observed wind conditions. Figure 6 a & c do not show any evidence that any observed wind speeds produce better gust forecasts. Figure 6 b & d similarly do not show any correlation between observed wind directions and better gust forecasts. The relatively poor performance of the GF model during the convective weather types thus appears to be due to a combination of inaccuracies in wind speed forecasts and, as mentioned earlier in section 4.1, the reduced ability of the meteorologically stratified gust factor to characterize gustiness caused by convective phenomena.

How well does the GF model perform compared to the peak wind gust forecasts provided by the LAMP system? For windy snow (Figure 4a), LAMP performs worse than both GFS MOS and NAM MOS by a significant amount, especially for the 24 hr lag, but still performs better than climatology. Less windy snow shows that LAMP outperforms NAM MOS for the 06 hr lag but does worse than both models for the later lags.

For both convective weather types, LAMP did better than both MOS models for all lags except the 18 hr lag, when it has nearly the same performance level as climatology. The 06 hr and 12 hr lags for convective with thunder and rain performed almost as well as the PProg MAE.

LAMP performs less well than NAM MOS and GFS MOS at all lags for the rest of the weather types (non-convective rain, nighttime conditions, and high pressure), and does worse than climatology for lags 12-24 hr for the nighttime weather types and again for lags 18 hr and 24 hr for high pressure. There is a general increase in MAEs per lag time for most of the weather types. Save for the convective situations, LAMP performs worse than the two MOS models for a majority of the weather types and lags.

The statistical significance testing for GFS MOS versus LAMP shows that GFS MOS performs statistically better than LAMP for all lags of windy snow, all lags of nighttime with clouds and no precipitation, the 24 hr lag of nighttime with clear skies and no precipitation, and the 18 hr and 24 hr lags of high pressure at a 5% confidence level. Further significance testing showed LAMP MAEs to be less than GFS MOS MAEs during less windy snow at the lags of 06 hr and 12 hr, and differences between GFS MOS and LAMP for the other weather types and lags for to be insignificant.

The mean biases for each weather type and model lag can be found in Table 13. Most of the weather types do not have a large specific bias (positive or negative) for all the models and lags. Windy snow gusts were largely underpredicted. High pressure and clear nighttime gusts were more commonly overpredicted for all the models. Both convective weather type gusts were underpredicted for all the model types and lags except for LAMP, which tended to overpredict the gusts.

The climatology results show that the mean bias is negative and generally large for all the weather types except for night with clear and dry conditions and for high pressure. The negative biases are associated with the weather conditions that produce stronger gusts (Tables 4-9), and the weather types with the positive mean bias are associated with weaker gusts (Tables 10-11).

PProg has mean biases that are close to zero for all weather types except the convective ones. This supports the results that the GFs are a good description of the wind speed- and wind direction- dependent gust climatology at KMKE, and the GF model provides good quality forecasts of peak wind gusts provided that the wind speed and direction forecasts are of high quality, except for convection.

5 Conclusions

Harris and Kahl (2017) showed that GF models demonstrate skill in estimating peak wind gusts and are improved with the use of meteorologically stratified GFs. Kahl (2020) showed that the meteorologically stratified GF method is a viable option for the operational prediction of peak wind gusts. In this study, we investigated how well the meteorologically stratified GF method coupled with various forecasting models performs for eight gust-producing weather conditions. The GF model estimates peak wind gusts by coupling gust factors, which are site-specific climatological measures of gusts, with wind speed and wind direction forecasts. These GFs were determined from one-minute resolution ASOS wind data. NAM MOS and GFS MOS wind forecasts were provided at lags ranging from 1-24 hr.

The PProg forecast MAEs ranged from 1.1 kt to 1.7 kt for the non-convective weather types that were analyzed, and up to 4.2 kt during the convective weather types. This confirms that the meteorologically stratified GF model has potential when provided with accurate wind speed and wind direction forecasts during non-convective weather events. Convective weather event peak wind gusts are forecasted more accurately using the LAMP model. The climatology forecast MAEs, the benchmark against which model skill is assessed, ranged from 4.8 kt for nighttime with clear and dry conditions to 17.6 kt for windy snow.

The GF model coupled with GFS MOS showed skill over climatology in predicting peak gusts for all weather types except convective at all lags analyzed (06 hr, 12 hr, 18 hr, and 24 hr). This is important for operational forecasting, because the GF method can be utilized for most gust-producing weather phenomenon provided that the site-specific, stratified GFs are available.

For most weather types and lags, except for windy snow, the GF model coupled with GFS MOS and NAM MOS performed approximately equally. When tested for statistical significance, the 24 hr lag for windy snow showed that the large difference between NAM MOS and GFS MOS was not statistically important.

The relatively poor performance of the GF model in predicting peak wind gusts during the two convective weather types studied appears to be due to a combination of large errors in wind speed forecasts and the inability of the gust factors to properly characterize gustiness during the convective conditions studied.

Predicting peak wind gusts remains a challenge today, despite its importance in forecasting the weather. After continued testing, the GF method remains a good option for the operational prediction of peak wind gusts for a variety of gusty, non-convective weather types. LAMP still provides better gust forecasts for convective situations.

Questions remain that were not addressed in this project. How well does the GF model perform beyond the 24 hr lag for specific weather types? How well does the GF model perform for other weather types not considered in this project that also produce high peak wind gusts? If this project were replicated at other sites, would the results be similar? If the results at other sites were different, why might this be the case? How well does the GF model perform coupled with other MOS products or other products that provide wind speed and wind direction forecasts? These questions serve as suggestions for further research on this topic.

Table 1 List of locations that responded to email survey (NWS=National Weather Service). Note: two replies were received from the Milwaukee NWS office.

Location
NWS Milwaukee (2)
UW-Milwaukee PhD Candidate
NWS Chicago
St. Cloud State University
NWS Hastings, NE
NWS Quad Cities, IA
NWS Duluth, MN
NWS Cheyenne, WY
NWS Grand Forks, ND
NWS North Platte, NE
NWS Gaylord, MI
NWS Green Bay, WI
NWS Chanhassen, MN

Table 2 Most Common survey answers

1. Under which situation(s) is gust forecasting the most difficult?	convection/severe thunderstorms/instability, shallow PBL, winter storms/blizzards, warm air advection, nighttime mixing/cooling, low wind speed environments, cloudy, low-level inversion, rain/snow showers
2. Under which situation(s) is gust forecasting the most important?	cyclones, days with elevated fire danger, when gusts are near safety limits, blowing snow, for aviation and mariners and truckers

Table 3 Number of occurrences for each weather type and occurrence frequency of each weather type for KMKE during 2010-2017

Weather Type:	**# of Hours:**	**Occurrence frequency of weather type**
Windy Snow	192	0.29%
Less Windy Snow	2402	3.59%
Convective with Thunder	666	1.00%
Convective with Thunder & Rain	505	0.76%
Non-Convective Rain	3772	5.64%
Night, Cloudy, Dry	7192	10.76%
Night, Clear, Dry	3325	4.98%
High Pressure	8816	13.19%

Table 4 Occurrence frequencies and wind/gust characteristics for windy snow.

Windy Snow

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	31	84	18	7	0	0	0	0	0	2	11	39												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	15	40	21	18	40	39	17	2																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	7	6	5	6	6	5	8	8	13	15	12	14	9	11	10	7	6	5	4	9	9	10	3	4
count by night/day	**Night**	**Day**																						
	85	107																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	20.2	2.9	17	29.3	32.6	4.8	24	56																

Table 5 Occurrence frequencies and wind/gust characteristics for less windy snow.

Less Windy Snow

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	723	636	286	71	1	0	0	0	0	10	142	533												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	303	282	215	401	338	290	324	249																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	105	98	103	105	115	115	106	94	95	105	90	78	94	85	90	88	102	100	100	106	107	115	104	102
count by night/day	**Night**	**Day**																						
	1378	1024																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	9.2	3.7	0.5	16.9	15.8	6.1	2	40																

Table 6 Occurrence frequencies and wind/gust characteristics for convective with thunder

Convective with Thunder

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	3	6	16	74	86	161	137	81	64	23	12	3												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	102	84	73	80	78	56	79	114																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	32	37	41	39	29	26	20	18	23	19	13	16	19	20	18	30	31	25	35	38	45	35	29	28
count by night/day	**Night**	**Day**																						
	314	352																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	9.1	4	0.7	29.1	18.8	8.7	3	57																

Table 7 Occurrence frequencies and wind/gust characteristics for convective with thunder and rain

Convective with Thunder and Rain

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	3	5	16	67	53	127	95	60	49	18	11	1												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	82	68	61	64	52	43	57	78																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	24	26	36	31	23	24	16	16	19	16	12	12	16	14	11	18	20	15	21	27	33	28	25	22
count by night/day	**Night**	**Day**																						
	249	256																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	9.1	4	0.7	29.1	19.3	8.8	3	57																

Table 8 Occurrence frequencies and wind/gust characteristics for non-convective rain

Non-Convective Rain

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	171	128	285	580	458	280	194	217	292	495	378	294												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	368	510	386	507	509	439	480	573																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	154	137	164	155	166	169	162	172	161	168	158	157	133	147	141	144	157	169	181	171	156	151	151	148
count by night/day	**Night**	**Day**																						
	1680	2092																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	10	4.6	0.7	27.8	17.5	7.6	2	53																

Table 9 Occurrence frequencies and wind/gust characteristics for night, cloudy, dry

Night, Cloudy, Dry

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	1061	774	707	551	410	287	192	240	309	634	813	1214												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	894	939	775	900	956	911	884	933																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	657	654	619	655	613	507	369	177	0	0	0	0	0	0	0	0	0	31	228	401	488	591	605	597
count by night/day	**Night**	**Day**																						
	7192	0																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	8.1	4.1	0	25.1	14.1	6.8	1	52																

Table 10 Occurrence frequencies and wind/gust characteristics for night, clear, dry

Night, Clear, Dry

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	289	305	253	177	175	205	267	285	400	340	416	213												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	89	75	96	527	606	668	653	611																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	516	330	344	347	298	197	144	23	0	0	0	0	0	0	0	0	0	0	72	87	159	244	275	289
count by night/day	**Night**	**Day**																						
	3325	0																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	6	3.7	0.2	27.8	10.4	6.2	1	46																

Table 11 Occurrence frequencies and wind/gust characteristics for high pressure

High Pressure

count by month:	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**												
	1420	1085	1271	625	288	37	65	21	480	751	1390	1383												
count by year:	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**																
	895	943	865	1165	1285	1471	1118	1074																
count by hour (LST):	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
	345	348	344	344	354	378	392	411	424	431	437	425	402	359	330	322	330	333	344	352	359	357	354	341
count by night/day	**Night**	**Day**																						
	4349	4467																						
Wind and gust characteristics (kt)	**Wind speed**				**Gust**																			
	Mean	**Stdev**	**Min**	**Max**	**Mean**	**Stdev**	**Min**	**Max**																
	7.5	3.8	0.1	23.4	12.6	5.8	1	42																

Table 12 Models used with details (GFs are doubly-stratified by wind speed and wind direction)

Model Name	**Abbreviation**	**Model Type**	**MOS Guidance Type**	**MOS Guidance Product**
Persistence	PERS	No-skill		
Climatology	CLIM	No-skill		
Gust Factor – NAM	GFNAM	GF model coupled with NAM MOS	NAM	Wind speed, wind direction
Gust Factor – GFS	GFGFS	GF model coupled with GFS MOS	GFS	Wind speed, wind direction
Perfect Prog	PPROG	GF model coupled with observed wind speed and direction		
Localized Aviation MOS Program	LAMP	MOS guidance	LAMP	Peak wind gust

Table 13 Mean bias (kt) of all models at all lag times for all weather types

Weather Type	Climatology	PProg	Pers 01	Pers 02	Pers 03	Pers 04	Pers 05	Pers 06	GFS 06	GFS 12	GFS 18	GFS 24
Windy Snow	-17.6	0.3	-0.6	-1.9	-2.9	-3.9	-5.2	-6.0	-0.1	0.6	0.2	0.0
Less Windy Snow	-1.4	0.2	-0.2	-0.3	-0.4	-0.5	-0.6	-0.7	0.9	1.2	1.1	1.2
Convective with Thunder	-6.3	-3.4	-1.7	-2.8	-3.1	-3.3	-3.5	-3.7	-3.5	-3.4	-3.1	-3.3
Convective with Thunder & Rain	-7.0	-3.8	-2.1	-3.4	-3.6	-4.0	-4.2	-4.4	-3.8	-3.5	-3.0	-3.2
Non-Convective Rain	-3.8	-0.7	-0.3	-0.6	-0.8	-1.0	-1.3	-1.6	-0.3	0.0	0.2	0.1
Night, Cloud, Dry	-1.7	0.1	-0.1	-0.1	0.0	0.1	0.4	0.6	-0.2	0.0	0.0	0.0
Night, Clear, Dry	1.2	0.5	0.3	0.9	1.6	2.4	3.3	4.1	1.1	1.1	1.0	1.1
High Pressure	1.7	0.4	0.0	0.0	0.1	0.2	0.3	0.4	0.4	0.4	0.5	0.4

	NAM 06	NAM 12	NAM 18	NAM 24	LAMP 06	LAMP 12	LAMP 18	LAMP 24
Windy Snow	1.2	-0.3	0.8	0.2	-6.0	-5.7	-5.4	-10.2
Less Windy Snow	2.4	0.8	2.1	0.7	-0.2	0.6	1.1	1.9
Convective with Thunder	-3.8	-4.1	-3.3	-3.7	1.1	2.4	0.2	2.6
Convective with Thunder & Rain	-4.6	-3.9	-4.2	-3.6	4.3	4.1	0.6	4.6
Non-Convective Rain	0.4	0.1	0.9	0.1	-0.4	-0.4	0.9	1.0
Night, Cloud, Dry	0.2	0.4	0.2	0.2	-0.2	2.1	1.7	1.6
Night, Clear, Dry	1.5	1.2	1.4	0.8	0.6	2.5	3.3	3.9
High Pressure	0.9	0.6	0.7	0.4	0.9	0.8	2.8	4.4

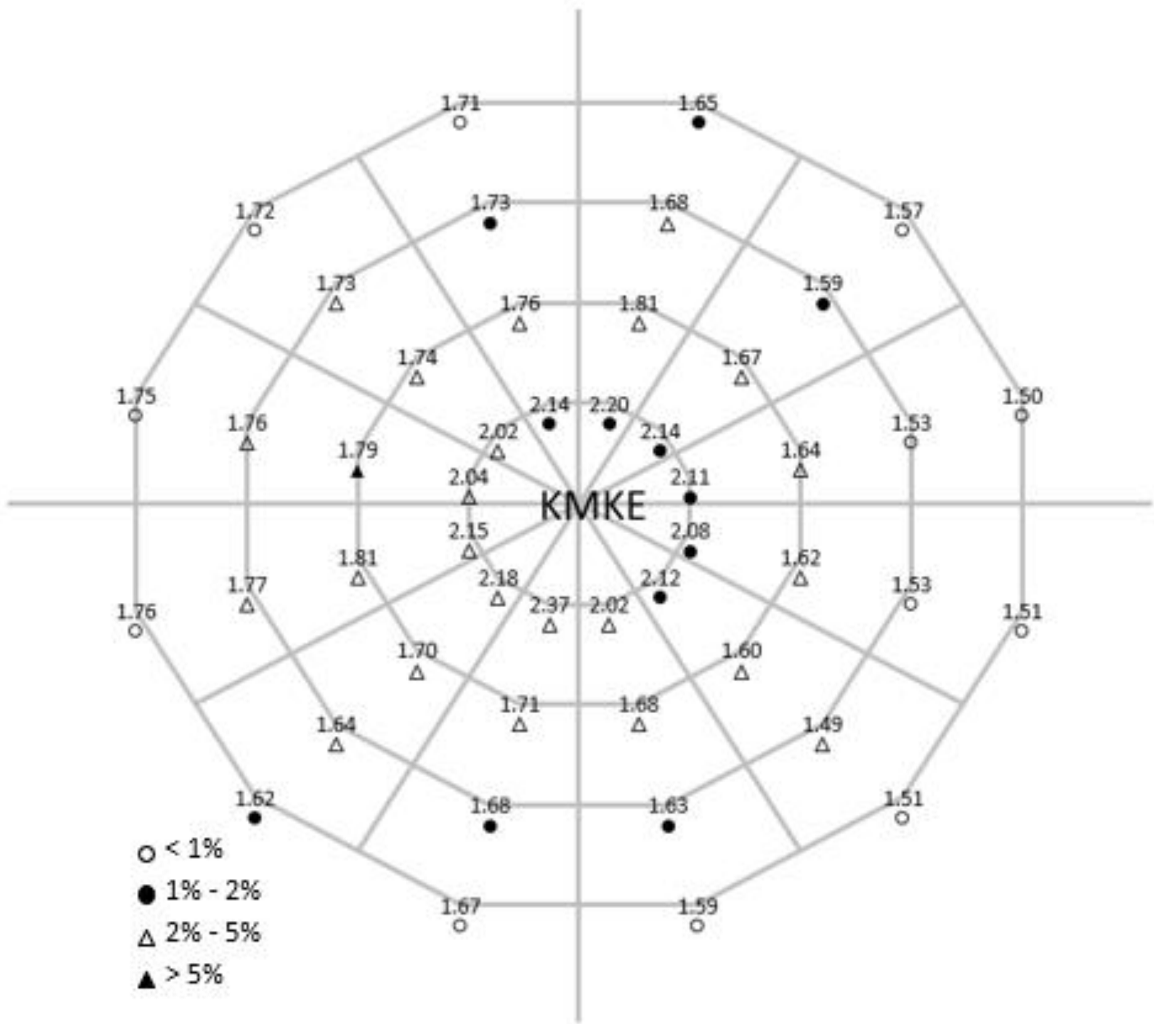

Figure 1 Gust web showing meteorologically stratified gust factors at KMKE based on 66,823 hourly wind speeds, wind directions, and peak gusts during 2010-2017. The rings represent mean wind speed ranges: 0-5 kt (center), 5-10 kt, 10-15 kt, and >15 kt (outermost). The radial lines represent the 30° wind sectors, clockwise from north. The symbols represent the occurrence frequencies of mean wind speed and direction combinations.

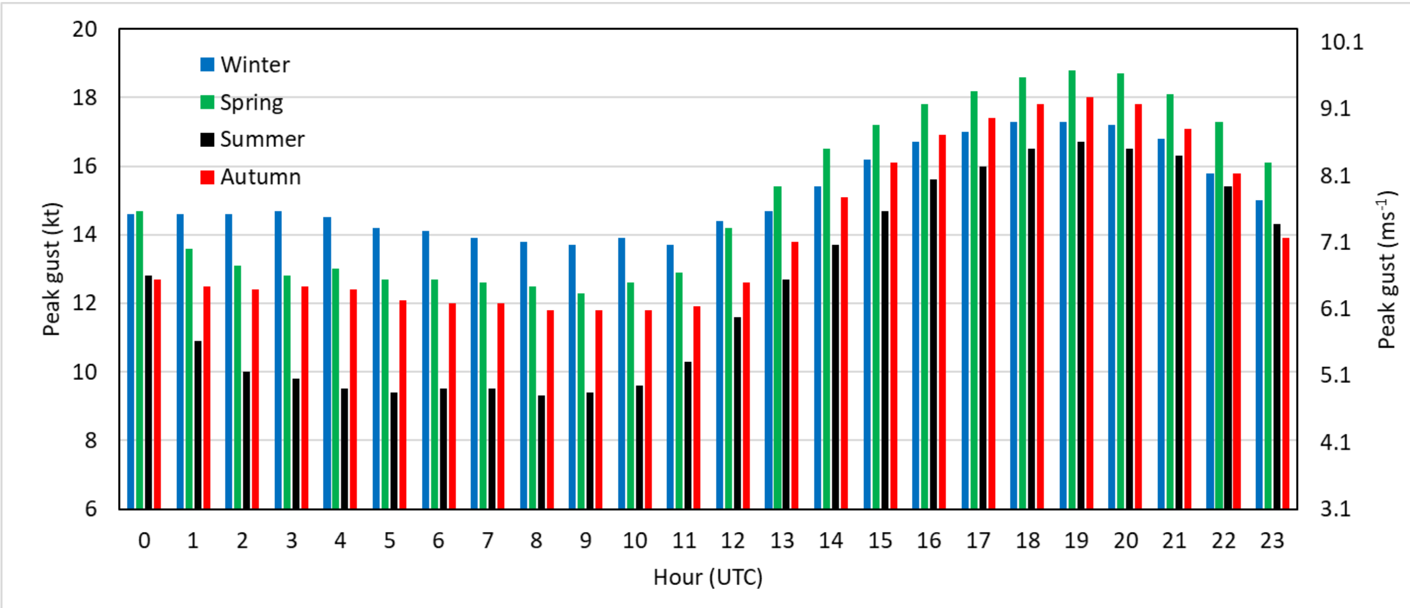

Figure 2 Gust climatology of KMKE for 2010-2017

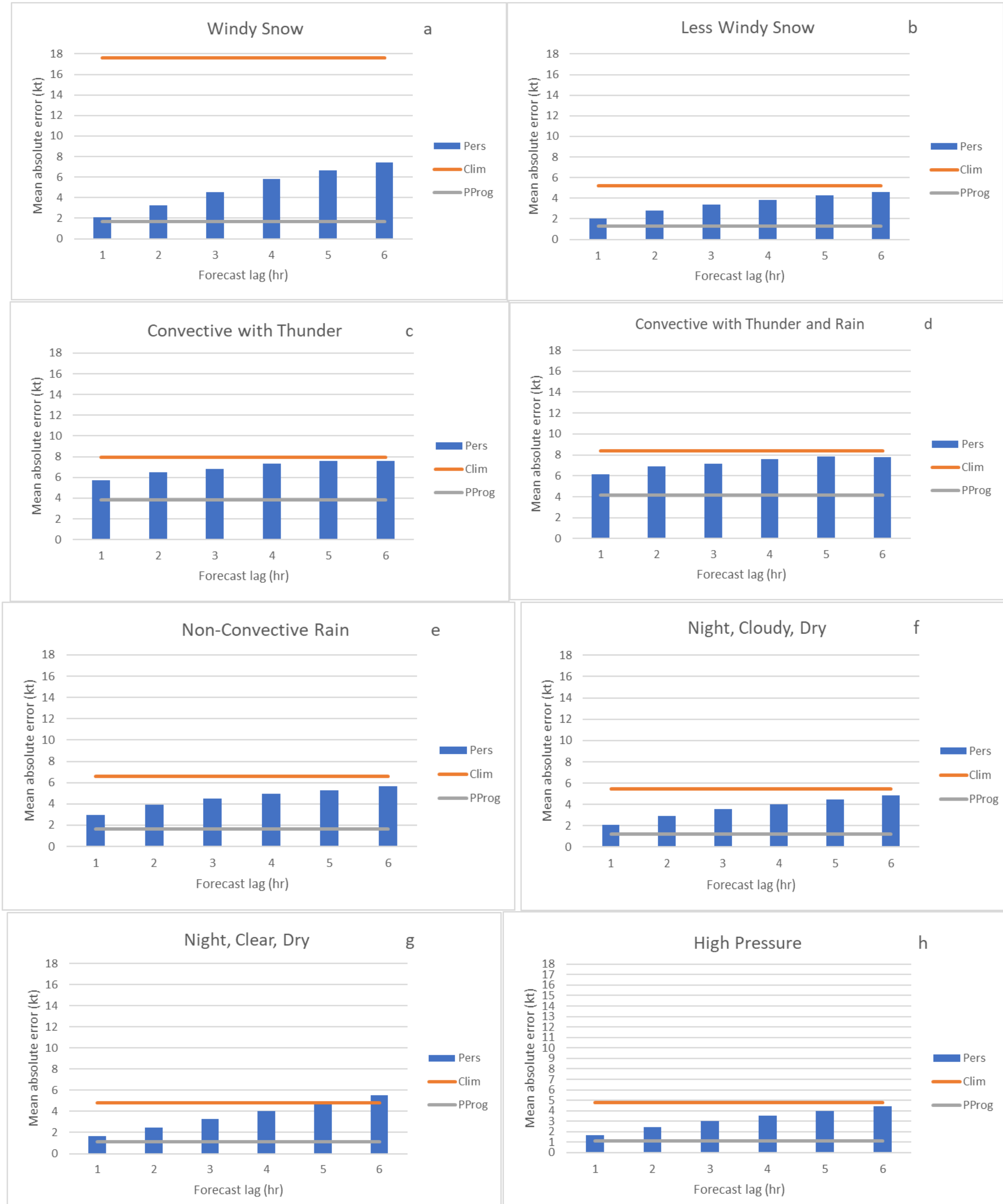

Figure 3 Mean Absolute Errors of peak wind gust forecasts for the persistence, climatology, and perfect prognosis models.

Figure 4 MAEs for each weather type and model

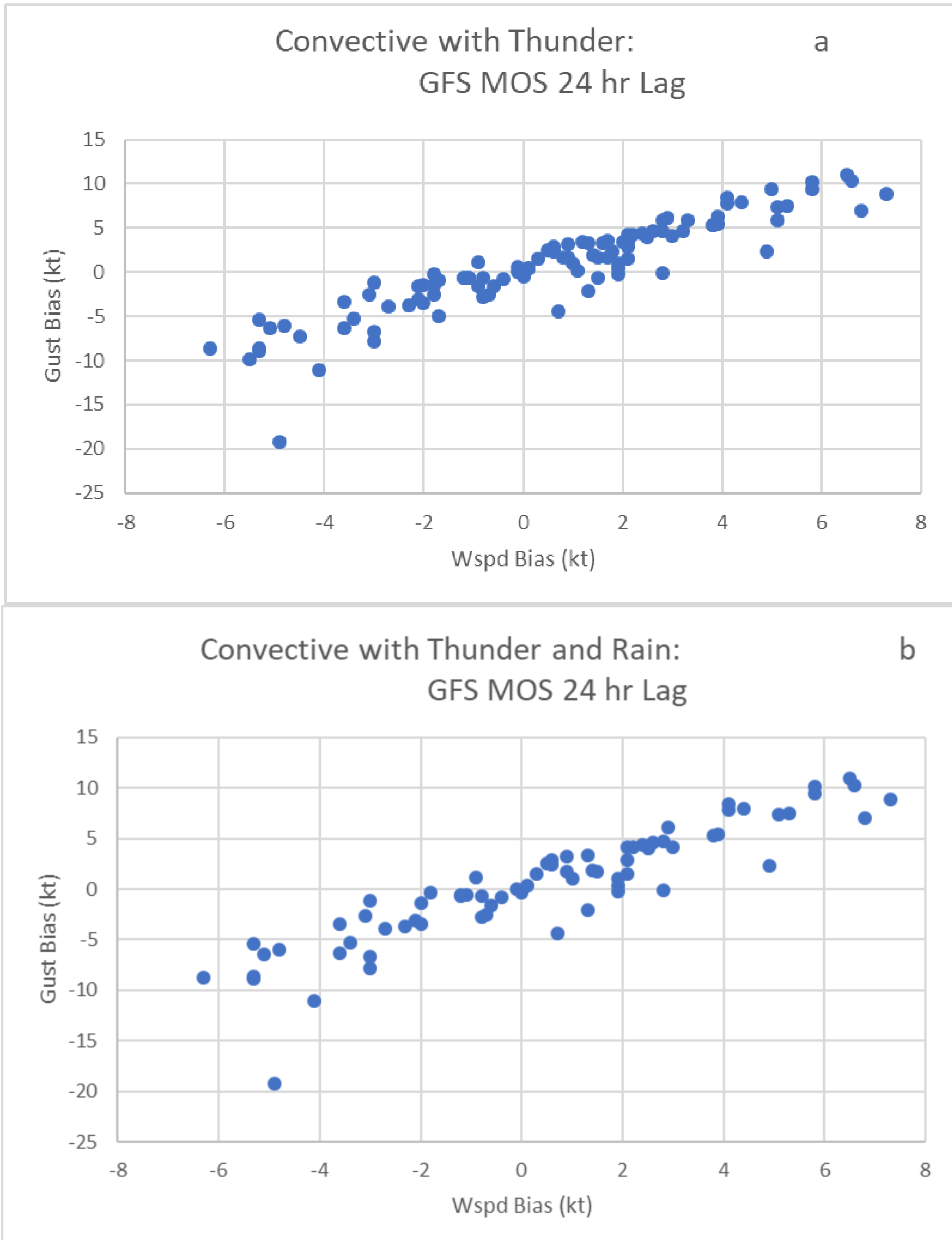

Figure 5 Gust forecast bias versus wind speed forecast bias during convective situations

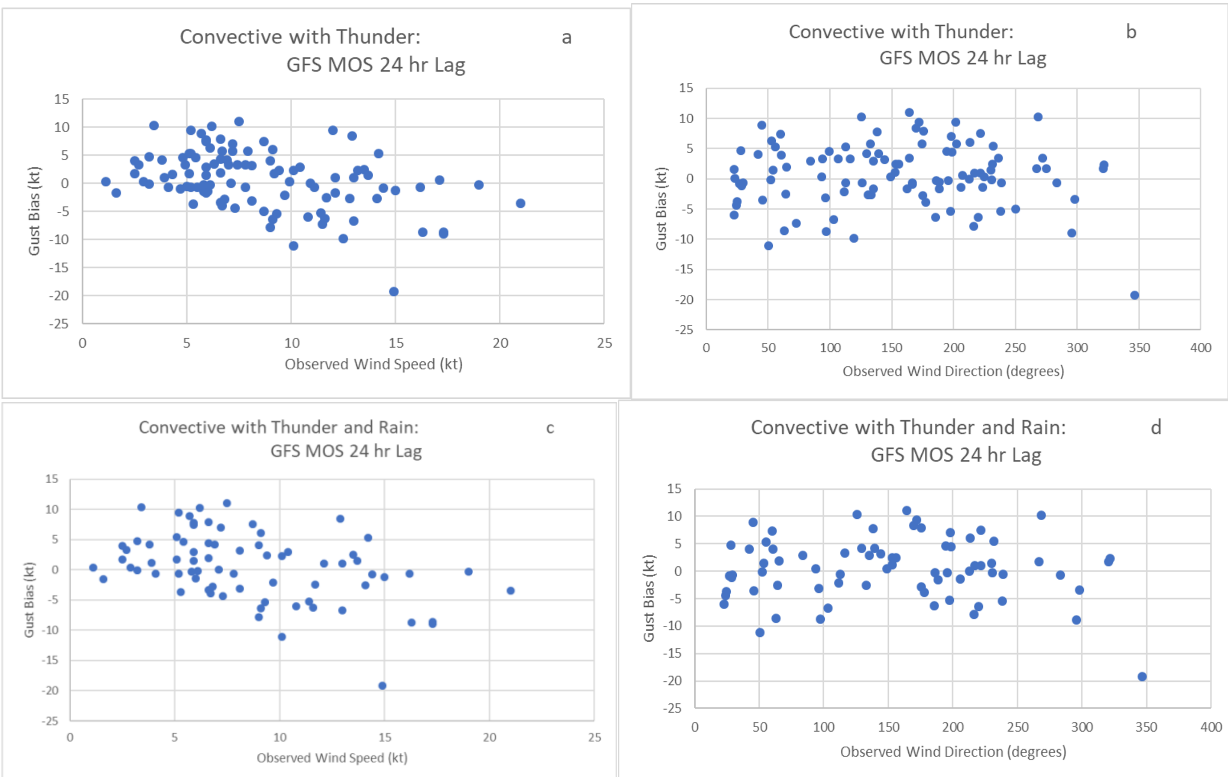

Figure 6 Gust forecast bias at KMKE for both convective situations as a function of observed wind speed and observed wind direction.

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