Exploring environmental and methodological sensitivities of forecasted and observed surface winds and gusts using underutilized datasets

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Exploring Environmental and Methodological Sensitivities of Forecasted and Observed Surface
Winds and Gusts Using Underutilized Datasets

by

Alex R. Gallagher

A Dissertation
Submitted to the University at Albany, State University of New York
In Partial Fulfillment of
the Requirements for the Degree of
Doctor of Philosophy

College of Arts and Sciences
Department of Atmospheric and Environmental Sciences
Summer 2021
ABSTRACT

Accurate forecasts and reliable observations of surface mean winds and gusts inhabit a vast and essential role in meteorological applications that range from wind energy, atmospheric transport, fire weather, and hazard assessment. This dissertation aims to address and explore known shortfalls in the prediction of mean winds and gusts as well as enhance evaluation and understanding of observed surface wind measurements. A variety of forecasts, methodologies, and observational dataset, many of which have been previously un- or under-utilized, are leveraged to tackle the differing needs of assessing mean winds, gusts, and the surface environment.

Detailed verifications of HRRR (version 3 and 4) forecasted mean winds and gusts were performed against ASOS and NYSM observations to assess the persistence and origin of systemic biases found in previous literature. Initial results showed the HRRR has a large degree of skill in forecasting network average wind speed, but also agreed with past works noting a systematic over- and under-prediction of wind speeds at locations with the slowest and fastest wind speeds. Subsetting the verification by assigned landuse category and local time revealed these biases to be the result of narrow and offset forecasted mean wind distributions that fail to capture the tails of the observed distribution at both slow and fast wind speeds. Certain landuse categories such as urban and forested exhibited endemic preferences towards negative and positive biases from shifts in the distribution while all other classifications struggled to properly represent moderate to fast wind speeds (4-8 m/s). Disagreement in the shape of the wind distribution was shown to be worse at night highlighting poor handling of the stable boundary layer. While there were improvements in resolving moderate wind speeds and some landuse changes when verifying HRRRV4 the bulk of these results remain largely the same.
With respect to gusts, their complex and turbulent nature often necessitates diagnostic tools to predict gust potential in lieu of information with sufficiently high temporal resolution. The robustness of one of the most well-known gust forecasting tools, the Durst curve, is critically examined and compared to modern observations. ASOS 1-min and NYSM 3-s resolution data were used to construct hourly maximum gusts of a variable duration, $t$-seconds long, with respect to hourly mean winds and generate gust curves similar to Durst. The resulting gust curves displayed significant disparities with much larger gust factors (GFs) compared to the historic curve but were gradually brought into agreement by filtering observations requiring minimum hourly mean wind speeds and maximum allowable standard deviation of wind direction. This filtering limited the fraction of the usable observation record to incredibly small percentages highlighting the small range of conditions the historic gust curve is actually applicable for.

Lastly, the influence of local obstructions on observations of mean winds, gusts, and GF were investigated through the use of airborne lidar data. While lidar data is relatively novel and largely heterogeneous in its configuration, after significant quality control efforts it provides and incredibly detailed and precise snapshot of the environment around surface observations. Comparisons of average GF and obstruction angles calculated from lidar point clouds indicated a strong agreement in the azimuthal variation of observed GF and the maximum obstruction angle in a direction. Composites of both ASOS and NYSM observations revealed that average mean wind speed, gust speed, and GF are all maximized when obstructions are absent or even with the horizon and drop of steeply as maximum obstruction angle deviates from $0^\circ$. Furthermore, for obstruction angles ASOS and NYSM have in common they were shown to be nearly identical in
their observed mean wind, gust, and GF values when factors such as averaging interval and gust duration were kept equal.
ACKNOWLEDGMENTS

I wish to thank all those that supported me in the efforts of this dissertation both professional and personal. This has been an incredibly long road leading up to the writing of this dissertation, marking the end of over a decade at SUNY Albany between the entirety of my degrees here. With that I would like to thank the entire Department of Atmospheric and Environmental Sciences for providing such a wonderful academic environment and culture that has helped me grow over the years and truly be a place I feel comfortable calling home. Among those that I would like to individually thank are the members of my committee: Dr. Justin Minder, Dr. David Fitzjarrald, and Dr. Liming Zhou. Thank you all for the continued feedback and encouragement throughout this process as well as teaching me during my time as a student here at UA.

I want to give a special thank you to my advisor Dr. Robert Fovell. I couldn’t have asked for greater opportunity than when you picked me up as your graduate student. Thank you for guiding me through the graduate school experience, teaching me to be a better scientist in every facet from research to presentations to writing. I will never forget your quotes both scientific and silly and I hope we have the opportunity to work more together in the future.

I would also like to give special thanks to the folks at the SMART Program whose scholarship funded my dissertation years of graduate school and connected me with my sponsoring facility and future employers at the Environmental Research and Development Center’s Cold Region Research and Engineering Laboratory. In particular I would like to thank Sandra LeGrand, Taylor Hodgdon, and Dr. Theodore Letcher for helping me further develop the range and applicability of my research and introduce me to a whole new world of research outside academia.

This research is made possible by the New York State (NYS) Mesonet. Original funding for the NYS Mesonet was provided by Federal Emergency Management Agency grant FEMA-4085-DR-NY, with the continued support of the NYS Division of Homeland Security & Emergency Services; the state of New York; the Research Foundation for the State University of
New York (SUNY); the University at Albany, SUNY; the Atmospheric Sciences Research Center (ASRC) at SUNY Albany; and the Department of Atmospheric and Environmental Sciences (DAES) at SUNY Albany. Additionally, raw 3-s data were provided by the NYS Mesonet’s Nathan Bain.

Lastly, I’d like to take a moment for some personal acknowledgements. There are far too many people that have helped support me in a personal capacity, keeping me going, especially during the past year and a half of the global pandemic but there are a few I cannot help but note. I’d like to thank my mom Lori Gallagher for being not only a constant cheerleader for me but also my point of contact for the world of photogrammetry and airborne lidar data. I speak no hyperbole when I say this dissertation would not have been possible without you. I’d also like to thank my younger brother Spencer Gallagher, you do so much more for me than you realize. It has been a privilege to watch and help you grow (and continue to grow) and be a source of strength and stability for each other when life wasn’t easy for us. Your perseverance, determination, and drive have been truly inspiring to me and I’m proud to be your sister. And of course, I’d like to thank my fiancé, Alex Carlson. My life has never been the same since you walked into it, and we’ve come so far together I could not imagine being here without you. You, more than anyone, have been my greatest source of support, joy, laughter, and stability.
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3 stations (green), class 4 and 5 stations (gold). Panel (b) curves are color coded by each stations average forecast bias verified against HRRR forecasts for April 2019 with greens indicating biases close to zero (±0.5 m/s) and reds indicating larger positive biases (≥ 0.5 m/s). The network average from panel (a) is duplicated in panel (b) with a thick dashed black line and Durst’s values are shown in the thin black line in both panels.

**Figure 3.25** Box and whisker plot of station average wind speed for NYISM delineated by their WMO wind classification. The median, interquartile range, and maxima/minima are denoted by the black center lines, colored boxes, and whiskers, respectively. Average of all station mean winds are shown in the red dots and line. Boxes are colored to be consistent with their maxwind curves in Fig. 3.24a. Note classes 4 and 5 are combined due to the small number of stations in both.

**Figure 3.26** Similar to Fig. 3.24 except for ASOS network average and station subsets (a) and all ASOS stations individually (b). Subsets 1 and 2 in panel (a) use all ASOS stations but only for hours when the hourly mean wind speed is ≥ 9 m/s and the standard deviation of wind directions is ≤ 10° (green) and hours when the hourly mean wind speed is ≥ 4 m/s and the standard deviation of wind directions is ≤ 20° (blue), respectively. Panel (b) individual stations are still color coded according to their average HRRR bias over April 2019 by large positive biases (≥ 0.5 m/s) in red, biases close to zero (±0.5 m/s) in green, and large negative biases (≤ -0.5 m/s) in blue.

**Figure 3.27** Same as Fig. 2.13c reiterated for convenience. Station average iGF vs. station average bias of forecast wind speed for ASOS (black dots) and NYISM (orange dots) stations. Each dot represents a temporal average over April 2019 for each station. The linear regression is shown in red line.

**Figure 3.28** Similar to Fig. 3.10 except just ASOS network average GFs for gust durations 3-s (a), 120-s (b), 300-s (c), and 600-s (d) using only hours when the hourly mean wind speed is ≥ 9 m/s and the standard deviation of wind directions is ≤ 10°.

**Figure 3.29** Similar to Fig. 3.28 except for network average iGF instead of GF.

**Figure 3.30** The mean curves of average GF (a) and iGF (b) from Fig. 3.28 and Fig. 3.29, respectively. Curves are color coded by gust duration: 3-s (red), 120-s (gold), 300-s (green), and 600-s (blue). Numbers adjacent each point indicates the total samples that constitute the mean. Error bars indicate ±1 standard deviation about the mean.

**Figure 4.1** Locations of Near NYS ASOS (black) and NYISM (red) stations.

**Figure 4.2** Existing lidar project areas as of November 2020 (a) and proposed lidar data collection areas between November 2020-November 2021 (b). Color coding indicates each unique lidar project area, commissioning department, and year of collection.

**Figure 4.3** Top-down heat maps of all (terrain, non-terrain, other) obstruction angles at NYISM stations HART (a-b), BURT (c-d), and WARW (e-f) smaller (left column; 0-50m HART, 50-
500m BURT and WARW) and larger (right column; 50-500m HART, 500-2000m BURT and WARW) scales. Terrain and obstacles above/below the horizon are shaded red/blue. Noise and unwanted objects are highlighted in deeper reds indicating they are much higher above the surface.

**Figure 4.4** Comparisons of ASOS (x-axis) and NYSM (y-axis) network average mean wind speeds (left column) and gusts (right column) for all matching observation times throughout 2017 in their native formats (a-b), normalized to a 10min averaging interval (c-d), using only WMO Class 1+2 stations for NYSM with a 10min averaging interval (e-f), using only observations greater than 1m/s from WMO Class 1+2 NYSM stations with a 10min averaging interval (g-h).

**Figure 4.5** Histograms of difference in mean wind speed (blue) and gust (red) observation frequency between the propeller and sonic anemometers (Propeller-Sonic) for all NYSM observations (a), PENN (b), and CROG (c). Note the bin size for gusts is wider (0.5 m/s compared to 0.25 m/s) owing to the mismatch in anemometer precision (0.5 m/s is the least common multiple of sonic and propeller precisions of 0.1 m/s and 0.166 m/s, respectively).

**Figure 4.6** Mean wind speed (left column) and gust speed (right column) wind roses (fraction of total observations) for NYSM stations PENN (a-b), HART (c-d), and GFAL (e-f), binned every 5⁰.

**Figure 4.7** Similar to Fig. 4.6 except for NYSM stations WBOU (a-b), SARA (c-d), and DUAN (e-f).

**Figure 4.8** Similar to Fig. 4.6 except for ASOS stations KPEO (a-b), KELZ (c-d), and KGFL (e-f).

**Figure 4.9** Similar to Fig. 4.3 except for PENN (left column) and OTIS (right column) for the mososcale (0-50m, a,d), misoscale (50-500m, b,e), and mesoscale (500-2000m, c,f) environments around each station.

**Figure 4.10** Similar to Fig. 4.9 except for HART (left column, after noise processing) and WBOU (right column).

**Figure 4.11** Similar to Fig. 4.9 except for GFAL (left column) and SARA (right column).

**Figure 4.12** Similar to Fig. 4.9 except for KPEO (left column) and KGFL (right column).

**Figure 4.13** NYS Ortho-imagery centered over NYSM stations (a) PENN, (b) OTIS, (c) HART, (d) WBOU, (e) GFAL, (f) SARA. 500m radius is indicated by a red ring.

**Figure 4.14** Same as Fig. 4.13 except for ASOS stations (a) KGFL and (b) KPEO.

**Figure 4.15** Azimuthal rings of maximum (red), average (blue), and minimum (magenta) obstruction angles in the misoscale environment every 1⁰ looking outward from the station (left column) and average GF for wind observations binned every 5⁰ color coded by direction.
frequency (fraction of total observations) for OTIS (a-b), WBOU (c-d), and SARA (e-f). The black circles indicate an obstruction angle of 0° (flat) and the total station average GF for the left and right columns, respectively.

**Figure 4.16** Similar to **Fig. 4.15** except for KPEO (a-b) and KGFL (c-d).

**Figure 4.17** Scatterplots of maximum terrain (left column) and non-terrain (right column) obstruction angles within the misoscale environment vs. average GF every 1° (N=360) around OTIS (a-b), WBOU (c-d), and SARA (e-f). Zero degrees, flat, off the horizon is indicated in vertical black lines and linear regressions are shown in red lines.

**Figure 4.18** Similar **Fig. 4.17** except for GFAL (a-b), DUAN (c-d), and OLDF (e-f).

**Figure 4.19** Scatter plots of maximum non-terrain obstruction angle within the mososcale environment vs. average GF (left column) and average mean wind speed (right column) every 1° azimuthally around all NYSM stations. Top row shows each 360 1° directions at all 107 stations (N=38520). Bottom row shows GFs/mean winds averaged by their maximum obstruction angle binned every 0.5° with grey lines indicating ±1 standard deviation of observations from the mean. Color shading indicates the fraction of observations (frequency) from a given direction with the corresponding maximum obstruction angle.

**Figure 4.20** Similar to **Fig. 4.19** except for the misoscale environment around all NYSM stations.

**Figure 4.21** Similar to **Fig. 4.17** except for ASOS stations KPEO (a-b), KGFL (c-d), and KELZ (e-f).

**Figure 4.22** Top-down heat maps similar to **Fig. 4.9** except of terrain (a) and non-ground (b) obstruction angles within the misoscale environment surrounding KELZ. Azimuthal rings of maximum (red), average (blue), and minimum (magenta) obstruction angles similar to **Fig. 4.15** (left column) except from terrain (c) and non-ground (d) sources.

**Figure 4.23** Similar to **Fig. 4.19** except for all available ASOS stations (N=6840).

**Figure 4.24** Similar to **Fig. 4.22** except for the misoscale environment.

**Figure 4.25** Scatter plots of maximum non-terrain obstruction angle within the misoscale environment vs. average GF (left column) and average iGF (right column) composited similar to **Fig. 4.19** by maximum obstruction angle binned every 0.5° for NYSM (blue) and ASOS (red) networks. (a-b) sonic anemometer data in their networks native averaging intervals, (c-d) shows sonic anemometer data using normalized ten-minute averaging intervals, and (e-f) shows NYSM propeller and ASOS sonic data using normalized ten-minute averaging intervals. Error bars indicate ±1 standard deviation of observations from the mean.

**Figure 4.26** Similar to **Fig. 4.25** except for average mean wind speeds (left column) and average gust speeds (right column).
Figure 4.27) Similar to Fig. 4.25 except for average gust increment and shaded by the percentage of observations composited into each 0.5° bin. NYSM is shaded in cooler colors (green/blue) and ASOS in warmer colors (yellow/red).
LIST OF ABBREVIATIONS

Weather Research and Forecasting Model, WRF Model
Advanced Research WRF, ARW
High-Resolution Rapid Refresh Model, HRRR Model
National Oceanic and Atmospheric Administration, NOAA
Automated Surface Observing System, ASOS
National Centers for Environmental Information, NCEI
Contiguous United States, CONUS
Gust Factor, GF
New York State, NYS
New York State Mesonet, NYSM
World Meteorological Organization, WMO
Moderate Resolution Imaging Spectroradiometer, MODIS
Coordinated Universal Time, UTC
Local Time, LT
Mellor-Yamada-Nakanishi-Niino Level 2.5, MYNN2
Inverse Gust Factor, iGF
Light Detection and Ranging, Lidar
3D Elevation Program, 3DEP
Digital Elevation Model, DEM
Digital Surface Model, DSM
Universal Transverse Mercator, UTM
State Plane Coordinate System, SPCS
Albers Conical Equal Area, ACEA
Transverse Mercator, TM
Lambert Conformal Conical, LCC
Land Use Classification, LU
LIST OF VARIABLES

Mean or Sustained Wind Speed, $M$ (m/s)

Maximum Wind Sample or Gust Speed, $\hat{u}$ (m/s)

Gust Factor, $GF = \hat{u} / M$

Network Average GF, $GF_{net}$

Inverse Gust Factor, $GF = M / \hat{u}$

Gust Increment, $GI = \hat{u} - M$ (m/s)

Record or Averaging Interval, $T$ (s)

Sample Averaging Interval or Gust Duration, $t$ (s)

Observed Mean Wind Speed, $\overline{U}_{obs}$ (m/s)

Observed Gust Speed, $\hat{u}_{obs}$ (m/s)

Forecasted Mean Wind Speed, $\overline{U}_{fcst}$ (m/s)

Forecasted Gust Speed (GF method), $\hat{u}_{fcst}$ (m/s)

Surface Roughness Length, $z_{0}$ (m)

Lidar Identified Obstruction Angle, $\theta$ (°)

Lidar Identified Terrain Classified Obstruction Angle, $\theta_{ter}$ (°)

Lidar Identified Unclassified (Non-Terrain Obstruction) Obstruction Angle, $\theta_{obs}$ (°)

Lidar Identified Other/No Classification Obstruction Angle, $\theta_{oth}$ (°)

Lidar Identified Water Classified Obstruction Angle, $\theta_{wtr}$ (°)

Maximum Lidar Identified Obstruction Angle, $\hat{\theta}$ (°)

Minimum Lidar Identified Obstruction Angle, $\check{\theta}$ (°)

Average Lidar Identified Obstruction Angle, $\bar{\theta}$ (°)
1. Introduction

1.1 Theme of This Dissertation

Accurate wind forecasts are obviously important in a number of areas, including and not limited to wind energy (Piccardo and Solari 1998, Peterson et al. 1998), pollution transport (Arya 1999), and anticipation and mitigation of damage resulting from strong winds (Holmes et al. 2014). An example of the latter is the “Santa Ana” weather event (Sommers 1978; Hughes and Hall 2010; Cao and Fovell 2016; Rolinski et al. 2019), a cool-season pattern of offshore flow in Southern California that is known to dramatically increase the risk of large wildfires (Westerling et al. 2004; Rolinski et al. 2016). Numerical modeling of Santa Ana events for the purposes of model verification and wind reconstruction (e.g., Cao and Fovell 2016, 2018; Fovell and Cao 2017; Fovell and Gallagher 2018) have revealed strengths and weaknesses of both the models and the observations. These simulations used the Weather Research and Forecasting (WRF) model’s Advanced Research WRF (ARW) core at resolutions (0.67 to 2 km horizontal grid spacing) that can be considered “mesoscale”\(^1\).

The above-cited modeling studies were primarily focused on directly predicting or reconstructing the sustained wind and diagnosing or estimating the wind gust, which is a subgrid-scale phenomenon at mesoscale grid spacings. Anemometers of different types, including the sonic, cup and vane, and propeller varieties, are used to sample the wind at some period we will term the sampling interval. The sustained wind is an average of samples over a specified period. The World Meteorological Organization (WMO 2014-2017) standard calls for 3-s samples to be averaged over a 10-min period, which we will call the averaging interval, with that interval’s

\(^1\) Although definitions vary, the mesoscale is often thought of as starting at a horizontal length scale of 2 km. However, the effective resolution of a numerical model is closer to 7 times the grid spacing (Skamarock 2004) such that a 0.67 km simulation has an effective resolution of between 4 and 5 km, which is within the mesoscale range.
fastest 3-s reading being reported as the gust. The standard also specifies an anemometer mounting height at 10 m above ground level (AG) with adequate clearance around the instrument. Ideally the surrounding environment would consist of open flat terrain with obstacles no taller than 4 m and more than thirty times their height away from the anemometer (2° above the horizon) (WMO wind class 1, WMO 2014-2017). Adherence to these guidelines, however, is not all that common in practice.

A theme of our present and already published work has been the employment of raw (or less processed) and infrequently utilized datasets to evaluate near-surface and boundary layer wind forecasts in more comprehensive and exacting fashions. For Fovell and Gallagher (2018), we started using raw, 1-min Automated Surface Observing System (ASOS) observations obtained from an archive at the National Centers for Environmental Information (NCEI). That paper was a study of winds and gusts associated with the massive 2017 Thomas Fire in Southern California. These raw ASOS data were also employed in Fovell and Gallagher’s (2020) evaluation of forecast errors in the operational High-Resolution Rapid Refresh (HRRR) model, Version 3. That study focused on month-long composites for several months (highlighting April 2019) to reveal issues latent in the modeling system. Fovell and Gallagher (2020) also made extensive use of both raw and less-processed high-frequency radiosonde information also hosted by NCEI to show how forecast errors evolved in the lower troposphere. Those data are much more sparse, far more difficult to work with, and are no longer being archived in the form that made Fovell and Gallagher’s (2020) analysis even possible.

The present work will utilize the raw ASOS data along with high-frequency reports from the New York State Mesonet (NYSM) (Brotzge et al. 2020) as well as airborne lidar measurements. ASOS is a network of mostly airport installations across the conterminous United
States (CONUS) and beyond. During the time period examined herein, ASOS employed sonic anemometers with a 3-s sampling interval, mostly mounted at 10 m AGL. ASOS observations are most easily obtained from the MADIS (Meteorological Assimilation Data Ingest System) archive, but these data are formatted in a manner that provides incomplete gust information (cf. Gallagher 2016; Harris and Khal 2017; Fovell and Gallagher 2018). Therefore, we use instead the 1-min observations that are available for a subset of the CONUS ASOS stations, 850+ locations (shown in Chapter 2, Fig. 2.3) from NCEI. This dataset provides 2-min average winds as the sustained winds and the fastest 3-sec sample recorded during that two-minute reporting period as the gust. In the present work, we employ these 1-min ASOS wind and gust data to extend the HRRR verification study (Chapter 2), to assess how winds change with averaging interval (Chapter 3), and to evaluate the role of obstacles on wind speed and the ratio of gust to sustained wind, which is called the gust factor (Chapter 4).

The New York State Mesonet is a relatively young network, the backbone of which is 126 standard surface installations spread across the state (shown in Chapter 3, Fig. 3.6). These measure winds at 10 m AGL using both sonic and propeller anemometers, albeit with different sampling intervals (1 and 3 second, respectively). We will make use of Mesonet data in two formats, 5-min observations and 3-s readings, from both instruments. The Mesonet also provides other measurements that will not be exploited in this dissertation.

Most of the lidar data we will use originated in the 3D Elevation Program (3DEP, Dewberry 2012), which provides high-resolution information for the CONUS and beyond. Airborne lidar data are collected using wide beam or sweeping lidar units mounted on the underside of low flying aircraft. Returns to the lidar unit create high resolution 3D point clouds of the earth’s surface, vegetation, and man-made structures. These point clouds contain
information on each points position and red-green-blue (RGB), intensity, and classification (ground, non-ground, water, noise etc.). As discussed in Chapter 4, those datasets are not yet complete but have considerable coverage over NYS.

1.2 Past Findings and Open Issues

We will motivate our research questions after reviewing some of findings from the studies cited above. First, regarding Santa Ana wind events, Cao and Fovell (2016) evaluated a sizable WRF physics-based ensemble to determine the best model configuration for predicting the magnitude and evolution of near-surface winds. The primary focus was on San Diego County and the model verification made use of observations recorded by the San Diego Gas and Electric (SDG&E) mesonet which spanned the county. During the time period under examination, the SDG&E wind observations were 10-min averages of 3-s samples measured via propeller anemometers mounted at 6.1 m (20’) AGL, and WRF model forecasts of 10 m wind speeds were adjusted to match the SDG&E measurement height. Cao and Fovell (2016) examined sustained winds averaged over the SDG&E network as a function of time, and temporally averaged at individual stations, as part of their evaluation of a mid-February 2013 event. Cao and Fovell (2018) expanded the study to encompass a total of six moderate to strong Santa Ana wind events that occurred since the deployment of the SDG&E mesonet.

Cao and Fovell (2016, 2018) found that the best model configuration skillfully reproduced the magnitude and evolution of network-averaged sustained wind speed. That best setup used the rather uncommonly used Pleim-Xiu (PX) land surface model (LSM) and Asymmetric Convection Model version 2 (ACM2) planetary boundary layer (PBL) scheme that were developed by Pleim and Xiu (1995) and Pleim (2007), respectively. Figure 1.1, reproduced from Cao and Fovell (2018), illustrates that the control (thick blue) and perturbed versions of the
PX/ACM2 configuration more closely matched the network-averaged observations (black dots) than did a much more commonly employed setup using the Noah LSM (Chen and Dudhia 2001; Ek et al. 2003) and Yonsei University (YSU) PBL scheme (Hong et al. 2006; Hong 2010) labeled Noah/YSU. The perturbed runs were made using the stochastic kinetic energy backscatter (SKEBS) scheme (Berner et al. 2011), a procedure for assessing sensitivity to unresolved turbulence. It is seen that the difference between the configurations was larger than the sensitivity to perturbations as revealed via SKEBS.

Note in particular in Fig. 1.1 that the Noah/YSU simulations overpredicted the network-averaged wind for most of the mid-February 2013 event, especially during the period when the winds were strongest. Cao and Fovell (2018) demonstrated that the main advantage provided by the PX LSM was in its treatment of the shrublands that dominate the Southern California landscape as being rougher than in the Noah LSM. This enters into the model via a “roughness length” $z_0$. Providing the Noah LSM with the PX $z_0$ specifications (termed configuration Noah/YSU/$z_0$mod) for shrubland resulted in forecasts that were just as skillful.

However, while the network-averaged winds for the PX/ACM2 (Fig. 1.1) and Noah/YSU/$z_0$mod (not shown here) configurations were predicted with nearly zero bias, Cao and Fovell (2016, 2018) found systematic over- and underpredictions at individual stations. Figure 1.2, also from Cao and Fovell (2018), present scatterplots of forecast wind bias (the vertical axis for the top six panels) averaged over six events (a total of 324 forecast hours) plotted against various quantities. Each dot is one of 135 stations that provided data for all six events, and bias is defined as forecast minus observation. While there is no relationship between the mean forecast wind and mean forecast bias, as illustrated Fig. 1.2a, there is a very clear trend seen between the mean observed wind and the bias (Fig. 1.2b). The slower/faster the observed wind, the more
positive/negative the bias, meaning the model was systematically overpredicting the wind at the slow wind stations and underpredicting the wind at the windier sites. In more colloquial terms, the bias was biased.

We consider the relationship between bias and the observed wind to be a serious concern because it raises the notion that we may be underassessing the wind threat at windier locations and times. Still, the Cao and Fovell (2018) finding, although extracted from a composite of multiple Santa Ana wind events, does not guarantee this issue is ubiquitous in space and/or among various weather conditions, occurs with observations from different networks or instruments, and/or whether it arises in operational models that (considering the effort placed in data assimilation) are initialized with a great deal more care than is typical for WRF-based modeling studies. That said, Fovell and Gallagher (2020) found similar results in their analysis of operational HRRR forecasts that composited forecasts and observations made over month-long periods at ASOS stations across the CONUS that used sonic anemometers.

This is seen in Figs. 1.3 and 1.4, reproduced from Fovell and Gallagher (2020). This analysis employed 733 CONUS ASOS stations for April 2019 along with hourly forecasts initialized daily at 00 or 12 UTC. Observations were from the 1-min database and represented top of the hour reports. First, we see that the network-averaged wind (now spanning four time zones) forecasts and observations were quite close for both 00 and 12 UTC runs (Figs. 1.3a,b). There was a negative bias of about -0.5 m/s at the analysis time (0-h forecast) that gradually disappeared over the first 24 h in both cycles. However, again, the slower wind stations were systematically overpredicted while windier sites were underforecasted, as shown in Fig. 1.4. This was true for both the 00 UTC and 12 UTC runs (left and right columns), for all forecast
times (top row), and at the analysis time and for the 24 h forecast (middle and bottom rows, respectively). This resolves some of the potential concerns raised above.

Fovell and Gallagher (2020) also provided an expanded way of assessing forecast bias in their Fig. 10, reproduced here as Fig. 1.5. This graph displays every forecast/observation pair (851,550 examples for all forecast hours, top row) from all available April 2019 forecasts and ASOS stations, before they were averaged on a station-by-station basis. The two obvious missing sectors exist because wind speed is non-negative, as explained in Fovell and Gallagher (2020). These heatmaps show that as the forecasted speed became higher, there was no clear tendency for the forecasts to be either too large or too small (Fig. 1.5a), but that was not true with respect to observations (Fig. 1.5b). Instead, as the observed wind increased, it was more likely it was overpredicted. Fovell and Gallagher (2020) noted that part of this may be because biases cannot be negative when the measured wind is slow, again owing to fact wind speed is non-negative. That said, the implication appears to be that the models are underspecifying the magnitude and perhaps frequency of higher wind events that likely represent the greatest threats.

Using the high-frequency radiosonde data, Fovell and Gallagher (2020) also showed that while the forecast bias was slightly negative for the 10-m wind at ASOS stations, it was positive in the boundary layer below 1 km AGL. Figure 1.6, from that paper, shows temporally- and spatially-averaged wind speed (left column) and bias (right column) for the analysis time and the 23-h and 24-h forecasts\(^2\) for the 00 (top row) and 12 (bottom row) UTC cycles, again for the month of April 2019. In this case, the averaging was performed over only the 60 radiosonde sites for which less-processed, high-frequency observations were available from NCEI. Furthermore, Fovell and Gallagher’s (2020) analysis clearly revealed that, owing to the manner

\(^2\) Both times were considered because typically balloon releases occurred within the 60-min period prior to 00 and 12 UTC.
in which the data were processed, the winds in the lowest ~200 m or so were spoiled and therefore wind speeds and biases beneath the horizontal dashed lines were ignored. (Unfortunately, that meant that no useful information about the atmospheric surface layer, the portion of the PBL closest to the surface, was available.) However, it is obvious that wind speeds tended to increase with time in the lower troposphere above the surface. The analyses in this paper consider only 10-m winds, so it should be borne in mind that inferences based on assessments of surface observations may not be informative regarding forecasts for heights farther above the ground.

Returning to their assessment of forecast wind bias for SDG&E stations during Santa Ana wind events, Cao and Fovell (2018) postulated that the systematic bias at a given station could reflect, at least in part, the inability of the model to “see” small features in the vicinity of the anemometer that could be influencing the wind measured there. These subgrid features could include obstacles such as trees, buildings, and sheer cliffs that can slow and/or divert the winds, or hills or channels that could act to enhance the flow locally. Furthermore, they hypothesized that these landscape properties have a greater influence on the sustained wind than the gust as the latter might represent air parcels descending from aloft while the former has more opportunity to interact with the surface. Thus, they reasoned that exposure characteristics might be revealed in the ratio of the gust to the wind, a quantity known as the gust factor (GF).

Specifically, the idea was that a station’s exposure relative to the network mean could be revealed through its GF relative to the network’s average value. Since the gusts are presumed to be less impacted by local features, the GF would be presumed to be higher than the network average for locations with wind-slowing obstacles and lower for places with characteristics favoring the wind. Since forecast bias was presumed to be driven by these unresolvable
properties, Cao and Fovell (2018) further postulated that the bias would be positively correlated with GF – which was found to be true, as shown in Fig. 1.2d. In other words, systematically overforecasted locales are anticipated to have large GFs (relative to the network mean) while underpredicted sites would have relatively low GF values. Particularly since the model was producing unbiased forecasts for the network-averaged wind, it was surmised that GF could provide a means of not only bias-correcting forecasts or explaining forecast errors but also yielding a very simple but potentially simple gust parameterization, to be described presently.

The short-period wind bursts that gusts represent cause a large amount of the damage caused by winds, so gust forecasting is also an important concern. However, gusts are associated with turbulent activity that is not resolvable at mesoscale grid sizes (cf. Wyngaard 2004). Thus, models like WRF, even at resolutions of about 1-3 km that are not uncommon in wind forecasting (e.g., the HRRR model uses a 3 km horizontal grid spacing), cannot resolve this turbulence. Thus, turbulence must be parameterized (in the model, by the PBL scheme) and gusts must be parameterized, or diagnosed, in some way. In models like WRF, we compare model forecast winds to sustained wind observations, and parameterize the gusts in some fashion.

There are quite a large number of gust parameterizations (see Sheridan 2011 for a summary), and many are rather complex. Some involve anticipating the GF or a gust increment (being gust minus sustained wind) and applying it to the forecast model’s mean wind predictions (e.g., Wieringa 1973; Beljaars 1987; Mitsuta and Tsukamoto 1989). Others, like Panofsky et al. (1977), Brasseur (2001), and Gutierrez and Fovell (2018), are more physically based, utilizing properties of the PBL or the surface layer that could be drawn from observations and/or simulations. Still others incorporate statistical methods like Patlakas et al. (2017) and Friederichs et al. (2009). The European Center for Medium-Range Weather Forecasting’s algorithm for non-
convective gusts was based on Panofsky et al. (1977) and uses friction velocity (the surface stress; see also Gutierrez and Fovell 2018). Some parameterizations also explicitly consider gusts due to convective activity, such as Nakamura et al. (1996) and Gutierrez et al. (2020).

Cao and Fovell’s (2018) gust parameterization was very simple and was based purely on observations – specifically, the network-averaged GF ($G_{net}$). The intent was to transform a systematically biased sustained wind forecast for an individual site into an unbiased estimator for that location’s gust, based on knowledge of the network-average GF and the fact that the network-averaged sustained wind forecasts were unbiased. This was accomplished by multiplying the model’s sustained wind forecast by the network-average GF. For locations with positive bias and GFs that exceed the network average, the multiplier is smaller than $G_{net}$ and thus mitigates the overprediction. Similarly, as underpredicted sites also tend to have site GFs < $G_{net}$, multiplying the too-slow wind by a larger value addresses the issue.

It remains to be seen if this simple gust parameterization works for other networks, locations, and weather conditions. However, there are some problems that need to be addressed. The forecast wind bias has been shown to be negatively correlated with the observed wind. But, as bias is the forecast minus the observation, the bias also incorporates the observed wind. Next, we have seen GF to be positively related to bias. But, as the ratio of the gust to the observed wind, the GF is not independent of the wind. There is some circularity here that is not completely satisfying. Ideally, we wish to explain and correct for the bias with a variable or factor that is independent of the wind. Yet, it is not clear if this is possible. As a consequence, we will pursue attempts to see if the simple gust parameterization works more widely and also to understand why it works.

1.3 Research Questions and Plan
Previous studies have shown there to be a considerable need for careful evaluation of wind forecasts as well as the observations themselves. It is critical to understand influential factors on both to better resolve lingering disparities between them and this has motivated the research questions this dissertation attempts to address.

The large body of work from Cao and Fovell (2016, 2018), Fovell and Cao (2017), Fovell and Gallagher (2018), and most recently Fovell and Gallagher (2020), have shown that even for skillful model forecasts there are persistent errors that have been hypothesized to be due to unresolvable sub-grid scale elements. Work has been made towards a better understanding of the patterns and sources of these biases, but we still require additional and more thorough investigation to confidently identify their causes and direct future work towards mitigating or resolving them. Thus, our first question(s) seeks to answer the following:

Q1) What are the systematic errors and weaknesses of a skillful operational model like the HRRR? Can observations from multiple unique observations platforms be used to expand understanding of existing errors? And can patterns and sources of these persistent errors be identified to put other verifications in a fairer light and direct future model improvements?

As noted above, gusts are turbulent features that are too small scale both in terms of space and time for operational weather models (Wyngaard 2004) and thus require parameterization. While there is an abundance of gust parameterizations that vary widely in their approaches to predicting gust speeds, a fairly large subset focuses on utilizing some form of GF (Wieringa 1973; Beljaars 1987; Mitsuta and Tsukamoto 1989; Fovell and Gallagher 2018; Fovell and Gallagher 2020). One of the most prominent historical examples of these is that of Durst (1960). While widely cited and used by the American Society of Engineers (ASCE), both the
original study and data it is derived from are quite old and there has been relatively little critical
evaluation of its ubiquity, at least outside the tropical cyclone environment (e.g., Krayer and
Marshall 1992; Yu and Gan Chowdhury 2009); Shu et al. 2015). This prompts the question:

Q2) How valid are the assumptions Durst (1960) used in the construction of his gust
curve and how robust is the resulting curve compared to those generated from other high
frequency data sources spanning a wide variety of geographic areas and environments?
Lastly, it has been hypothesized that GF contains information about the local
environment surrounding observations sites and may be indicative of relative exposure and
obstruction. As previously discussed, past studies have posited this as being due to the
correlation of average GF with mean wind speed which has been shown to be strongly related to
average bias. As a consequence, GF may be related to sub-grid exposure issues that are thought
to be the cause or a dominant factor driving these biases. Testing this theory requires both a wide
variety of surface observations as well as detailed information about their local environments on
a very fine scale. The greater variety of surface observations helps increase confidence in our
ability to draw conclusions about the overarching link between GF and the environment while
still appreciating complexities that may be unique to a singular or small group of locales. So, our
final question asks:

Q3) Can variations in observed wind speed, gust, and direction be linked to obstacles in
the local surrounding environment? Can novel airborne lidar data be used to assess the
relative degree of obstruction winds at a location are subjected to? And can GF be used as
a simple proxy for site obstruction?

1.4 Structure of This Dissertation
Given these questions, this dissertation is structured as follows. Chapter 2 presents our continuation and enhancement of Fovell and Gallagher’s (2020) detailed evaluation of HRRR forecasts to address Q1. Chapter 3 details our critical assessment of the original Durst curve and data as well as constructions of similar gust curves using high temporal resolution observations and various filters restricting data used in an effort to answer Q2. Chapter 4 shows our work leveraging airborne lidar data, which has been unutilized for meteorological purposes, to precisely characterize the small-scale environments around surface observations and relate them to observed quantities in our attempt to resolve Q3. Additional details on the motivating and background literature and specific methods employed to answer the question posed by each chapter are provided in their respective introductions and data and methodology sections. The synthesis of all major findings from each towards answering their respective research questions is recounted in Chapter 5 for the conclusion of this dissertation.
Fig. 1) Cao and Fovell (2018) Fig. 2: Time series of network-averaged observed (black dots) and predicted (blue, PX–ACM2 control run; green, Noah–YSU control run) 6.1-m sustained winds (m/s) for the 14–16 Feb 2013 Santa Ana wind event. The gray and light green plumes reveal the ensemble spread created via SKEBS perturbations.
Fig. 1.2) Cao and Fovell (2018) Fig. 11: Scatterplots of six Santa Ana wind event mean (a) forecast sustained wind vs sustained wind bias, (b) observed sustained wind vs sustained wind bias, (c) observed sustained wind vs observed GF, (d) observed station-averaged GF vs sustained wind bias, (e) PX–MODIS LSM roughness length vs sustained wind bias, (f) observed station average GF (after high z0 station adjustment) vs sustained wind bias, and (g) observed sustained wind vs GF-bias model residuals for 135 SDG&E stations. Each dot represents a station. A least squares fit (red line) is shown in each panel for reference, with $R^2$ values indicated. The vertical blue lines represent network-averaged values. (Units are m/s for winds, biases, and residuals; m for roughness lengths; and GF is nondimensional.)
Fig. 1.3) Fovell and Gallagher (2020) Fig. 7: ASOS observations (red) and HRRR forecasts (black), averaged spatially across the ASOS network and temporally over the month of April 2019, of 10-m wind speeds (a, b) and 2-m temperatures (c, d) for every hour of the 00 UTC (a, c) and 12 UTC (b, d) forecast cycles. The vertical grey bars denote the standard deviation of the averaged observations.
Fig. 1.4) Fovell and Gallagher (2020) Fig. 9: Similar to Fig. 8 except comparing temporal averages of observed wind speed to forecast bias for ASOS stations. Panels are representative of the same forecast cycles and forecast hours as in Fig. 8 and dots still represent individual stations color coded by the density of nearby points. Zero bias lines are shown in light grey.
Fig. 1.5) Fovell and Gallagher (2020) Fig. 20: Forecast wind bias vs. forecasted 10-m wind speed (a, c) and observed 10-m wind speed (b, d) for individual forecast observation pairings during April 2019 from all forecast hours (a, b) or only for the analysis times (c, d). As in Figs. 8 and 9, the color coding indicates point neighborhood density. Additionally, frequency contours of 100, 1000, and 10000 have been plotted and smoothed, introducing some artifacts. The diagonal dashed lines represent bounds represented by zero (calm) observations in (a) and zero (calm) forecasts in (b). The resolution of ASOS wind speed observations is 0.51 m/s (1 kt).
**Fig. 1.6** Fovell and Gallagher (2020) Fig. 14: April composite wind speed profiles and forecast wind speed biases aggregated among available radiosonde launch sites. The observation (red), analysis (black), and 23- and 24-h forecasts (dashed and solid green, respectively) profiles were constructed from the same April 2019 subsets to maximize comparability. This subset consisted of the fifty launches between 00 UTC 2 April and 12 UTC 27 April, inclusive. The grey horizontal bars on the observation profiles represent only ±0.25σ to permit more detail to be displayed.
2. In-Depth Verification of Surface Wind Forecasts and Observations Using the High-Resolution Rapid Refresh, Versions 3 and 4

2.1 Introduction

Fovell and Gallagher (2020, hereafter FG20) presented a verification of Version 3 of NOAA’s operational High-Resolution Rapid Refresh (HRRR) model. The HRRRV3 model is based on the Weather Research and Forecasting (WRF) model’s Advanced Research WRF (ARW) core and has 3-km horizontal resolution covering the conterminous United States (CONUS). The 00 and 12 UTC cycles were selected for their relatively long (36-h) forecast periods. (Although new HRRR cycles were launched hourly, only the 00 and 12 UTC model runs ran longer than 18 h in Version 3.) Also, while other select months were also examined, the primary focus was on April 2019.

In addition to the boundary layer analysis that employed high-resolution radiosonde data, an evaluation of 2-m temperature and 10-m wind speed forecasts at ≈ 800 Automated Surface Observing System (ASOS) sites was conducted. These installations are typically, but not always, found at airports. FG20 demonstrated that the HRRRV3 produced skillful forecasts when averaged over the ASOS network although temperature biases revealed a robust relationship with station elevation and wind biases were negatively correlated with observed speed. The latter means that “sites characterized by slower observed winds were systematically more likely to be overpredicted while windier sites were underestimated” (FG20), consistent with the results of prior studies focusing specifically on “Santa Ana” wind events (Cao and Fovell, 2016, 2018; Fovell and Cao 2017; Fovell and Gallagher 2018) in Southern California.

In this work, FG20’s evaluation of forecasts for ASOS stations is reconsidered from scratch and considerably extended and improved. While again other months were examined, the discussion herein is confined to winds and gusts from April 2019 and HRRR Version 3 forecasts from the 00Z cycle in order to streamline the presentation. In this effort, data from the New York State Mesonet (NYSM) are also analyzed. The goal of this work is to identify systematic errors and weaknesses of a very skillful operational model for the purposes of highlighting areas for
potential future improvements. Another goal is to identify and understand issues with available observational data. Section 2 describes the data and methods used in this study and Section 3 presents our analysis for April 2019. Version 4 of the HRRR (HRRRV4) became operational in December 2020, following publication of FG20. To assess improvements in HRRRV4 and remaining challenges, forecasts for the month of April 2021 are also examined later in Section 3, emphasizing comparisons with our primary findings. Finally, Section 4 presents some conclusions and recommendations.

2.2 Data and Methodology

As in FG20, we use 1-min ASOS observations obtained from the National Centers for Environmental Information (NCEI) archive. These are available for more than 850 sites in the CONUS. The 1-minute observations provide measurements of sustained winds and gusts made from sonic anemometers nominally at 10 m above ground level (AGL). The sustained wind (hereafter usually termed simply as “wind”) reading represents an average of 3-s samples taken over the 2 min period prior to the report. The fastest 3-sec sample during that averaging interval is provided as the gust. Gust information was not utilized in FG20. The consequences of the relatively coarse (1 kt or 0.5144 m/s) precision of ASOS wind and gust readings will be noted in the analyses to come. Although not utilized in this study, the observations also include wind and gust direction information with a precision of one degree.

NOAA makes HRRR model outputs available hourly and on the hour, providing forecasts representing an instant of time. The FG20 analysis used top-of-the-hour ASOS reports and model fields were interpolated to station locations using the Model Evaluation Tools (MET) (Bullock et al. 2017). However, owing to the model’s horizontal resolution, which does not resolve small turbulent eddies, there is very likely less temporal variability in the forecasts than in the observations. To assess whether this was unduly influencing the results, we elected to pursue an alternative strategy in this new effort. Observations from each site were averaged through a 60-min window centered at the top of each hour. Only station records with no missing or invalid data were retained. Thus, we are using hourly-averaged winds instead of 2-min
averages in the verifications. It was thought that this approach might provide sustained wind information that is more representative of the relatively slowly varying fields generated by the model. However, in practice, the results were nearly unchanged.

There was a reasonable and expected change in the gusts and thus the gust factor (GF), being the gust divided by the sustained wind. In prior work using 1-min ASOS observations (including Cao and Fovell 2016, 2018, and Fovell and Gallagher 2018), the gust for each station record represented the fastest sample during a 2-min period. In the present analysis, the gust is the fastest sample within an hour-long period. Averaged over the CONUS, the 2-min GF is about 1.29 and this increased to 1.86 with the new strategy. As we are interested in the wind threat that could occur in a given hour, retrieving the 60-min maximum instead of a 2-min maximum makes more sense. Furthermore, this consideration of hourly maximum gusts is consistent with other chapters in this document.

The New York State Mesonet consists of 126 stations distributed across the state. Each standard site possesses two anemometers, a sonic and a propeller model, both mounted at 10 m AGL. This would seem to represent an opportunity to evaluate the influence of hardware on the wind measurements but there are some unfortunate complications. Like the ASOS sonic anemometer, the NYSM propeller instrument is providing a 3-sec average wind every 3 seconds, consistent with the World Meteorological Organization’s (WMO) standard definition of “gust”. In contrast, the NYSM’s sonic installation is sampling once per second but only every third reading is recorded. Thus, the NYSM sonic gusts are actually 1-s and not 3-s average winds. The precision for the sonic and propeller anemometers are 0.1 and 0.17 m/s, respectively (G. Lufft Mess und Regeltechnik GmbH 2021, R.M. Young Company 2000).

As with the ASOS data, we used the NYSM 3-second readings to construct hourly average winds and hourly maximum gusts centered on the hour for both instruments. Again, hours with missing or corrupted records were excluded. For the present analysis, the sonic and propeller records were then merged for each site, so that only hours having valid data for both instruments were retained. This facilitates comparison of the instruments and interpretation of
the results. As there is essentially no concern that the missing information from the sonic (i.e.,
two of every three readings) influences the hourly means, sustained wind discrepancies between
instruments would be considered as valid representations of differences in instrument
performance. However, gusts from the sonic instrument, representing 1-s samples, can be
expected to be higher than their 3-s propeller counterparts, if only because of the likelihood of
detecting a stronger sample (cf. Durst 1960, Ashcroft 1994). Generally, there were more missing
or corrupted records from the sonic instrument than from the propeller. The reasons for this are
unknown.

2.3 Results

2.3.1 HRRRV3 Wind and Gust Evaluation for April 2019

Figures 2.1 and 2.2 show the topography and primary landuse assignments used by the
HRRRV3. Gridded landuse information was obtained from the WRF Geogrid file made available
on NOAA’s HRRR web site (http://rapidrefresh.noaa.gov/hrrr/). HRRRV3 used the MODIS
(Moderate Resolution Imaging Spectroradiometer) database consisting of 21 landuse categories
or classes. Much of the upper Midwest and Ohio Valley had a primary landuse classification as
croplands (category 12, gold), giving way to grasslands to the west and south (category 10, light
green). Much of the Northeast and Southeast was represented by one of the forested land
categories (evergreen, deciduous, and mixed forest types, spanning categories 1-5 and colored
dark green) and a sizable portion of the Western CONUS was classified as open shrubland
(category 7, maroon). Blue areas are water covered (categories 17 and 21). Urban areas (category
13, bright red) are interspersed across the landscape.

We started with \( N = 833 \) ASOS stations from the NCEI archive having at least a partial
month of data for April 2019. For the analysis that follows, we removed sites having fewer than
500 forecast/observation pairs for the month. The typical retained station had 1021 such pairs.
The landuse associated with each site was determined from the HRRR grid cell in which the

\footnote{The origin of this dataset is currently unknown according to J. Dudhia and W. Wang (2021, personal
communication).}
station’s coordinates fell. Eleven sites were determined to be misclassified as being over water, owing to finite resolution and close proximity to lakes or the ocean, and were removed. The final dataset consisted of $N = 807$ stations.

Although the urban class occupies a very small fraction of the CONUS area, it is overrepresented among the retained ASOS sites, representing 23% of stations. This is unsurprising as most ASOS installations are at airports, of which all major urban areas have at least one, but it reminds us that ASOS stations do not uniformly sample the landscape. The most common ASOS assignment is cropland, accounting for 41% of stations, followed by grassland (14%), forested land (11%), and open shrubland (6%). Only a handful of sites fell in the classes of closed shrubland, woody savanna, and barren land, and these will largely be ignored.

**Figure 2.3** shows the locations of these retained sites, with marker size representing monthly average wind speed. The fastest mean winds were found in the upper Midwest and Ohio Valley and also generally in coastal areas. Weak winds characterized much of the Southeast, largely coinciding with forested lands, and in the mountainous areas in the West. Some installations had particularly low wind speeds and the reasons for these will be examined presently.

### 2.3.1.1 Analysis by Forecast Hour and Local Time

As in FG20, we first consider network-averaged winds expressed in terms of forecast hour (**Fig. 2.5**), which extended out to 36 h for the 00 UTC cycle. This figure is nearly identical to the version presented in FG20 (their **Fig. 2.8a**), illustrating that the adoption of hourly mean observations made essentially no difference. Again, the model started with a small negative bias (defined as forecast minus observation) of about -0.5 m/s that became smaller in magnitude with time over the first 24 forecast hours. This bias is small compared to the spatial variation of the observations (illustrated by the grey vertical bars) owing to fact we are averaging across a very wide area spanning four time zones.

New to this evaluation are examinations of forecast and observation spatial and temporal variability and an analysis by local time (LT) instead of forecast hour. **Figure 2.6a** reveals that
the spatial variation of the forecasts, expressed as the standard deviation, is smaller than that of
the observations at all forecast hours. There is a diurnal cycle in both, again smeared by
averaging across time zones. This reveals that there is greater variability among the observations
across space than among the forecasts, possibly as a consequence of local landscape features
(valleys, hills, obstacles and/or land surface variations) that cannot be resolved in the model.
Since the mean forecast and observed winds are quite similar, it can be anticipated that the model
may fail to represent the frequency of both slower and faster winds. This will be examined
presently. Additionally, Fig. 2.6b presents time series of the difference between forecast and
observation standard deviation and the forecast wind bias. They are similar in that they both are
negative but decrease in magnitude with time.

Expressed in terms of local time, the network-averaged forecasts retained a negative bias
through the day (Fig. 2.7), with the model apparently ramping up the afternoon winds too slowly
and diminishing them too quickly into the evening\(^2\). The HRRR model employs the Mellor–
Yamada–Nakanishi–Niino Level 2.5 (MYNN2) planetary boundary layer parameterization
(Nakanishi and Niino 2004) and its associated surface layer scheme, which have been refined in
recent years (cf. Olson et al. 2019). This finding may hold clues for further parameterization
improvements. There was a diurnal cycle in both forecast and observation spatial variation (Fig.
2.8a) but again the forecast variability was slightly smaller and the diurnal variation in standard
deviation difference and forecast bias was very small (Fig. 2.8b). It is emphasized that this is an
excellent, if not completely perfect, forecast, at least with respect to the network average.

2.3.1.2 Station Analysis

The present study also enhances the station-based analysis of FG20 and the previously
cited work on Santa Ana winds. We start by comparing forecasted and observed sustained winds
averaged over all available pairs for each station (Fig. 2.9a). Each dot is a station. While there
are a few, non-impactful outliers, the squared linear correlation coefficient between the series is

\(^2\) The analysis time, forecast hour 0, was removed from this analysis owing to the shift in bias behavior seen
between the analysis and forecast hour 1 in Figs. 2.4 and 2.5.
moderately high ($R^2 = 0.56$) and largely arrayed along the 1:1 correspondence line. Forecast wind bias is defined here as the difference between the mean forecast and observation for each station. The relationship between bias and various variables is examined in Fig. 2.10. Similar to previous studies already cited, Fig. 2.10a reveals that the forecasts themselves were not correlated with the forecast bias. Also similar to past findings, the observations were significantly and negatively correlated with bias (Fig. 2.10b). Cao and Fovell (2018) demonstrated (their Fig. 11d) that the forecast wind bias was also positively correlated with the station gust factor. This could be expected because GF itself contains the observed wind, in the denominator. They used station GF relative to the network average value to interpret the forecast bias and infer site exposure. Locations with significant obstructions would be expected to have relatively slower wind speeds than similar although unobstructed sites, but short period gusts might be anticipated to be less impacted, leading to higher GF values. These stations would be expected to be overforecast as the model cannot “see” and account for these obstructions. In contrast, sites with lower GFs might have local features, such as hills, that might help speed up the wind relative to a more average setting. These stations would likely be underpredicted.

In Fig. 2.10c, we see a sizable negative correlation between bias and GF, although here we have elected to employ the inverse gust factor (iGF) instead. The usage of iGF, being wind divided by gust, is motivated by the fact that it linearizes the relationship with bias better and has the further advantage that it is bounded between 0 and 1. GF, unfortunately, increases without limit as the observed wind goes to zero, making very large values possible at low wind speeds. Like GF, iGF is necessarily a function of the sustained wind. That being said, iGF, like GF, is a function of the observational data only, and we see the model tends to overpredict when the sustained winds are slow relative to the gust and underpredict when they are more comparable.

Cao and Fovell (2018) also considered a simple gust parameterization that was inspired by the association between bias and GF (and thus iGF). That strategy partially compensated for the biases by applying the network-average gust factor to all forecasts, yielding less biased gust predictions. Underpredicted stations also tended to have smaller GF (larger iGF) values than
average, so multiplying the too-slow forecasts by the network average at least partially mitigated the model’s negative sustained wind bias. Similarly, overpredicted sites often had larger than average GFs (smaller iGFs) so multiplying the positively biased forecasts by the smaller network-average GF compensated for some of the overprediction.

This idea applied to the April 2019 HRRR forecasts is shown in Fig. 2.9b. In this case, wind forecasts were multiplied by 1.86, being roughly the network-averaged GF for the ASOS. Keep in mind that GF in this study is the ratio between the hour’s fastest 3-s gust and the hourly mean wind. This GF is being applied to forecasts made for the top of the hour because we have insufficient information to determine the hourly mean forecasted wind speed. With that caveat, we note this very simple gust parameterization appears to do quite well, with an even higher $R^2$ (0.62) than the forecast/observed wind relationship. Again, there is a tendency for forecasts to spread along the 1:1 line as the observed gust speed became faster.

Finally, Fig. 2.10d demonstrates that the difference between forecast and observation standard deviation is also well-correlated with forecast bias. In this case, the standard deviations represent the temporal variability of the forecasts and observations at each station. Stations at which the forecasts vary more than the observations tend to be overpredicted and underprediction often results when the observations possess more variation. As with GF and iGF, however, this variable is not independent of the observed wind. The standard deviation of a variable like wind speed, which has the hard constraint of being non-negative, can (and, in this case, does) increase with the variable magnitude. This is obvious in Figs. 2.11a,b, but it is also clear that the observations possess a wider range and stronger relationship between the mean wind and temporal variation than the forecasts.

Still, one can expect sites possessing significant obstructions to have not only slower mean winds but also suppressed temporal variability owing to the exposure issues. Another factor that may do the same thing is surface roughness. The bottom two panels in Fig. 2.11 assess the relationship between the mean and standard deviation of wind speed with HRRRV3 surface roughness length ($z_0$). Roughness lengths were extracted from the HRRR model outputs,
and values were found to vary between 0.8 m (in forested locations) and 0.05 m (mainly grasslands and open shrublands) with mean and median values of 0.28 and 0.26 m, respectively. The panels reveal negative but fairly weak relationships between mean wind speed and temporal variability with $z_0$ that is stronger in the model than the observations. Other factors being equal, the gap between forecast and observation variability is larger for locations the HRRRV3 designates as rougher.

### 2.3.1.3 NYSM Forecast Hour and Station Analysis

It might seem odd to expect any ASOS sites to suffer from substantial obstructions given that they are largely installed at airports and near runways laid out with the prevailing wind direction in mind. However, we will encounter some sites possessing very questionable siting issues. Before that, however, we pause for an examination of observations from the NYSM. Similar to Fig. 2.3, Fig. 2.4 shows the location of all NYSM standard locations and their monthly mean wind speed. The propeller data were selected for this analysis owing to the compatibility of gust duration (3 s), and thus GF and iGF, with the ASOS observations.

Figure 2.12 presents network-averaged winds for April 2019 representing 126 NYSM sites. In sharp contrast with the ASOS analysis (Fig. 2.5) the HRRR systematically overpredicted wind speeds at Mesonet sites by an average of 1.04 m/s. Another difference is that the temporal variability of the forecasts (Fig. 2.13a) was larger than the observations at every forecast hour with the biases and standard deviation differences being relatively constant with forecast hour (Fig. 2.13b). We need to emphasize at this point that the ASOS and NYSM networks serve different needs and represent markedly different siting philosophies. Instead of being sited at airports, NYSM stations sample the landscapes and geography of the state. That being said, we still need to appreciate the HRRR tends to be more biased for NYSM sites than for ASOS locations as a whole and strive to understand why.

Figure 2.14 adds the NYSM propeller sites (indicated by orange diamonds) to the ASOS CONUS results previously examined in Fig. 2.10. In isolation and in combination with the ASOS stations (now totaling 933 sites), the forecasts were still uncorrelated with the bias (panel
a), despite the average Mesonet station bias being positive, and the negative relationship between observed wind and bias persisted (panel b), with the Mesonet sites being concentrated into the low speed, positive bias end of the station distribution. Similar results are seen in the iGF and standard deviation difference plots (panels c and d). The NYSM is a relatively low wind speed network and we have seen the HRRR overpredicts winds at slower wind sites, and, as a consequence, the network-averaged forecasts are too high. It is also seen that the NYSM sites do not appear particularly unusual, apart from the fact they tend to represent less windy locations. These results do not differ significantly if forecasts are verified against sonic anemometer observations and are mainly characterized by small shifts in mean wind and gust speed.

2.3.1.4 A Closer Examination of the ASOS Station Analysis

The map of April-average wind speeds (Fig. 2.3) revealed not only that winds varied across the CONUS but also the presence of some sites with particularly low mean speed readings. Figure 2.15 takes the April-mean statistics for the 807 ASOS sites and ranks them in various ways. All four of the distributions shown are roughly, albeit not precisely, normal. While a few outliers are expected in any normal distribution, we do see a few items of concern in the ASOS dataset. The windiest station (at 8.5 m/s) by a comfortable margin in the ranking by wind speed (Fig. 2.15a) is KDGP (Guadalupe Pass) in west Texas. This is a non-airport site with a reported anemometer height of only 5.8 m (19’) but is also poised near a steep cliff. The second fastest site, KWJF in Lancaster, CA, had a mean wind of “only” 6.6 m/s. KDGP was also an outlier with respect to forecast bias at -3.3 m/s (Fig. 2.15b), the second most negative being KIDA (Idaho Falls, ID) at -1.96 m/s. Although clearly an outlier, and probably not a “true” 10-m wind (owing to its proximity to a cliff), KDGP was retained in subsequent analyses because it was not found to drive our findings or conclusions.

Figure 2.15a also reveals only 13 stations (1.6% of the total) had mean winds less than 2 m/s. The slowest site was KMEH (Meacham, OR) at 0.95 m/s; this site also had the second

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3 As recorded at https://www.weather.gov/asos/ASOSImplementation.
largest bias (+2.2 m/s; Fig. 2.15b). Satellite pictures reveal this non-airport station to be heavily obstructed. Sites ranked #2-4 were also non-airport, obstructed locations, being Lowell, ID (KP69), Oak Ridge, TN (KOQT), and Yellowstone Lake, WY (KP60), respectively. Of the 10 slowest sites, even the half that were airports appeared to have obstructions close to the runways. The calmest airport station was KVPC (Carterville, Georgia) at 1.73 m/s (ranked 5th slowest). This site’s runway is oriented north-south with tall trees immediately to the west. This was also true for #6 (K1JO, Bonifay, Florida) and #8 (KJKL, Jackson, KY).

The most positively biased site (+2.84 m/s) was KMHS (Mt. Shasta, CA), another heavily obstructed, non-airport installation (Fig. 2.15b). This is one of the relatively few Western stations with high forecast biases (Fig. 2.16), and nearly all of those locations possess obvious sitting issues. Viewed spatially, negatively biased sites (colored blue) clearly dominate the CONUS; 507 of the 807 stations (63%) are underpredicted in the mean even though the average bias was only -0.2 m/s. Positively biased stations are concentrated in the Southeast, the Appalachians generally, and into the Northeast where forested land is more common (Fig. 2.2).

Figure 2.15c ranks sites by the squared linear correlation between the forecast and observed winds, based on an average of 1000+ forecast/observation pairs for each site. $R^2$ values ranged between 0.03 (KP69) and 0.77 (KARR - Aurora, IL) with a mean of 0.57 and median of 0.59. Viewed spatially (Fig. 2.17), it is clear that correlations are high throughout most of the country, even in the Southeast where mean winds were relatively light, and lowest in the mountainous West. Like the correlation coefficient, $R^2$ is not sensitive to means or mean differences between series and is most likely low where the predictions are somewhat out of phase with the measurements. The concentration of low correlations in the western CONUS may reflect the influence of local features on diurnal winds that the model fails to properly represent.

The last panel in Fig. 2.15 ranks the standard deviation difference between the forecasts and observations. We have already seen in Figs. 2.10d and 2.14d that the former tends to be the larger when observed wind speeds are low and forecasts are positively biased. The mean and median differences are -0.15 and -0.17 m/s, respectively, with 581 (72%) of the sites with less
variability in the forecasts than in the observations. The spatial view (Fig. 2.18) reinforces this fact. In particular, this measure could be used to identify problem sites for potential removal, rather than bias or $R^2$. While all three quantities can be indicative of poor model performance rather than problematic observations, using standard deviation difference reduces the influence of potential timing issues by considering the temporal variability of all observations and forecasts.

Taken together, this analysis suggests that the small negative forecast bias seen in the network averaged winds (Figs. 2.5 and 2.7) is actually more significant than it might appear at first glance. The majority of locations have insufficient forecast variability that is strongly correlated with negative biases. That suggests the model is not capturing something that is important to determining real winds measured in the field. However, in the current model, this is partly compensated by the inclusion of stations that are not airports and/or have obvious siting issues. Had those been removed from the analysis, the underprediction would have been more pronounced. The model is still very skillful, but steps could be taken to address its tendency to understate the mean winds at better exposed locations.

2.3.1.5 Analysis of Forecast/Observation Pairs

In their analysis, FG20 examined scatterplots involving all individual forecasts and observations over a full month and this provided insight into the source of forecast biases. In this section, we improve and extend that analysis, examining all 827,230 forecast/observation pairs generated for the month of April 2019\textsuperscript{4}. This represents the concatenation of forecasts and observations from 807 stations and all forecast hours from the daily 36-h HRRRV3 00 UTC cycle forecasts.

Figure 2.19a plots all forecast/observation pairs as a heatmap, color coded by point density. Although there is scatter about the 1:1 correspondence line, there is a reasonably good relationship ($R^2 = 0.56$) between these variables, comparable to that seen in the station-averaged

\textsuperscript{4} There are fewer pairs in the present analysis than in FG20 (851,550) owing to the more stringent restrictions employed in the construction of hourly averaged observations.
analysis (Fig. 2.9a). The majority of observations and forecasts were for less than 5 m/s, and this
fact drives the relationship. For higher observed winds, however, the forecasts largely spread
along the 1:1 line, indicating some usable skill. Similarly, all forecasted gusts – created via the
constant GF of 1.86 – are plotted against observed gusts in Fig. 2.20b. As was the case with the
station-averaged analysis, the correlation is higher for the gust forecasts than their sustained wind
counterparts.

We will now look at these same data in three different ways that emphasize different
things. First, for Fig. 2.20, the 827,230 forecasts and observations were sorted and ranked
*separately* and then superimposed. This can reveal the relative distributions of the predicted and
actual winds. We see that less than 2% of the sustained wind observations exceeded 10 m/s but
winds this strong were slightly more common in the field than in the model (Fig. 2.20a). For Fig.
2.20b, these individual forecast and observation ranks were subtracted, yielding a rank difference
plot. The sum of these ranked differences is numerically identical to the mean bias, even though
the forecasts and observations being subtracted are very likely not coincident in time and space.
Over two-third of the ranks, the observation exceeded the forecast, which is why the mean bias
was negative (-0.2 m/s). The rank difference was more negative than -0.5 m/s and -1 m/s only 7
and 1% of the time, respectively. At the extreme right end of the scale, there is a small number of
ranks associated with much larger observations than forecasts. It is conceivable that some of
these observations represent bad data.

The bottom row of Fig. 2.20 presents the same exercise but for forecasted and observed
gusts. Again, the gust forecasts were created using a constant GF multiplier of 1.86. Only about
3% of both the observed and forecasted gusts exceeded 15 m/s for April 2019 (Fig. 2.20c). In the
rank difference plot (Fig. 2.20d), we see only 11 instances in which the discrepancy was less
than -1 m/s, and only one rank with a positive difference exceeding 1 m/s. Taken together, this
figure makes it appear the sustained wind and gust forecasts are quite good overall, at least with
respect to their relative distributions.
Figure 2.21 presents more traditional histograms of the forecast and observed winds (top) and gusts (bottom). This rendition of the data emphasizes more clearly that the forecasts and observations have differently shaped distributions. For the sustained winds (Fig. 2.21a), the forecasts possess a sharper peak such that the occurrence of both slower and faster winds were more frequent in the observations than in the model. This result was suspected in the discussion of Fig. 2.6a above. Both the mean and median of the observations are (slightly) higher than their forecast counterparts because observations of all wind speeds exceeding about 4 m/s are more common than forecasts, as also revealed in the individual rank plots Fig. 2.20a,b. The gust distributions (Fig. 2.21b) indicate to us the single GF approach does not mitigate the discrepancy in distributional shape.

Finally, Fig. 2.22 presents all 827,230 forecasted and observed sustained winds (top row) and gusts (bottom row) plotted against their respective biases. A similar plot, limited to sustained winds, was presented in FG20. As they discussed, the missing sectors in these plots are a consequence of the non-negativity of wind speed: since bias is forecast minus observation, bias cannot be positive when the forecast is calm and cannot be negative as the observation approaches zero. These very hard constraints could impact distributions of biases and conclusions drawn from them. However, as anticipated from Fig. 2.10a, we see the forecasts appear unbiased – larger forecasts (say, above 7.5 m/s) appear to be as likely too fast as too slow – despite the missing sector. In contrast, there is a clear tendency for higher wind observations to be underpredicted. It is acknowledged that this plot may visually exaggerate the role played by the faster observations, but it is also recognized that these comparatively rare events are of special importance. We may be relatively unconcerned with the accuracy of wind forecasts when both the predictions and verifications reflect near-calm conditions. Now we attempt to isolate factors contributing to the average negative forecast bias, the more frequent occurrence of higher winds in the observations, and the differences in the distributional shapes. We first rule out any role for phase differences between forecasts and observations, and evaluate the impact of the aforementioned hard constraints, by subsetting these data into daily maximum values. For each
station, the fastest forecasted wind or gust for each calendar day was captured and compared to that day’s fastest observed wind or gust, resulting in Fig. 2.23. We see no substantial difference between this figure and Fig. 2.22; if anything, the bias tendency in the observations is somewhat more sharply defined. Also, the constraints imposed by the nonnegativity of wind speed (which still exist) are seen as less potentially impactful because this technique necessarily increased the means of both the forecast and the observations. We also performed a similar analysis of sustained wind observations and forecasts from the NYSM data, for both anemometers (Fig. 2.24). As found earlier, the mean bias over NYSM sites is positive, and this shifts the point clouds rightward, but this figure resolves potential concerns regarding the data source or instrument type. While there appears to be a more apparent relationship between the bias and forecasted wind speeds for the NYSM compared to ASOS (Fig. 2.22a) this is merely an artifact of the shift to the right clashing with the hard boundary of bias (bias ≤ forecast). The point cloud itself is symmetrically distributed about the mean bias of 1.04 m/s.

2.3.1.6 The Roles of Landuse and Local Time

The potential roles of landuse type and local time are now investigated to understand the differences between the observations and forecasts, especially with respect to their distributional shapes. The emphasis will be on sustained winds as characterized by histograms like Fig. 2.21. As mentioned earlier, the primary landuse classification for each ASOS and NYSM station was determined from the HRRRV3 Geogrid file made available on the HRRR website. Actually, WRF-ARW utilizes fractional landuse values, and more than half (53%) of the stations possess more than one assignment. This can and does influence surface characteristics such as the roughness used in a given grid cell. That being said, the class representing the primary assignment had an average landuse fraction of 0.84 over the 807 sites, this ranging from 0.74 among the forested lands to 0.88 for the cropland and urban classes.

Figure 2.25 reveals the existence of a systematic association between primary landuse assignment and forecast wind bias. Each class possesses two horizontal bars, representing the average bias (blue, units m/s) among stations with that classification and their weighted
contribution (red, units dm/s for convenience) reflecting station count towards the total average bias of -0.2 m/s. The most negative bias (-0.6 m/s) was associated with the open shrublands stations, but the urban and grassland sites had larger weighted shares owing to their greater numbers. Similarly, although cropland stations had a small average bias (-0.08 m/s), their aggregate effect was not minor owing to their ubiquity (41% of stations). In contrast, the roughly 11% of installations residing in forested grid cells were positively biased, by as much as +0.52 m/s in the evergreen needleleaf cells. If these overpredictions were resolved in isolation, the network-averaged skill would actually decrease.

Figure 2.26 presents histograms of forecast and observed sustained wind similar to Fig. 2.21 but now segregated by primary landuse class. All of the forecast distributions are too sharp and narrow relative to the observations. In urban areas (panel a), the observed wind distribution has spread farther to the right. The grassland and open shrubland group (panel b), which have been combined owing to their similarity, had too many low wind speed forecasts and too few faster ones. The small negative bias in the cropland class (panel c) occurred despite general overprediction of winds weaker than 1.5 m/s.

Importantly, the model has obviously failed to properly represent the general slowness of the winds in the forested areas (Fig. 2.26d). This elucidates why the network-averaged sustained winds for the NYSM are so overpredicted. Note that the Mesonet’s sonic anemometer histogram of sustained winds (Fig. 2.27) bears a strong resemblance to that of the ASOS forested class. While only 11% of the ASOS sites were classified as forested in the HRRRV3, that category represented 43% of the Mesonet stations, and thus they exert a powerful influence on the network-averaged winds. Landuse type influences wind forecasts largely through the roughness length, $z_0$. However, it is not clear that simply raising $z_0$ would improve these predictions, especially given the weak correlation between bias and $z_0$ seen in Fig. 2.11, although that would require testing.

5 Precise percentages vary slightly between the stations and forecast/observation pair analyses owing to minor data dropouts.
It is worth noting that, unlike many models, the HRRRV3 positions its lowest model level (where the scalars and horizontal wind components are defined) at approximately 10 m AGL, the nominal anemometer height for both the ASOS and NYSM networks. WRF uses a terrain-following mass coordinate and the default configuration of the ARW typically places the lowest level at 25-27 m above the surface. With the default setup, a stability-adjusted logarithmic wind profile is usually employed to determine the wind speed at 10 m AGL. Some models further modify the logarithmic profile to incorporate a “displacement height” (cf. Brutsaert 1975; Wieringa 1986) to compensate for the presence of sizable albeit unresolvable obstacles. It is not clear this strategy would be useful or possible in the HRRR because the 10 m winds are essentially being directly predicted.

In our view, what is not being handled optimally in forested areas is the fetch of wind approaching an anemometer, and it is not presently clear how that could be improved. Furthermore, it is also uncertain whether this is merely a “cosmetic” issue with no impact on the model skill in non-forested areas – or even in the vertical direction above wooded cells – that could simply be addressed through bias correction in post-processing. It appears that high-quality information in the vertical direction might be needed to resolve this matter. Unfortunately, as shown in FG20, high-resolution radiosonde information cannot be used for this purpose, owing to irreversible processing that spoils wind observations below \( \approx 250 \) m AGL. However, the largely forested NYSM might be useful for this effort, owing to its collection of 17 wind profilers distributed across the state.

When the day is subdivided into four 6-hour segments as in Fig. 2.28, we clearly see the underprediction of observed winds exceeding 4 m/s seen in Fig. 2.21 is largely confined to the nocturnal period between 6 PM and 6 AM local time (LT), when the boundary layer is likely to be stable\(^6\). This period is also largely responsible for the distribution differences between the forecasts and observations noted above. Thus, this issue appears to represent a problem with how

\(^6\) The number of forecast/observation pairs varies among the segments because we are only using the 00 UTC cycle and its 36 h simulations, which means some times have more forecasts than others.
the stable boundary layer is handled in the model. In contrast, the daytime period of 6 AM to 6 PM LT seems to be rather well represented in the HRRRV3 forecasts.

Those histograms aggregated all landuse classes. Figure 2.29 focuses on the 6 PM to midnight LT period differentiated by the landuse groupings examined in Fig. 2.26. Only the forested lands (panel d) did not have systematic underprediction of relatively faster winds, again reflecting the less than optimal handling of those areas in the model. For the afternoon (noon to 6 PM LT) period (Fig. 2.30), however, only the urban classification failed to capture the frequency of stronger winds. Thus, except in the vicinity of cities, the model’s inability to capture the frequency of stronger winds appears to be a nocturnal issue and one that might be addressed by reconsidering assumptions employed in the stable boundary layer regime. It is surmised that the urban issue may also stem from overly high specifications of surface roughness in those areas that are in contradiction with the high degree of exposure surface observations strive for. Finally, we reiterate that resolving the issue with forested land or removing those stations from the analysis would tend to make the nocturnal underprediction issue appear even worse.

2.3.2 HRRRV4 Wind and Gust Evaluation for April 2021

Version 4 of the HRRR (HRRRV4) became operational on 2 December 2020. The revised model incorporates a number of improvements to the planetary boundary layer and radiation schemes, the land surface model, and numerical methods and diffusion, and adopts a new gravity wave drag treatment (Alexander et al. 2020). It also shifts from HRRRV3’s 21-class MODIS landuse database to the 20-class version that was released with WRF Preprocessing System (WPS) version 3.9 in 2017, with consequences as discussed presently.

In this section, we examine 10-m wind forecasts at ASOS stations for April 2021, for comparison with our preceding analysis. Instead of a full analysis, points of similarity and difference will be emphasized. The verification is again restricted to the 00 UTC cycle and through forecast hour 36, even though HRRRV4 now integrates out two full days for that start time. Unfortunately, relative to April 2019, there are more missing observations in the ASOS 1-min database for April 2021, at least at time of access in mid-May 2021. As a consequence, the
database of hourly mean sustained wind and maximum gust had 32% fewer observations than for April 2019, averaging about 15400 observation/forecast pairs per forecast hour instead of 22650. Only 766 sites remained after removal of misclassified stations and those with 500 or fewer observations. This is not believed to have negatively affected the evaluation.

There are more differences between these two MODIS-derived databases than just the removal of the separate class for lakes. In HRRRV4 (Fig. 2.31), a large fraction of the original croplands class (#12, gold; see Fig. 2.2), especially for grid cells in the eastern CONUS, has been transferred into the previously unused “cropland/vegetation mosaic” group (#14, cyan). The croplands category now accounts for only 18.3% of ASOS station primary assignments, while the mosaic claims 14.9%. In the west, a portion of the open shrublands (#7, maroon) primary assignments now belong to grasslands (#10, light green), constituting 4.3% and 21.0% of ASOS sites in the 20-class database, respectively. We will continue combining those landuse types owing to their similarity with respect to model performance. The HRRRV4 grassland area has also spread eastward into the former croplands, so the grassland and open shrubland combination now totals 25% of the April 2021 ASOS primary assignments, an increase of 5 percentage points. Some area that had been assigned to one of the forest classes (categories 1-5) are now designated as woody savannas (#8), increasing its share of the network from 2.6% to 7.2%. Owing to their similarity, class 8 will be analyzed with the forested land, and this combination represented 13% of the ASOS stations retained in the April 2021 analysis.

As in Section 3, above, these are primary landuse assignments. The fractional landuse apportionments represent another difference with HRRRV3. In HRRRV4, 87% of ASOS stations reside in grid cells assigned more than one landuse class, up from 53% for V3. The average fraction claimed by the primary class was 0.7, a decrease from 0.83 for V3. Again, this was relatively smaller for the forested group and now the new cropland/vegetation mosaic classes (both about 0.6) than for the urban and croplands (both ≈ 0.7) and grasslands (0.8). The HRRRV4 landscape is more finely divided and this makes analyzing by primary landuse assignment less precise, but again we find some value in this effort.
Figures 2.32 and 2.33 present the forecast hour analysis for April 2021, for comparison with Figs. 2.5 and 2.6, respectively. The small negative forecast bias that was previously seen is largely absent (indeed, the mean bias is now essentially 0.0 m/s) although the spatial standard deviation of the forecasts is still smaller than that of the observations at all forecast hours. The local time versions of these figures also reveal some improvements (Figs. 2.34 and 2.35). Although involving fewer sites, the station analysis results and conclusions are little changed (Figs. 2.36 and 2.37). $R^2$ values for the sustained wind and gust fits are higher and the average forecast wind is again uncorrelated with bias but the faster wind stations are still underpredicted and slower sites overforecast in a manner that is predictable from iGF or GF. The association between bias and the difference between forecast and observed standard deviation (Fig. 2.37d) also remains. Turning to the forecast/observation pair analysis, we see again the tendency for higher wind observations to be missed by the model sustained wind and simple gust forecasts (Fig. 2.38). The histogram version (Fig. 2.39), however, suggests forecasts for speeds exceeding 4 m/s are no longer as clearly underrepresented among either the winds or the gusts, indicating an improvement relative to April 2019. We still see that the (now zero) network average forecast wind bias as being driven by compensating overprediction in the more densely treed areas (the forest and woody savannas categories) and underprediction in the urban areas and grasslands (Fig. 2.40). The now more spatially confined croplands class is still the best modeled and the newly separate mosaic group has a positive bias, which is unsurprising as much of this group’s stations are in the southeast, the site of slower wind observations and positive biases (not shown, but similar to Figs. 2.3 and 2.16). However, the histograms for the urban and combined grassland and open shrubland categories (Fig. 2.41, top row) also reveal better model behavior at relatively higher wind speeds compared to HRRRV3 (Fig. 2.26). For convenience, we have combined the cropland and mosaic classes in Fig. 2.41c, despite their differences, and we see that the forested and woody savanna grouping remains the most poorly handled (Fig. 2.41d). In the end, and despite these perceived improvements in model performance, we see that the glaringly different distributional shapes noted previously still exist and that this is still driven by the 6 PM to 6 AM
period (Fig. 2.42). Clearly, more work on the stable boundary layer remains to be done.

Although 10-m wind speeds during this period are typically not strong, sizable wind errors may have implications for boundary layer pollution transport, wind energy, etc.. Taken together, we see evidence of further improvement in the HRRRV4 relative to its already skillful predecessor, at least in the spring month selected for close analysis. The gust parameterization inspired by Cao and Fovell (2018) continues to work well, despite its simplicity. Challenges with respect to the stable boundary layer and the treatment of some landuse classes (especially forested areas) remain. Other important variables, such as temperature and moisture, have not yet been assessed. These should be foci of future work.

2.4 Conclusions

Our previous study, Fovell and Gallagher (2020, FG20), presented a detailed verification of the operational model focusing on evaluation of surface and boundary layer winds. The study was motivated by a large body of preceding work (Cao and Fovell 2016, 2018; Fovell and Cao 2017; Fovell and Gallagher 2018) and their findings of systematic biases in forecast wind speeds at individual locations even when network average bias was mitigated for a variety of model configurations. These previous works gradually scaled up the scopes of their verifications, still focusing on downslope winds in southern California but incorporating additional observations from a variety of platforms (ASOS, RAWS, SDG&E, and CWOP) to test the ubiquity of persistent overprediction in numerical models of the slowest wind speeds and underprediction of the fastest wind speeds in both time and space. FG20 built on this, leveraging highly underutilized observations (1-min ASOS and high-frequency radiosondes), to investigate pervasive background biases across the entirety of the CONUS in the operational HRRR model. The conclusions of FG20 were consistent with the previous body of work, detailing a troubling systematic bias of surface wind speed that is highly correlated with the observed value itself.

This work was motivated by questions arising from FG20’s conclusions, namely what is nature of these systematic surface wind biases and what is their root cause? Our methodology follows closely to that of FG20, except with a sole emphasis on surface winds (largely due to the
discontinuation of the radiosonde data that made FG20’s analysis possible), utilizing ASOS 1-minute data to verify HRRR forecasts for April 2019 in much greater detail. Improvements were made through inspection of the temporal and spatial variability of forecasted and observed winds and also biases, reframing the verification in terms of local time in addition to forecast hour to reduce smoothing over time zones, and the incorporation of additional surface observations from the NYSM. Additionally, gusts were assessed and verified alongside mean wind speeds, using the network average gust factor (GFnet) employed in previous studies (Cao and Fovell 2016, 2018, Fovell and Cao 2017, Fovell and Gallagher 2018) to generate gust forecasts.

The results from our evaluation of HRRRV3 forecasts for the month of April 2019 is largely consistent with that of FG20 but shows some more detailed features as a result of our improvements to the methodology. Analysis of network average forecasts and observations with respect to local time revealed the influence smoothing over four time zones had on our previous work. While the model still initializes with a negative bias and the overall forecast is quite skillful, surface winds are underforecasted throughout the day with the model ramping up winds in the afternoon too slowly and decaying too quickly transitioning into the evening (Fig. 2.7).

The station analysis (Fig. 2.10) confirms the findings of FG20, reiterating the lack of relationship between station average bias and forecasted wind speed while noting its strong correlations with station average observed wind speed and GF. The later echoes our theory that GF can be interpreted as a proxy for site exposure with more obstructed sites observing lower mean wind speeds that result in larger GFs (and positive biases) while better exposed sites experience faster mean winds and subsequently smaller GFs (and negative biases). New to this analysis is the examination of differences in forecasted and observed standard deviations of wind speed. Figure 2.10d showed that locations where the model standard deviation was smaller than observed (less temporal variability of forecasts) tended to be negatively biased, whereas locations where standard deviation of forecasts were larger than observed were largely positively biased. Additionally, NYSM stations were also evaluated independently and alongside ASOS observations. While the average bias for the NYSM is much more positively biased (+1.04 m/s)
over all forecast hours, the behavior of its stations are similar to that of ASOS stations, albeit largely on the positive side of the bias phase space (Fig. 2.14) owing to NYSM’s relatively low wind speeds.

Spatial maps of station average quantities like bias and standard deviation difference made it increasingly clear while the network average bias may be small, biases are much more significant for individual stations (Fig. 2.16 and Fig. 2.18). Conjointly, these maps can be used to identify regional trends, such as the clustering of positive biases in the Southeast, Appalachians, and New England, as well as individual outliers, such as KGDP (Guadalupe Pass) and KMEH (Meacham, OR).

Analysis of all forecast and observation pairs (Fig. 2.19b) shows both the significant amount of scatter among forecasted and observed mean wind speeds and gusts and that this scatter is centered along the 1:1 line. This underscores the fact that the HRRR has a great deal of skill overall but can exhibit large errors at individual points in space and time. Our efforts to better understand the origin and patterns of these biases were investigated through separate ranks plots, histograms, and bias dependent heat maps for forecasted and observed wind speeds. Ranked separately, mean wind speed forecasts and observations (Fig. 2.20) appear to agree quite well with the exception of a few (< 2%) extreme values, but differencing forecasts and observations after independent ranking show that the HRRR favors slightly slower wind speeds for over two-thirds of all pairs contributing the average bias of -0.2 m/s.

When pairs are viewed with more traditional histogram plots (Fig. 2.21), the difference in distribution shape of forecasts and observations becomes more apparent. The model produces a narrower distribution with a sharper peak that results in underprediction of wind speeds above 4 m/s and over prediction of wind speeds below 2 m/s. Figure 2.22 shows forecast and observed mean wind and gust speeds relative to their biases for all forecast/observation pairs, building on similar plots in FG20. These show that, ignoring missing sectors owing to the non-negativity of wind speed, wind and gust forecasts are equally likely to exhibit positive and negative bias regardless of the forecasted wind speed. In contrast, negative biases become much more likely
when observed winds are faster and can be seen in the tilt of the phase space of bias and observed wind. This dependency of bias on observed wind speed was proven not to be the result of phasing issues through use of daily maximum winds and is also observable for NYSM observations, albeit shifted to towards positive bias overall, as well as ASOS.

We investigated the roles of landuse type and local time of day to better understand differences between observed and forecasted winds, especially with respect to their distributions. The systematic relationship between primary landuse assignment and forecast bias was shown in Fig. 2.25 and highlights the relative importance of spatially common classifications such as croplands despite their small overall bias and the insignificance of rarer assignments like barren or savannas in spite of their larger biases. Classifications with notable negative biases like urban, grasslands/open shrublands, and croplands, were seen to have longer more prominent tails in their distributions of wind speed compared to those forecasted by the HRRR (Fig. 2.26a-c). Alternately, assignments with overall positive biases like each category of forest and woody savannas, had distributions that were shifted closer to zero and were more skewed than those produced by the model causing overprediction of winds of all speeds (Fig. 2.26d). This distribution shift and systematic overprediction at forested areas is a dominant driver of the large average bias seen in the NYSM verification (compare Fig. 2.26d to Fig. 2.27) since a larger percentage of NYSM are sites at locations assigned as forests (43% compared to 11% in ASOS).

We do wish to note that landuse assignments with uniform shifts between forecasted and observed wind speed distributions, such as urban and forest, may be additionally complicated by other factors besides model performance. As we’ve discussed previously there may be disparities between the type of environment the observation samples and the forecasts are attempting to represent. For example, ASOS stations that are nominally at airports may exist at small airports cleared out of forests and thus be classified as forested in the model but exist in a sufficiently large enough clearing this is not necessarily accurate. Similarly, an airport may be classified as urban but in a significantly flat and well exposed fetch beneficial for aviation that does not match the “built up” urban downtown high model surface roughness suggests.
Further assessing distributions of observed and forecasted wind speed with respect to local time (LT; Fig. 2.28) showed the HRRR actually captures the shape of the observed wind distributions quite well between 6 AM and 6 PM LT, despite the high wind speed (> 8 m/s) tail still being underrepresented in the forecasts. The root of previously noted distribution differences occur largely at night, between 6 PM and 6 AM LT, suggesting improper handling of the nocturnal stable boundary layer. Subsetting by landuse assignment and LT simultaneously show that, with the exception of urban locations, overprediction of faster wind speeds is a largely nocturnal issue (Fig. 2.29). The forecasted shape of wind distributions for all landuse categories more closely match those of observations during the day despite consistent overprediction and underprediction of wind speeds for forested and urban locations, respectively (Fig. 2.30). It should be noted that the persistence of bias trends at urban and forested locations are not solely a result of model misrepresentation but also the tendency for surface observations to be located in cleared open areas within cities and forests that may not be representative of the environment a model grid cell represents.

Because of the operational implementation of HRRR version 4 (HRRRV4) on 2 December 2020, we repeated our verification of surface winds for the month of April 2021. HRRRV4 implemented a number of improvements for model physics, but of largest concern for our current analysis was the change to a different version of the MODIS landuse database because of the heavy dependency of distribution differences on landuse assignment. This resulted in large shifts in primary landuse assignments (as well as drops in fractional area of the dominant category), the most notable of which is the reclassification of a large portion of croplands into the previously unused category called “cropland/vegetation mosaic”.

Time series of network average forecasted and observed wind for April 2021 (Fig. 2.34) show notable improvements of the average diurnal cycle in terms of local time, with the growth and decay of surface winds in the late morning and evening, respectively, matching more closely to observations. While the station average and pair analysis (Fig. 2.37 and Fig. 2.38) remain largely unchanged between HRRR versions 3 and 4, the improvement in the diurnal cycle is seen
in the better representation of faster wind speeds (>4 m/s) in the tail of the model distribution (Fig. 2.39). This better capturing of higher wind speeds is evident in the distributions of the urban (despite continued underprediction), grasslands/open shrublands, and croplands categories. In spite of this, the now zero average bias is still composed of large compensating biases, with forested areas driving overprediction and urban and grasslands dominating underpredicted winds. Furthermore, distributions of wind speed remain much better captured during daytime hours while nocturnal winds are still continually overforecasted and poorly represented.

In summary, this work was motivated by the need for additional insight into observed behaviors of forecast bias in FG20. Attention was specifically paid to the ubiquity of bias trends through verification of both ASOS and NYSM observations. Our principal finding is that while numerical weather models can display overall skill with near zero average biases this does not translate to uniform skill for all locations and times. The bias was found to be biased with respect to the observed wind speed for all observations. The average bias of a network consists of large compensating biases that have a strong dependency on both landuse assignment and local time. The most problematic issues remain disparities in the distribution of forecasted wind speeds resulting in over- and under-prediction (largely dependent on landuse type) and poor representation of the stable nocturnal boundary layer that drives large positive biases of low wind speeds.
Fig. 2.1) HRRRV3 topography (shaded) from GEOGRID. Lakes and rivers are colored blue for reference.
Fig. 2.2) HRRRV3 primary landuse assignments (shaded). Ocean and lakes (blue), croplands (gold), grasslands (light green), evergreen, deciduous, and mixed forests (dark green), open shrubland (maroon), urban (bright red), barren (white).
Fig. 2.3) Locations of 833 ASOS stations with observations available during April 2019. Marker size indicates the station’s average wind speed for April 2019.
Fig. 2.4) Similar to Fig. 2.3 except for the 126 NYSM standard stations.
Fig. 2.5) Time series of ASOS observations (red) and HRRRV3 forecasts (black) of 10-m wind speeds, averaged spatially across the ASOS network and temporally over the month of April 2019, with respect to HRRR forecast hour. The vertical grey bars denote ±1 standard deviation of the averaged observations.
Fig. 2.6) (a) Spatial standard deviation of ASOS observations (red) and HRRRV3 forecasts (black) of 10-m wind speed. (b) Forecast minus observation average wind speed (bias, red) and spatial standard deviation (black). Both are averaged temporally over the month of April 2019 and shown with respect to HRRR forecast hour.
Fig. 2.7) Similar to Fig. 2.5 except plotted with respect to local time.
Fig. 2.8) Similar to Fig. 2.6 except plotted with respect to local time.
Fig. 2.9) Forecasted vs. observed wind speed (a) and gust speed (b) averaged over all forecast observation pairs in April 2019 for each station. Here each dot is an individual station representing the temporal average forecast vs. observation. Forecasted gust speeds were calculated by multiplying the station average wind speed by 1.86 (ASOS network average GF). Linear regressions for each are shown in the red lines and the 1:1 line is denoted in the dashed grey line.
Fig. 2.10) Station average forecasted wind speed (a), observed wind speed (b), iGF (c), and temporal standard deviation difference (forecast-observation) (d) vs. station average bias of forecast wind speed. Each dot represents a temporal average over April 2019 (a-c) or standard deviation of observations/forecasts throughout April 2019 (d) for each station. Linear regressions are shown in red lines.
Fig. 2.11) Station average forecasted (a) and observed (b) wind speed vs. standard deviation of forecasts (a) and observations (b) throughout April 2019 with linear regression lines in red. HRRRV3 prescribed station surface roughness ($z_0$) vs. average observed (orange dots) and forecasted (black dots) wind speed (c) and temporal standard deviation (d). Linear regression lines are shown for observations (red) and forecasts (blue).
Fig. 2.12) Similar to Fig. 2.5 except for NYSM (propeller) network average observed and forecasted wind speeds with respect to forecast hour.
Fig. 2.13) Similar to Fig. 2.6 except for NYSM stations and propeller observations.
Fig. 2.14) Similar to Fig. 2.10 except with NYSM station average quantities (orange dots) overlaid on top of ASOS station averages (black dots).
Fig. 2.15) ASOS station average observed mean wind speed (a), forecast wind bias (b), $R^2$ value of linear regression between forecasted and observed wind speeds (c), and forecasted minus observed temporal standard deviation difference (d) in rank order for all 807 stations. Averages and standard deviations are of forecast/observation pairs during April 2019. Horizontal grey lines denote 2 (m/s) (a), zero average bias (b), $R^2 = 0.57$ (c), and ±0.5 (m/s) or 0 (m/s, dashed) (d).
Fig. 2.16) Similar to Fig. 2.3 except marker size denotes station average forecast bias for April 2019 and color coding indicates positive (red) and negative (blue) biases.
Fig. 2.17) Similar to Fig. 2.3 except marker size denotes $R^2$ value for the linear regression of station observed and forecasted wind speeds.
Fig. 2.18) Similar to Fig. 2.3 except marker size denotes the difference between temporal standard deviations of forecasted and observed winds for a given station during April 2019. Color coding indicates positive (forecast standard deviation greater, red) and negative (observation standard deviation greater, blue) differences.
Fig. 2.19) All pairs of forecasted vs. observed wind speed (a) and gust (b) for ASOS stations during April 2019 (N=827230). Color shading indicates the density of neighboring points (warmer colors are more dense, cooler colors are less dense) and the linear regression line for each is shown in red. Gust forecasts are produced using the ASOS network average GF. The 1:1 line is denoted by the grey dashed line and additional lines with a slope of 1 and variable intercepts are shown in grey dotted lines.
ASOSCONUS HRRR April 2019 independent ranking analysis

Fig. 2.20) ASOS observed (red) and HRRR forecasted (black) wind speeds (a) and gusts (c) ranked separately, and the difference (forecast-observation) between independently ranked wind speed (b) and gust (d) for all forecast/observation pairs (N=837230).

(Images of graphs showing observed versus forecast wind speeds and gusts with rank differences and biases indicated.)
Fig. 2.21) Histograms of all forecasted (blue) and observed (red) wind speeds (a) and gusts (b). Vertical solid lines indicate mean values and dashed lines represent median values. Bin width for (a) is 0.05 m/s (0.1 kt) while bin size for (b) is wider, 0.51 m/s (1 kt) owing to the coarse precision of ASOS observations.
Fig. 2.22) All pairs of forecasted wind speed (a), observed wind speed (b), forecasted gust speed (c, GF method), and observed gust (d) vs. their respective forecast bias for April 2019. Color shading indicates the density of neighboring points (warmer colors are more dense, cooler colors are less dense) and the linear regression line for each is shown in red. Note the missing sectors are due to the non-negativity of wind values bounding it so bias \( \leq \) forecast and bias \( \geq \) observation. The banding seen in (c, d) is a consequence of the coarse 1 kt precision of ASOS gust observations.
Fig. 2.23) Similar to Fig. 2.22 except for daily maximum values from each station instead of all forecast/observation pairs (N=19667).
Fig. 2.24) All pairs of forecasted wind speed (a, c) and observed wind speed (b, d) vs. forecast bias for NYSM propeller (a, b) and sonic (c, d) anemometer observations, respectively. As with Fig. 2.22 color shading indicates the density of neighboring points (warmer colors are more dense, cooler colors are less dense) and the linear regression line for each is shown in red. Note all panels consider sustained winds only (no gusts).
Fig. 2.25) Average forecast wind bias (blue bars) aggregated over ASOS stations with the same primary landuse assignments. Red bars represent the weighted contribution of each class towards the network average bias. Landuse categories are organized according to their weighted bias in ascending order. The righthand axis denotes the percentage of the 807 ASOS stations used that are classified as the landuse category on the left-hand axis. Precise percentages vary slightly between the station and forecast/observation pair analyses owing to minor data dropouts.
Fig. 2.26) Similar to Fig. 2.21a but separated by landuse category: urban (a), grasslands and open shrublands (b), croplands (c), forests (includes deciduous, evergreen, and mixed) (d).
Fig. 2.27) Similar to Fig. 2.21a except for NYSM sonic anemometer observations and associated forecasts.
Fig. 2.28) Similar to Fig. 2.21a but separated by local time: midnight to 6 AM (LT) (a), 6 AM to noon (LT) (b), noon to 6 PM (LT) (c), 6 PM to midnight (LT) (d).
Fig. 2.29) Similar to Fig. 2.26 but only for observations and forecasts between 6 PM to midnight (LT).
Fig. 2.30) Similar to Fig. 2.29 but only for observations and forecasts between noon to 6 PM (LT).
Fig. 2.31) Similar to Fig. 2.2 except displaying HRRRV4 primary landuse assignments. Color shading is the same with the addition of cropland/vegetation mosaic (cyan).
Fig. 2.32) Similar to Fig. 2.5 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.33) Similar to Fig. 2.6 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.34) Similar to Fig. 2.7 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.35) Similar to Fig. 2.8 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.36) Similar to Fig. 2.9 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.37) Similar to Fig. 2.10 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.38) Similar to Fig. 2.22 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.39) Similar to Fig. 2.21 except ASOS observations and HRRRV4 forecasts for April 2021.
Fig. 2.40) Similar to Fig. 2.25 except ASOS observations and HRRRV4 forecasts for April 2021. Note the addition of the cropland/vegetation mosaic landuse assignment.
Fig 2.41) Similar to Fig. 2.26 except ASOS observations and HRRRV4 forecasts for April 2021. Here the new cropland/vegetation mosaic is combined with the cropland category (c) and woody savanna is combined with the aggregated forest assignments (d).
Fig 2.42) Similar to Fig. 2.28 except ASOS observations and HRRRV4 forecasts for April 2021.
3. Evaluating Gust Duration of Surface Wind Observations and a Historic Gust Forecasting Tool

3.1 Introduction

Durst (1960) presented an attempt to estimate the magnitude of maximum short-period winds (i.e., gusts) relative to the hourly mean wind, a quantity often termed the gust factor (GF). The curve that commonly carries his name is shown in Fig. 3.1a and was constructed from data collected at Cardington Airfield in Bedfordshire, England, and reported in Giblett et al. (1932). Durst’s original motivation was to close the observation gap between existing hourly mean wind speeds and 2-3 second maximum wind speeds (gusts). Because of the importance of high wind speeds in industries like aviation, engineering, agriculture, and fire weather, he focused on the maximum average wind over a duration \( t \) within an hour (i.e., gust of duration \( t \) seconds).

This curve has attracted quite a lot of interest and found a number of uses. The American Society of Civil Engineers (ASCE) uses the curve as shown in Fig. 3.1a in a number of studies (Behncke and Ho 2009; Zhou and Kareem 2002; Porterfield and Jones 2001; Kwon and Kareem 2014) and it is listed as an engineering tool in the most recent version of engineering textbooks concerning wind load (Coulbourne and Stafford 2020). The Durst curve is commonly used to estimate the maximum hourly gust of varying durations and to convert wind speeds between different averaging periods. Both of these are critical for engineering and hazard mitigation in numerous fields, making the Durst curve quite popular. The curve can additionally be used to estimate shorter duration winds from numerical model output which often lacks the magnitude of temporal variability seen in observations (cf. Tang and Bassill 2018, and Chapter 2 of this dissertation) for some of the previously mentioned applications.

There are few alternatives to Durst’s methodology for estimating winds of varying durations, some of which are rather similar. Wieringa (1973) followed a similar approach to Durst but incorporated more empirical data and assumptions that resulted in a GF dependent only on the averaging interval, gust duration, and surface roughness. Suomi et al. (2014) developed a
method using observed “turbulence intensity” \( I = \frac{\sigma_u}{M} \) and peak factor \( \hat{g} = \frac{(\bar{U} - M)}{\sigma_u} \) resulting in:

\[
GF = 1 + \hat{g} I = 1 + \left[\frac{(\bar{U} - M)}{\sigma_u}\right]\left[\frac{\sigma_u}{M}\right],
\]

where \( \bar{U} \) is the gust speed, \( M \) is the mean wind over a particular interval, and \( \sigma_u \) is its standard deviation. This equation appears largely similar to Durst’s except with peak factor (a single empirical value calculated from long periods of observations at individual locations) replacing the assumption of normality. Both of these studies suffer from having only small pools of data to produce gust curves, and were limited by their number of locations, temporal range, or both. Additionally, Suomi et al. (2014) only explored gust durations between 1-30 s in length. The lack of studies assessing gust curves or exploring gust intensity with duration is in part due to the scarcity of high frequency observations needed to construct these curves. This shortage of appropriate data narrows the spatial and temporal range of data used in previous studies, resulting in uncertainty regarding their application outside a set of very specific circumstances.

This is rather worrisome given that GF is known to be sensitive to numerous environmental and observational factors. One of the most important and obvious sensitivities of GF is to mean wind speed. In every definition of GF, mean wind speed appears in the denominator of the ratio (due to its inherent definition as the ratio of maximum to mean wind speed) and the relationship between the two has been well-examined (e.g., Deacon 1955; Davis and Newstein 1968; Monahan and Armendariz 1971; Ashcroft 1994). These past works have consistently shown that GF has an inverse relationship mean wind speed and decreases asymptotically at high wind speeds. However, the relationship between GF and mean wind speed is less clearly defined when wind speeds are relatively low. Gallagher (2016) showed that GFs can grow extremely large or small when wind speeds are low as the small denominator value makes the ratio increasingly sensitive to small changes in gust speed.

Additionally, because gusts are a turbulent feature, GF is also sensitive to factors that influence turbulent production and measurement such as surface roughness, stability, and averaging interval. While the averaging interval for constructing gust curves similar to Durst is
fixed at one hour, it is important to note the effect this has. Monahan and Armendariz (1971) and Gallagher (2016) have shown that GF increases noticeably with averaging interval due to the increased span of samples aggregated raising the probability of detecting larger observed gusts. Suomi et al. (2013, 2014, 2016) have performed extensive work investigating the sensitivity of GF to stability and surface roughness. Their findings show that GF tends to increase as the atmospheric boundary layer becomes more stable, inhibiting vertical mixing, and preventing mean winds from growing at a proportional rate to gusts from sporadic or remnant turbulence. Most importantly, Suomi et al. (2016) asserted that GF was more sensitive to surface roughness than stability. Comparing GFs among multiple locations and upstream wind directions with variable fetches and roughness (open water, sea ice, open grasslands, and forests) revealed far greater disparities in GF associated with upstream roughness than stability class at any location or wind direction.

Despite its prevalent use in practicality, relatively little attention has been given to critically evaluating the Durst curve and its robustness for the variety of applications it can be used for. Studies by Krayer and Marshall (1992) and Yu and Gan Chowdhury (2009) constructed curves for tropical cyclone environments using Automated Surface Weather Station (ASOS) and Florida Coastal Monitoring Program (FCMP) observations, respectively, and compared them to the Durst curve. Both highlighted disparities between the historic curve and their data, noting significant differences in the slope of GF with gust duration. Shu et al. (2015) found similar results comparing GFs of varying gust durations for tropical cyclone, thunderstorm, and monsoon environments, noting marked differences in GF dependency on gust duration particularly during thunderstorm events. This erodes confidence in the idea that Durst’s curve is applicable for a variety of weather systems, geographical areas, stability classifications, observation types, and surface roughnesses. Furthermore, there are concerns regarding Durst’s methodology and assumptions, including Durst’s assumption that fluctuations about an hourly mean are normally distributed, as well as the age of the Cardington data itself. These are discussed at greater length in the following section.
In this work, we attempt to critically review Durst’s data, methodology, and assumptions as well as evaluate the robustness of the Durst curve itself. New and underutilized data sources, including high frequency New York State Mesonet (NYSM) and one-minute ASOS observations, allow us to explicitly construct gust curves similar to those of Durst and assess the shape of gust curves constructed from longer periods of time representative of much larger areas. Additionally, we aim to test the validity of Durst’s assumption of normality, the restrictions imposed on wind observations in his study, and the sensitivity of gust curves to influential factors such as site surface roughness and exposure.

Section 3.2 outlines and investigates the data and methodology of Durst (1960) as well as describes the data and methods used in this study. Analysis of gust and maximum wind curves are presented in Section 3.3. Finally, Section 3.4 discusses our findings and plans for future work.

3.2 Data and Methodology

3.2.1 Durst’s Methodology

The Cardington setup was collocated with the Royal Airship Works and consisted of four anemometers (at stations labeled A-D) mounted at 50 ft (15.2 m) AGL and positioned in close proximity (separations as small as 350 ft or 107 m). All anemometers were of the Dines pressure-tube variety with data recorded as traces on a rotating drum. The “ultra-quick-runs” captured winds every 5 seconds over 10-min periods, sometimes at stations A-D simultaneously. From some of these runs, 10-min mean wind speeds \( [M(10 \text{ min})] \) were calculated as well as the means and standard deviations of speed fluctuations about the 10-min means associated with averaging periods \( t < 10 \text{ min} \), referred to as \( M(t) \) and \( \sigma(10 \text{ min}, t) \), respectively.

Durst’s task was to determine the maximum \( t \)-second wind, where \( t \) is an averaging period less than an hour, likely to occur within a period of an hour and expressed relative to the hour’s mean wind \( M(1 \text{ h}) \). He explicitly assumed that the \( t \)-second fluctuations about the hour’s mean were normally distributed. This required estimates of the standard deviation of the \( t \)-second fluctuations within a given hour, \( \sigma(1 \text{ h}, t) \). However, as he only had high-frequency
measurements at his disposal only over 10-min stretches, Durst had to resort to a multi-step process involving some assumptions.

First, he used independent tabulations of $\sigma(24 \text{ h}, 10 \text{ min})$ and $\sigma(24 \text{ h}, 1 \text{ h})$ from the Cardington site to obtain the standard deviation for 10-min fluctuations within an hour period via the so-called translation theorem,

$$\sigma(1 \text{ h}, 10 \text{ min})^2 = \sigma(24 \text{ h}, 10 \text{ min})^2 - \sigma(24 \text{ h}, 1 \text{ h})^2 .$$

This explicitly assumes the two time series for which the standard deviations are computed (one consisting of 10-min deviations within an hour, the other of hourly fluctuations over 24 h) are uncorrelated. In that case, the standard deviations of these variables obey the Pythagorean relationship expressed in (3.2). In any event, the data he used for these estimates came from 44 cases with an average wind speed of about 7.6 m/s (17 mph); see his Table IV. Durst then estimated the normalized standard deviation $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ for $t$-second wind fluctuations within a given hour via

$$\sigma(1 \text{ h}, t)/M(1 \text{ h}) = \sqrt{[\sigma(1 \text{ h}, 10 \text{ min})/M(1 \text{ h})]^2 + [\sigma(10 \text{ min}, t)/M(10 \text{ min})]^2} ,$$

again making use of the translation theorem. The quantity $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ is again the “turbulence intensity” seen earlier and will be referred to as “nondimensional standard deviation”. It was further assumed that $M(10 \text{ min}) = M(1 \text{ hr}) = M(24 \text{ h}) = M$, based on the idea that “the means are made up of a sufficiently large number” of observations. The $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ values were found to vary somewhat with mean wind speed (see his Table V), although he determined the differences were “not great”.

Finally, an hour’s $t$-second gust factor, $\text{GF}[1 \text{ h}, t]$, was defined as the largest expected $t$-second wind in the hour divided by the hourly mean $M$. With the normality assumption, this was computed as

$$\text{GF}[1 \text{ h}, t]_D = 1 + k\sigma(1 \text{ h}, t)/M ,$$

where $k = z (1 - t/1h)$, sometimes termed the peak factor, and the suffix $D$ signifies Durst’s method. For a Gaussian random variable, values of $k$ range from 3.0 for $t = 5$ sec to 0.97 at $t =$
600 sec (cf. Table 1 of Brook and Spillane 1968). This yielded the curve shown in Fig. 3.1a. Figure 3.1b presents Durst’s $\sigma(1 \text{ h}, t)/M$ values, but only for the range computed using the Giblett et al. data ($5 \leq t \leq 600$ sec). Extending the curve at both ends, making for the curve as usually presented (and as seen in Fig. 3.1a) appears to require information beyond what was published in Durst (1960).

With the Gaussian assumption, the Durst curve is fundamentally dependent on $\sigma(1 \text{ h}, t)/M$ values, as that is the only part of (3) that is free to vary. Durst examined some of the Cardington data and found no evidence contradicting the presumption of normality. It is worth recalling these values were based on limited and incomplete records representing one site (Cardington). At the outset, it could be presumed that the normalized standard deviations would vary with local terrain, surface roughness, anemometer mounting height, and weather type, among other factors, as found in the studies cited above. If they do so, the gust factors associated with short-period winds would deviate from the Durst curve, perhaps substantially.

3.2.2 Durst’s Observations

Before we start our own analysis, we examine some of the observations referenced in Durst (1960). Figure 3.2 shows data from three of the 10-min long ultra-quick-runs (numbered 97, 147, and 314) referenced in his Tables I and III, the latter run having had four anemometer records available. These runs are broadly representative of the stronger, medium, and lighter wind conditions identified in that study. Normality of the 5-sec winds about their respective 10-min means is assessed via the quantile-quantile (Q-Q) plots shown in Fig. 3.3. Normally distributed observations would fall along the red 1:1 line. Consistent with Durst’s conclusion, the plots reveal that these runs do conform to such a distribution, at least over the short (10 min) time periods for which he had data. It is noted again that Durst extended the normality assumption to apply to deviations within an hour although that went undemonstrated owing to

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7 Had the Gumbel distribution been adopted instead, the GF[1 h, 600 s] values would have been slightly larger.
lack of data. As we are interested in hourly periods and have many more observations available, we will test this presumption in this study.

3.2.3 Our Observations

We now have considerably more (if not always better) data available to us. This study will draw upon observations from the ASOS and NYSM networks described below. As these data are much more complete and extensive than what Durst had to work with, we can not only estimate \( \sigma(1 \text{ h}, t) \) values without resorting to the translation theorem but also compute the gust factors directly, both following subdivision of each hour into segments for various averaging intervals \( t \) and both without having to make any assumptions regarding normality. These can be compared with Durst’s curve as well as his method of constructing it.

The strategy for direct computation of the gust factor is illustrated in Fig. 3.4. Suppose an anemometer samples every second and these data are aggregated into hour-long sequences of non-overlapping segments of \( t = 600 \) seconds, each representing the \( t \)-second mean. There would be 6 such segments per hour. For each hour, the segment with the largest mean wind speed is identified as representing the 600-s gust and then divided by the mean of the 6 samples (the hourly mean wind) to produce the gust factor GF\([1 \text{ h}, 600 \text{ s}]\) for that hour. From a collection of hours spanning a period, say a month, the GF\([1 \text{ h}, 600 \text{ s}]\) mean is obtained by averaging over the hourly values (i.e., producing the *mean of ratios*). There will likely be variability about this mean value that will represent useful information. We note that the GF could also be defined as the mean of all 600-s gusts divided by the average of all hourly means (i.e., representing the *ratio of means*). These are not the same, especially because the distributions of winds and gust factors can have long tails (demonstrated presently). In this study, the mean of ratios is adopted as being most consistent with past computations of gust factor, although both will be supplied.

The same strategy could be pursued for other sub-hourly averaging intervals. For each hour, the hourly means computed for each of these averaging intervals are identical because they are composed of the same information. What is varying in GF\([1 \text{ h}, t]\) is the numerator. In addition, values of \( \sigma(1 \text{ h}, t) \) can be computed from each hour-long sequence, as also illustrated in
Fig. 3.4. The Durst method gust curve would use the mean of the $\sigma(1\ h, t)$ values over the collection of hours.

3.2.3.1 The Automated Surface Observing System Network

We believe the ASOS network (National Oceanic and Atmospheric Administration 1998) provides the highest quality wind information over the widest area. There are currently about 850 sites within the conterminous U.S. states (CONUS) for which 1-min data are available from the National Centers for Environmental Information (NCEI). For April 2019, there were $N = 833$ sites available as shown in Fig. 3.5. Most (but not all) ASOS installations are at airports and equipped with sonic anemometers that are typically (but not always) mounted at 10 m AGL. By their nature, airports are generally built on locally flat terrain with good exposure along the axis of the prevailing wind. The deployment of sonic (“ice-free”) anemometers at ASOS stations operated by the National Weather Service and the Federal Aviation Administration was completed by the end of 2009.

The ASOS sonic anemometers take a wind sample every 1 second. In the 1-min dataset, sites report a 2-min running average (sustained) wind each minute along with the fastest 3-s average wind (gust) obtained during that period, both given in whole knots that we convert to m/s. For each station, hourly data segments were compiled and examined for corrupted and/or missing observations. Only complete hours possessing valid readings were retained, and this totaled 31,180,200 1-min records for the month.

From these data, temporally adjacent samples within each hour can be aggregated into segments with lengths that are both integer multiples of 60 and integer fractions of 3600 (being 120, 180, 240, 300, 360, 600, 720, 900, 1200, and 1800 s). This results in a gust curve spanning averaging intervals between 60 s and 1 h, inclusive. However, the 2-min averaging interval

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8 Some notable exceptions include KCQT (Downtown Los Angeles), KDGP (Guadalupe Pass, TX), and KNYC (Central Park, NY).
10 ASOS documentation found online describes aggregation of wind samples into 5-s blocks prior to construction of the two-minute means. This does not appear to influence this analysis. See https://www.weather.gov/media/asos/ASOS%20Implementation/IFWS_BelfordWS_comparison.pdf
means that while we have independent wind observations only every 120 s. As a consequence, the 60 s interval data will be considered “tainted”. That being said, Durst’s normality assumption will be checked via examination of both the 60 and 120 s deviations from the hourly means, to determine if there is any difference.

We also process the 3-s gust reports. However, as we do not have a complete set of 3-s observations within each hour, we cannot be aggregate them to fill in the gap in the gust curve between 3 and 120 s. As a consequence, we will connect 3-s averaging period values to the balance of the gust curve, starting with the untainted 120-s interval, with dashed lines. Nor can we expect 3-s deviations from the hourly mean wind to have a zero mean. By the nature of ASOS observation reporting, our 3-sec samples are necessarily biased high as they represent peak values for a particular time interval. This means the 3-sec observations will not be used to evaluate the Durst method.

3.2.3.2 The New York State Mesonet

Deployment of the New York State Mesonet (NYSM) started in 2016 and presently consists of 126 standard sites (Brotzge et al. 2020). There is at least one such site in each of New York’s 62 counties, and all possess both a sonic and a propeller anemometer mounted at 10 m AGL. We have readings at 3-s intervals from both anemometers for various time periods, including April 2019. On the basemap shown in Fig. 3.6, marker size indicates mean wind speed for the selected month.

The ability to provide raw, high temporal resolution wind data is a significant advantage of the NYSM. This will help us construct gust curves sampling a larger range of averaging intervals. However, there are several issues in dealing with these data. A few mesonet installations are on rooftops in New York City, including BRON (Bronx), BKLN (Brooklyn), MANH (Manhattan), and QUEE (Queens), and these often emerge in the analyses as outliers. Many other sites have relatively poor exposure, especially those in the densely forested western and northern parts of the state. Perhaps because of the latter, the NYSM is a fairly low speed network. However, some NYSM sites are located close to ASOS stations and are well exposed,
including Penn Yann (PENN) and Fredonia (FRED). This permits some comparisons of gust curves, which is useful to us owing to the lack of complete high-frequency observations from the ASOS network.

According to Nathan Bain at the NYSM (personal communication, January 2021), the raw propeller data represent averages over three seconds and so truly represent 3-s gusts. However, at this writing, the sonic anemometer readings represent one-second samples archived only every 3 seconds, with the other two readings from the 3-sec interval not being retained. Thus, there is an inconsistency between these sources, and an incompleteness in the sonic record, that we need to bear in mind. After a comparison of the two anemometers, we will focus primarily on the propeller data, owing to this data availability issue.

3.2.3.4 The High-Resolution Rapid Refresh Model

For this study, we will also utilize hourly sustained wind forecasts and land cover information from Version 3 of the High-Resolution Rapid Refresh (HRRR), the NOAA operational model we examined in Fovell and Gallagher (2020) and Chapter 2 of this dissertation. The HRRR is a close relative of the operational Rapid Refresh model described in Benjamin et al. (2016), is based on the Advanced Research version of the Weather Research and Forecasting (WRF) model (Skamarock et al. 2008), and uses 3 km horizontal grid spacing over a domain that encompasses the CONUS. Fovell and Gallagher (2020) included a comparison of HRRRV3 forecasts with ASOS observations for several months, including April 2019, and found the model had considerable skill in reproducing the diurnal variation of winds averaged (by time in UTC) across the CONUS. At that time, there were no public archives of HRRR model analyses and forecasts, but that has since changed thanks to NOAA’s Big Data Program. We will make use of HRRR forecasts for ASOS and NYSM sites for April 2019, representing an extension of the Fovell and Gallagher (2020) study. This verification employed the Model Evaluation Tools software (Bullock et al. 2017) and is more fully described in Chapter 2.

Information regarding HRRR landuse assignments for individual station locations was extracted from the model’s publicly available Geogrid model output\textsuperscript{12}.

3.3 Results

3.3.1 Gust Curves

3.3.1.1 ASOS Network for April 2019

3.3.1.1.1 Analysis of All Available Observations

\textbf{Figure 3.7} presents the gust analysis for the ASOS network for April 2019. The network average gust factors GF[1 h, \(t\)] (left) and temporal normalized standard deviations \(\sigma(1 \text{ h}, t)/M(1 \text{ h})\) (right), both shown in red, were constructed from about 520,000 samples representing hourly data from the 833 stations for the month. These were computed for each hourly interval separately and then averaged across all hours (mean of ratios) and their variability is indicated by the vertical \(\pm 1\) standard deviation bars (light red). For gust factor, the ratio of means (blue) is also shown as is the Durst curve (black). As noted above, the separately computed 3-s GF for each curve is connected to the \(t = 120\) s value via a dashed line. Although not perfect, the 3-s and \(t \geq 120\) s data fall roughly along a straight line, as anticipated from the Durst result over the same interval range. We note the 60-s GF deviates somewhat from this relationship and speculate that this is due to lack of independence of samples at this interval.

Compared to the Durst curve, ASOS GFs are larger for every averaging interval considered. The mean 3- and 120-s GFs are 1.87 and 1.38, respectively, in the ratio of means calculation. Past studies (Davis and Newstein 1968; Suomi et al. 2013, 2014, 2016; Gallagher 2016) have found that gust factors tend to increase towards the surface, so slightly higher GFs from the 10-m ASOS data might be expected relative to the 15-m AGL readings at Cardington. However, based on the findings of Suomi et al. 2015 and Gallagher 2016 that showed GF decreased by approximately 0.05 moving from 10-m to 15-m AGL, we suspect that is making only a small contribution.

\textsuperscript{12} https://rapidrefresh.noaa.gov/hrrr/.
Another potential discriminator is siting. The Royal Airship Works was set within “level country” – agricultural land with only a few trees – while most ASOS installations are at airports. While airport sites can be expected to be well-exposed, there are a few problem sites (KVPC in Carterville, GA, and K1JO in Bonifay, FL, being particular examples) where small airstrips are laid out near tall trees. A larger concern is that airports tend to be located near cities, where people live. Although cities represent a very small fraction of the total CONUS land area, about 23% of ASOS sites reside in grids having a primary landuse assignment of urban land in HRRRV3 (see Chapter 2). Even if airports are themselves well-exposed, their mesoscale environment (including their wind fetch) is probably rougher than the open countryside. This reminds us that the ASOS stations are not uniformly sampling the CONUS landscape.

Also shown at left is the gust curve (dark grey) computed via Durst’s method (3), which utilizes the $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ information and presumes wind deviations from the hourly mean are Gaussian. It is important to note that the other ASOS GF$[1 \text{ h}, t]$ estimates were directly computed from the hourly records and do not directly presume normality. Durst was compelled to make that assumption, among others, owing to a dearth of observations. The Durst method (dark grey) also results in larger GF estimates because $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ values it depends on are larger at every averaging interval.

Furthermore, we note the variations around these average GF values are substantial. This indicates a wide range of GF$[1 \text{ h}, t]$ values occur through the month and across the CONUS. That being said, the GF variabilities depicted by the error bars on Fig. 3.7a are somewhat deceptive because, owing to the constrained nature of gust factors (bounded from below by 1.0), these distributions actually are skewed in only one direction. Figure 3.8a displays the distributions of GF for the selected averaging intervals ≤ 600 sec. For each interval, note that the gust factors possess very long tails at the high end, especially for the 3-s gusts.

Finally, we saw that the Cardington observations were approximately normally distributed around their mean values, at least over 10-min stretches. (Again, Durst also presumed that deviations about hourly means were Gaussian but this was not demonstrated, owing to
insufficient data.) Figure 3.9 depicts the deviations of 60- and 120-s deviations from hourly means from the ASOS analysis, the latter also examined owing to observation overlap in the 1-min data. This is the complete dataset, consisting of 31.2 and 15.6 million deviations for the two time intervals, respectively. The distributions for these averaging intervals are very similar and it is clear both deviate far from normal, having sizable kurtosis, indicating a skinnier shape with longer tails at both ends. Although relatively infrequent, there are some very large deviations (up to 20 m/s above and 10 m/s below) the hourly means. As this may indicate the presence of problems occurring within the hours retained for analysis, this motivates some filtering of this dataset.

3.3.1.1.2 Filtered Observations

In addition to siting, two additional, important differences between the present analysis and Durst’s are that his $\sigma(1\ h, \ t)/M(1\ h)$ values were based on wind speeds averaging about 11.5 m/s (26 mph; his Table III) for his 10-min runs and 7.6 m/s (17 mph; his Table IV) for the longer periods and were also computed for periods said to lack significant wind shifts. The average hourly wind speed over the entire ASOS CONUS network was only 4.1 m/s for April 2019. Although not explicitly addressed in the Durst study, it is well known that gust factors tend to exhibit wider scatter when wind speeds are low (examples may be found in Mitsua and Tsukamoto 1989; Fovell and Cao 2017; and other studies). It can be anticipated (and will be shown that) normalized standard deviations also vary substantially for less windy hours.

Figure 3.10 reveals how GFs and normalized standard deviations for the 3- and 120-s averaging intervals behave across the ASOS network. Regarding GF (left column), both mean values and their variability decreased as hourly mean winds increased, approaching the Durst values for these intervals (indicated by the horizontal grey lines). However, hourly wind speeds as large as 9 or 11 m/s are fairly infrequent (occurring about 5 and 1% of the time, respectively).

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13 A similar analysis is not performed on the 3-sec data because we do not have a full set of these observations in each hour.
A similar result was found for normalized standard deviations (right column). In fact, beyond 9 m/s these values were smaller than their corresponding Durst values.

Many different strategies for filtering observations have been employed in past studies, sometimes having been motivated by their specific applications. Some have applied minimum or maximum wind speeds over specific periods and/or have excluded periods exceeding specified wind shifts. A few examples: Cheynet et al. (2018) confined their analysis to the 5-28 m/s range (as recorded at 81.5 m AGL) relevant to wind power and also designated an acceptable range for their normalized standard deviation. Mitsua and Tsukamoto (1989) emphasized periods with winds ≥ 14 m/s while Chen et al. (2007) required an hourly mean wind of 4 m/s and Paulsen and Schroeder (2005) used a minimum of 5 m/s for their applications. The latter was motivated by the large scatter among GF readings (and the presence of particularly large values) that occur when wind speeds are relatively low. Yu and Gan Chowdhury (2009) applied a minimum wind speed of 10 m/s, presumed to correspond with neutral stability conditions, and removed segments with wind shifts exceeding 20° “to avoid records that . . . may correspond to more than one terrain exposure”.

Other studies, including some of those cited above, sought to identify and remove periods of time in which assessments indicated nonstationary behavior. Wind data are often nonstationary owing to diurnal and other changes in conditions, which is why time periods of an hour or less might be examined (cf. Brook and Spillane 1968). As nonstationarity may be exhibited via linear trends, some studies identified and removed periods (such as over 1 h) having slopes exceeding a threshold magnitude and/or used the reverse arrangement test (e.g., Chen et al. 2007, Yu and Gan Chowdhury 2009) or moving average windows (e.g., Cheynet et al. 2018, Nybo et al. 2019) to identify blocks of time possessing means and variances that deviate substantially from their corresponding hourly values. Wind segments affected by specific, transitory weather events such as thunderstorm outflows or drylines may also be identified and either removed or retained, depending on the needs of the study (e.g., Paulsen and Schroeder 2005).
Regarding wind shifts, Fig. 3.11 reveals how the standard deviation of wind direction within an hour varies with the hourly mean wind in the ASOS network for April 2019. The wind direction standard deviation was computed using Yamartino’s (1984) method, with each 60-s observation weighted by its wind speed. Similar to GF and normalized standard deviation, wind direction variability within an hour is large when winds are relatively calm but decreases as conditions become windier. For large wind speeds, mean standard deviations approach about 5°.

Since GF and $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ in the ASOS analysis asymptotically approach relatively small values at larger wind speeds, our first filter retains only hours for which the hourly mean was $\geq 9$ m/s. By itself, this removes all but 4.6% of records, but these come from 725 of the original 833 stations (87%), suggesting the network as a whole is still being represented. Next, motivated by Fig. 3.11, hours with wind direction standard deviation $> 5$ degrees were excluded. Only 2.1% of the original records survive this step although that still represented 10806 station-hours distributed among 604 sites (72.5%). With this subset, 60- and 120-s deviations are rather more (but still not perfectly) Gaussian (Fig. 3.12), and extreme values within the hourly segments retained are smaller and rarer.

The gust curves generated from this subset are shown in Fig. 3.13. Gust factors are now much more comparable with the Durst study. We note the mean of ratios and ratio of means GFs are nearly identical at 1.57 for the 3-s interval and 1.18 at 120-s. The 60-s interval still appears to deviate from linearity and again the lack of independence is suspected. Apart from the 3-s interval, variability around these means are much smaller. Distributions of GF for this subset are shown in Fig. 3.8b; note the 3-s values still retain a somewhat longer tail than would be expected from a normal distribution. To further illustrate this, Fig. 3.14 displays the 3-s gust factors for this subset in rank order. The largest value is 2.54, with 2.05 and 1.78 representing the 99th and 90th percentiles, respectively.

We note the Durst method now generates lower gust factors than the other approaches, and below the Durst study values. This is because the subset-average $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ are smaller than found in Durst (1960), as anticipated from Fig. 3.8b. Again, we do not have to
resort to the Durst method to construct a gust curve, owing to greater data availability, but this comparison helps us appreciate the limitations of the method and of the curve constructed using it. Other observational filtering approaches have also been evaluated. Following a suggestion by Nybo et al. (2019), we computed the maximum moving mean and standard deviations, in absolute value, among overlapping 600-s windows within each hourly record in an attempt to identify nonstationary periods within the observations. Although they ultimately did not implement this, Nybo et al. (2019) proposed retaining only hours for which both differed from the hourly values by less than 40%. Applying these rather stringent criteria to the ASOS data resulted in only 1.1% of the original dataset (5931 records) being retained, largely a consequence of the standard deviation threshold. While the resulting gust curve (Fig. 3.15) also resembles Durst’s, at least for $t \geq 120$ s, we note that the 3-s gust factor is still high as is variability around the mean GF and $\sigma(1 \text{ h}, t)/M(1 \text{ h})$ values for all averaging intervals. The long tails seen in the GF distributions have not been pruned (compare panel c with a in Fig. 3.8). The mean wind speed of the retained hours is 4.7 m/s, and thus we see that filtering in this manner does not effectively remove the less windy hours that are driving variability.

The standard deviation portion of the Nybo et al. (2019) appears to be less useful for ASOS data owing to its smaller temporal frequency. As we do not have a full sequence of 3-s observations, the moving averages were applied to 600-s windows of the 1-min readings, so each window contained only 10 samples. This filtering removes hours possessing windows with much larger or smaller variance than the hour as a whole. It is easier for smoothed data to exhibit shorter periods with relatively little variation (lulls) that would be excised via this procedure. Using just the wind speed component of this filter removes only 22% of the hours and yields gust curves (not shown) that do not differ significantly from those from the full dataset. This is probably because the network average wind speed of retained hours remained at 4.7 m/s. As a consequence, this strategy is not adopted for ASOS observations.

Although not shown, comparable results have been obtained using ASOS observations for other months, representing different seasons. To summarize thus far, the Durst curve does an
adequate job of characterizing how gust factor varies with averaging interval, at least for airports and with respect to hours characterized by faster and directionally steadier winds. These are the time periods for which we would be more concerned about large gusts. However, directly computing the GF variation appears to be superior to estimating the extreme values presuming normal or Gumbel distributions. Also, the lack of complete observations at the 3-s averaging interval impedes our ability to understand how gust factor distributions and variation changes between this period and the next shortest, nonoverlapping averaging interval (120 s). This motivates examination of wind data from other networks.

3.3.1.2 NYSM Network for April 2019

Compared to the ASOS network, the NYSM is smaller in size and concentrated within a single state. Another contrast is that, at least according to the HRRRV3 primary landuse classification, NYSM sites are much less likely to be found in urban environments (7% vs. 23% for ASOS) and significantly more likely to be classified as forested (42% vs. 11% for ASOS). This is likely a major reason that the NYSM is a relatively low wind speed network and very slow readings are not infrequent. In the ASOS record for April 2019, hourly mean winds were lower than 0.5 m/s less than 1% of the time. In contrast, such weak winds occurred in the NYSM sonic data 4.7% of the time and in the propeller record for 7.5% of all hours. These two instruments will be more closely compared in the next chapter.

For our analysis, hourly means for our analysis were computed from the 3-s readings from both anemometers. As with the ASOS data, we only retained hours for which complete and valid data were available. Missing or corrupted records were more frequent in the sonic record, which left 77449 station-hours for April 2019 compared to 89107 for the propeller. For this analysis, we decided to merge the two instrumental records, keeping only hours represented in both; this yielded 77064 station-hours. However, owing to the substantial fraction of nearly calm observations, and the very large GFs they tend to possess, we further elected to exclude hours in which the propeller mean wind was less than 0.5 m/s. This reduced the dataset by 7.5% to 71317 station-hours.
Figure 3.16 compares hourly mean and maximum (gust) winds for the two anemometers. For this subset, the monthly network-averaged wind speeds (panel a) were $3.41 \pm 2.11$ m/s and $3.13 \pm 2.01$ m/s for the sonic and propeller instruments, respectively, and the $R^2$ was 0.994. Overall mean gusts were $7.5 \pm 3.9$ m/s for the sonic readings and $6.8 \pm 3.7$ m/s for the propeller data (panel b). Higher gusts from the sonic were expected anyway as the former are actually 1-s samples, as mentioned above. However, the difference between 1- and 3-s samples should decrease as the averaging period gets longer, so the difference in the hourly means is more likely due to instrument operating characteristics. (Again, this will be explored more thoroughly in Chapter 4.) As both hourly mean winds and maximum gusts are larger for the sonic data, it is not surprising that the gust factors for the two instruments are about the same (roughly 2.39). There are obviously a few hours with substantial discrepancies, but these will not affect our analyses.

Figure 3.17 presents the April 2019 gust curves computed from both anemometers. Given the sonic data are 1-s winds, at least the first point on its sonic gust curve should be shifted leftward. That being said, there is strong resemblance between the curves in that the mean of ratios gust factors are roughly similar for the two instruments and the ratio of means versions are even more comparable (panel a). As with the ASOS network, the GF values are much higher than Durst’s with huge variability, and this applies to the normalized standard deviations as well (panel b).

The NYSM GF distributions for the propeller data shown in Fig. 3.18a help us appreciate what the gap in the ASOS record between the 3- and 60- or 120-sec averaging intervals might look like. There is a fairly systematic progression towards wider distributions (greater variability) with higher mean values and longer right-side tails as the averaging interval gets shorter. This is also observable in the gust curve (Fig. 3.17a) via the error bars. As with the ASOS dataset, 3-sec GFs and normalized standard deviations have far greater variability when the wind speeds are lower (Fig. 3.19a,b). They approach the Durst study values more slowly and less successfully, owing in part to the smaller range of hourly mean winds among the NYSM observations. The 120-sec interval plots are also included, for direct comparison with ASOS.
As with the ASOS observations, we now examine subsets of the NYSM propeller dataset based on wind speed and wind direction variability thresholds. Likely because of the relatively slower wind speeds, wind direction variability is quite a bit larger (Fig. 3.20), and the cutoffs adopted for ASOS would remove nearly all observations from the subset. Requiring hourly mean winds ≥ 4 m/s and wind direction standard deviations < 20° increased the mean hourly wind of retained observations to 6 m/s for the 21% of hours remaining, producing the gust curve seen in Fig. 3.21a. The mean of ratios and ratio of means curves are nearly identical but both possess considerably larger gust factors at each averaging interval compared to Durst (and the more heavily filtered ASOS observations). The standard deviations also remain larger (Fig. 3.21b).

Although it removes all but 243 (0.3%) of the original 71317 records from the NYSM propeller dataset, we also show gust curves for when the hourly mean wind and direction standard deviations are required to be greater than 9 m/s and less than 10°, respectively (Fig. 3.22). The NYSM gust curves now agree with Durst’s values to an uncanny degree, as do the normalized standard deviations, with even smaller variability for the shorter averaging intervals than obtained from ASOS data. Only sixteen NYSM sites (nearly all classified as croplands by the HRRRV3) contributed to the 714 hourly observations that survived this filtering, but this is not a tiny number relative to the data available to Durst. The 3-s deviations about their hourly means are very close to normally distributed (Fig. 3.23), with only a small divergence from expected, mainly in the left (less interesting) tail and from the limited number of records available the GF distributions appear to have shorter tails (Fig. 3.18b). As an aside, applying stationarity-based filtering removes observations (about half in this case) without changing the GF variability much (Fig. 3.18c), similar to the result with the ASOS dataset.

It is likely coincidental that we have managed to find a filtering strategy that yielded a gust curve comparable to Durst’s. Figures like 3.10 and 3.19 demonstrate that GFs for given averaging intervals tend to decrease as the hourly mean wind gets faster, and that these approach (and sometimes become smaller than) the values in the Durst curve. Also, part of the reason we are exploring the relationship between GF and mean wind is to understand when and how gust
factors can help us understand site exposure, which is the subject of the next chapter. The central problem here is that when wind speeds are low, it could be because conditions are relatively calm or because obstructions at the site are slowing the wind. In the latter case, but not the former, the wind speeds would have been higher had the obstructions not been present. How do we differentiate between these two cases?

3.3.2 Maximum Wind Curves

The Durst approach examines gusts normalized by the hourly mean wind. We have seen the shape of the curve is strongly affected by the mean wind speed. As an alternative, we could use the very same data to create “maximum wind (maxwind) curves” that are normalized by the 3-s gust instead. This is motivated by our previous and current research (e.g., Cao and Fovell 2018, and Chapter 4 of this dissertation) suggesting gust factors may reveal exposure issues at sites and our finding that gusts vary among networks less than sustained winds (again, see Chapter 4). The basic idea is that, in an obstructed environment, short-period gusts are relatively less likely to be impacted by obstacles than hourly mean winds.

With the maxwind curve, we reintroduce the inverse gust factor (iGF) from Chapter 2, which may be a new concept but is simply the reciprocal of the standard GF, i.e., observed wind divided by the observed gust. One issue with gust factor is that it is unbounded as the observed wind approaches zero. In contrast, iGF is bounded between 0 and 1 and we see its compressed range as an advantage in the analysis that follows. In our application, when not otherwise indicated, iGF is specifically the hourly mean wind divided by the 3-sec gust, so it represents the right-hand-side end point of the maxwind curve.

**Figure 3.24** presents maxwind curves for the NYSM and also the Durst version, created by normalizing the Durst curve values by the 3-s gust instead. No speed or direction filtering has yet been applied. We start with the red curve in **Fig. 3.24a**, which represents the composite of all NYSM sites. Note the curves slope downward, indicating that the fastest wind expected in a particular interval decreases smoothly and quasi-linearly as the averaging period gets longer. For all sites, the hourly mean wind is about 45% of the speed of the hour’s fastest 3-sec gust.
(representing its iGF). This is a lot smaller than that obtained from the Durst curve, in which the hourly mean is about 64% of the gust. As the iGF becomes smaller, the maxwind curve displays more curvature. We speculate, but cannot yet prove, that this is a consequence of obstruction.

Mesonet sites have been classified according to World Meteorological Organization (WMO) criteria. The WMO designates guidelines for meteorological surface observations to ensure the highest quality and most “representative” observations (WMO 2014-2017). For wind, the 126 sites are distributed among 5 classes, with class 1 being the least obstructed\(^{14}\). These wind classifications are determined by the relative height, distance, and abundance of obstacles surrounding a measurement site. The thresholds for each of these classes are detailed in Table 3.1. About 43% of the 126 stations are Class 1 while 10% (12 sites) are in the two lowest classes.

**Figure 3.24a** also presents maxwind curves stratified by class and shows that the least compromised classes (1-3, shown as blue and green) have the smallest dropoff (about 47%) from the 3-s to hourly average wind although all of the curves reside well below the Durst reference curve. Again, part of this reflects the fact that wind speed tends to decrease with increasing WMO class, shown in Fig. 3.25, and GF (and thus iGF) varies with wind speed, as already demonstrated. That being said, we believe we can interpret this in the following way: as a site becomes relatively more obstructed, the maximum wind speed expressed as a fraction of the 3-sec value will decrease more swiftly as the averaging period lengths. This is congruent with Cao and Fovell’s (2018) interpretation of gusts and gust factors.

We showed in Chapter 2 that that forecast wind bias in the operation HRRR model – for both Versions 3 and 4 – is linearly related to iGF with a moderately high \(R^2\) for forecasts made for ASOS and NYSM stations. As in Cao and Fovell (2016, 2018), we start with an interpretation that GF (and iGF) is revealing of site characteristics including exposure such that stations with lower iGF or higher GF than the network average indicate potential obstructions that can lead to positive forecast bias. However, now that multiple networks are being considered

\(^{14}\) WMO site classes for wind, temperature, and other measures can be found through the NYSM website, [http://www.nysmesonet.org](http://www.nysmesonet.org).
jointly, and also presuming the potential “universality” of the Durst curve, we will now interpret site iGF relative to a *multi-network* average. This will accommodate the NYMS, which has lower mean wind speed and lower iGF than the ASOS network in part because site characteristics tend to be different (i.e., more likely sited in forested areas).

In Fig. 3.24b, maxwind curves for each of the 126 NYMS sites are superimposed, color-coded by the site’s average forecast wind bias for April 2019 from the analysis presented in Chapter 2, along with the mesonet mean (now indicated by the thick dashed black curve). As we are not able to cleanly differentiate sites with naturally and artificially slow winds, we are leveraging the HRRR forecast bias as a rough and very arguable proxy for exposure. Sites with the largest negative slope are colored red, indicating positive forecast bias (overprediction). Again, we believe at least part of the rapid decline in wind speed with lengthening averaging interval reflects the presence of obstructions that act more powerfully over longer time scales and the HRRR overforecasts for these sites because it cannot capture the site’s local and mesoscale characteristics. The site with the most positive bias is Tannersville (TANN) at 2.7 m/s, a value that exceeds this Class 5 site’s mean wind (1.8 m/s). This station is closely surrounded by trees and in a heavily forested area. Green is added to curves having biases closer to zero (±0.5 m/s) and we note these have less steep slopes. Negatively biased sites contain blue but there are only a few of these (9 of 126).

Figure 3.26 shows April 2019 maxwind curves for the ASOS stations. As we do not have WMO site classifications for the ASOS stations, we instead examine curves for two subsets based on hourly wind and wind direction standard deviation (Fig. 3.26a). Subset 1 (green) uses 9 m/s and 10° for the speed and direction thresholds, respectively, as employed earlier, and subset 2 (blue) employs the less restrictive criteria of 4 m/s and 20°. As anticipated from prior results, the maxwind curves approach the Durst version as less windy and more directionally variable hours are excluded.

In Fig. 3.26b, curves for the many individual ASOS stations are superposed, again color-coded based on HRRR forecast bias for April 2019. Now there are many stations (264 of 817, or
32%) with biases < -0.5 m/s (colored blue). These have smaller slopes, representing less decline in maximum wind speed with lengthening averaging period. Note the Durst maxwind curve (now in white) falls among the blue-colored ASOS curves, suggesting the HRRR model would probably underpredict the hourly mean wind at the Cardington site. We showed in Chapter 2 that the HRRR’s negative biases are especially large among ASOS sites classified by the model as grassland, which is probably most similar to the open country around the Cardington site in the early 20th century.

For convenience, Fig. 2.13c from Chapter 2 is reproduced here as Fig. 3.27, showing combined iGF for the hourly mean wind vs. forecast wind bias information for ASOS and NYSM HRRR forecasts for April 2019. Each dot is a station with ASOS and NYSM sites colored black and orange, respectively. For each site, the mean bias and iGF were computed over all forecast hours for April 2019. The iGF values are slightly different than those seen in Figs. 3.24 and 3.26 because they were averaged over all forecast-obs pairs rather than all hours, and some hours have more than one forecast since the HRRRV3 integrated for 36 h, such that a subset of hours were represented more than once. Also, in contrast with the present study, some hours in which the propeller mean wind was less than 0.5 m/s were retained. These differences are considered negligible.

Taken together, we can see site mean iGF is inversely correlated with bias to a moderately high degree ($R^2 = 0.65$ or $r = 0.81$) and that stations with smaller iGF are systematically underpredicted. Further, we see the average bias over ASOS stations is much closer to zero than for the NYSM sites, which tend to be clustered in the plot region with large iGF and positive bias, but the two sets of stations appear to be drawn from a larger overall population. Moreover, based on our inspections of other months, this relationship appears to be relatively robust over time (not shown).

Because iGF can be interpreted as a (not independent) proxy for the HRRR model forecast wind bias, we can further contemplate using either iGF or bias as an empirical proxy for site classification, which may provide a means of comparing stations from different networks.
This is based on the notion that the model generates skillful forecasts overall but will possess biases at individual sites owing to unresolvable features that can either enhance or suppress wind speeds. Examples of the former are small-scale terrain features like canyons or hills that can funnel or accelerate the wind. For the latter, close proximity of trees, buildings, or sheer cliffs can cause sheltering.

Thus, a WMO-like empirical classification (EC) with 5 members might consist of two to represent sites with negative biases and smaller iGFs (ECs 1 and 2), two for stations with positive biases and lower iGFs (ECs 4 and 5), and one (EC 3) for sites near the mean. Based on such a rough classification, it would be seen that NYSM sites would be classified mainly as EC 4 and 5 while ASOS would have sites distributed among all classes. This classification, which leverages the operational model as an “honest broker”, could be used to help interpret and adjust forecasts for unresolved site characteristics as well as adjust observations prior to ingestion in data assimilation. This is again not a perfect solution to the problem since both iGF and bias both contain the mean observed wind speed and thus are not independent of the measures we are trying to correct, but it seems to be a useful step in the right direction.

3.4 Discussion and Conclusions

Durst’s famous gust curve (Fig. 3.1a) relates the typical magnitude of the largest t-second average wind (i.e., gust) within an hour to the hourly mean wind, a ratio called the gust factor. The curve was created indirectly from a limited set of observations taken at one location, in a rural area of England, using a now antique instrument that could only capture data over very short intervals of time onto paper tape. Fluctuations of the t-sec wind within an hour were assumed to be normally distributed. The curve showed that for a typical hour, the largest 3-sec gust could be expected to be about 1.5 times the hourly mean. Longer averaging times resulted in smaller gust factors, yielding a curve that is approximately straight between 3 ≤ t ≤ 600 sec when plotted on a semi-log graph. That the Durst curve is not universally applicable is known from subsequent studies that examined GFs for tropical storms and in other situations as discussed in
Section 3.1. Obtaining sizable amounts of high-quality data from wind-observing networks is a major challenge facing the construction of gust curves.

In this study, we have constructed Durst-like gust curves using 1-min reports for the ASOS network and 3-s observations from the NYSM. These networks yield a large amount of relatively high-frequency data but they also come with some significant limitations. As discussed in Chapter 2, most ASOS installations are at airports and can be expected to be well-exposed, particularly in the prevailing wind directions owing to aircraft operations. While the data are available at 1 min intervals and are constructed from WMO-standard 3-s samples, it remains that the ASOS sustained winds are actually two-min averages (so only every other reading can possibly be “independent”) and only the fastest 3-s reading within each minute is provided. As a consequence, a complete gust curve cannot be constructed because averaging periods between 3 and 120 s, exclusive, are either unobtainable or tainted. In addition, since only one 3-s reading is available per minute, the distribution consisting of all 3-s deviations within an hour cannot be constructed. Furthermore, as also discussed in Chapter 2, while ASOS stations are sited across the CONUS, the urban landscape is significantly overrepresented and stations in complex terrain are not all that common.

In contrast, the NYSM provides raw 3-s observations from two anemometers, a sonic (like ASOS) and a propeller-based instrument. Unfortunately, the two data sources are made somewhat less comparable because while the propeller’s readings are true 3-s averages, the sonic observations are 1-s samples reported only every third second. For this reason, our analysis has concentrated mainly on the propeller dataset. Additionally, the NYSM is confined to one state (New York) and some of the sites have significantly limited exposure.

Analysis of the ASOS and NYSM readings for a selected month, April in 2019, revealed that the typical maximum t-sec wind was larger relative to the hourly mean in both networks in comparison with the Durst curve (Figs. 3.7 and 3.17). For ASOS, the 3-sec GF was about 1.86 for April 2019, and the 120-sec GF was approximately 1.4. NYSM (propeller) factors were higher still, at about 2.4 for the 3-s gust. Curves that more closely resembled Durst’s in shape
and magnitude were obtained when hours with relatively lower mean wind speeds and relatively larger variations in wind direction were excluded. However, this involved excluding very large parts of the original data sets, especially for the NYSM which is a relatively low-speed network.

GF is a poorly behaved measure that increases unbounded as the hourly mean wind goes to zero. For that reason, we also inspected the inverse GF (iGF), being the reciprocal of the GF, which was introduced in Chapter 2. The iGF is conveniently bounded between 0 and 1. When not otherwise specified, iGF should be assumed to represent the hourly mean wind divided by the 3-s gust. (A further rationale for employing iGF is that it linearizes the relationship with HRRR forecast bias, as shown in Chapter 2 and in Fig. 3.27 herein). However, maximum wind curves relating iGF to averaging interval (e.g., Figs. 3.24 and 3.26) show significant deviations from the Durst-derived reference iGF curve as the hourly mean wind decreased and/or the site was less exposed by WMO standards, at least until low-speed hours and periods with varying wind directions were excluded.

Up to now, we have been examining effectively two-dimensional (averaging interval vs. GF or iGF) plots. Owing to the variability of gust factors with hourly mean wind speed, we now consider a higher dimensional representation of gustiness. This analysis was restricted to ASOS stations but expanded to include not only April 2019 but also October 2019, January 2020, and July 2020, so four seasons were sampled. After hours with missing or invalid data were excluded, this composite dataset consisted of 2,117,634 station-hours. These data were then filtered to remove hours having wind direction standard deviations ≥ 10°, reducing the number of records to 978,415, or 46% of the original total.

Figure 3.28 presents the filtered composite dataset’s GFs for the \( t = 3, 120, 300, \) and 600 sec averaging intervals plotted against hourly mean wind speed, and the iGF version is shown in Fig. 3.29. On both, the connected red dots indicate the means for 2.5 m/s wide bins and the vertical lines represent ±1 standard deviation. As the hourly mean wind increased, mean regular and inverse gust factors varied in a relatively linear fashion, until about 18 m/s, beyond which
there were very few examples even in this very large, CONUS-wide dataset\textsuperscript{15}. Figure 3.30 superimposes the mean curves for these four averaging intervals onto a single plot. The gust or maximum wind curves could be obtained by averaging these figures with respect to the hourly mean wind.

These figures may be used as follows. Given an hourly mean wind speed, a range of reasonable gust and inverse gust factors could be obtained to estimate the largest 3- to 600-sec wind that could have transpired within that hour. This can be useful to augment observational data for which gust information within the hour is not complete but significant variations in wind direction are not anticipated. As noted earlier, numerical model output at typical mesoscale grid spacings cannot resolve short-period gusts and generally lack higher frequency temporal variability anyway. They also may not be available at intervals less than 60 min. Under most situations, a forecast available on the hour could reasonably be treated as an estimate of the hour’s mean wind and plots like Figs. 3.28, 3.29, and 3.30 could be used to assess what range of gusts might be expected to have occurred during that period. Mindful of Fig. 3.27, however, forecasts may need to be bias-corrected before gusts are estimated.

While exceptional weather conditions may result in atypical gustiness, it remains that our dataset is comprised of an enormous number of observations spanning the lower 48 U.S. states. That being said, we need to recognize these are generally well-exposed airport stations that are more likely to found in urban landscapes than in complex terrain and largely represent winds and gusts at 10 m above level ground. Also, we need to keep in mind that gust estimates associated with hourly mean winds > 18 m/s are not based on very much information.

\textsuperscript{15} All of these examples survived filtering and so represented only 0.115 of the full data set.
<table>
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<th>WMO Wind Classification</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>Class 5</th>
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<td>5 m</td>
<td>6 m</td>
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</tr>
<tr>
<td>Additional Notes</td>
<td>Narrow objects taller than 8 m must be 15 times further away than their width</td>
<td>Narrow objects taller than 8 m must be 15 times further away than their width</td>
<td>Narrow objects taller than 8 m must be 10 times further away than their width</td>
<td>No objects wider than 60° azimuth and taller than 10 m within 40 m of the site</td>
<td>Site subject to “doming”</td>
</tr>
</tbody>
</table>

Table 3.1) WMO guidelines for determining site classification for wind exposure.
Fig 3.1) Curves of hourly GF (a) and nondimensional standard deviation (standard deviation divided by mean wind speed, b) with respect to sample averaging interval (gust duration). Black lines show the curves constructed form data directly listed in Durst (1960), while grey curves show continuation of curves from extrapolation and data outside of the original Cardington dataset.
Fig 3.2) Time series of wind speed from three ultra-quick runs, 97 (a), 147 (b), and 314 (c-f), recorded at Cardington and used in Durst’s (1960) study. Measurements from multiple neighboring anemometers are shown for Run 314.
Fig 3.3) Quantile-Quantile (Q-Q) plots of ranked theoretical and observed deviations from the mean wind in the ultra-quick runs shown in Fig. 3.2. Theoretical values are derived from an ideal normal distribution. The 1:1 line is shown in red and denotes perfect agreement of normality between the wind distributions.
**Fig 3.4**) Schematic detailing how $t$-second gusts and GFs are calculated ($t = 600$-s in this example). For each hour $i$ sub-samples are generated by averaging shorter duration data (60-s or 120-s for ASOS and 3-s for NYSM) in consecutive non-overlapping windows of width $t$. Hourly maximums (gusts), means (mean wind), and standard deviation are calculated using the aggregated sub-samples of gust duration $t$. 
**Fig 3.5**) Locations of 833 ASOS stations with observations available during April 2019. Marker size indicates the station’s average wind speed for April 2019.
Fig 3.6) Similar to Fig. 3.5 except for the 126 NYSM standard stations.
Fig 3.7) Similar to Fig. 3.1 except also showing gust curves (a) for the mean of all network average GFs (mean of ratios, red line), the ratio (GF) of network average gust speed and network average wind speed (ratio of means, blue line), GF calculated using Eq. 2.4 from Durst (1960) (maroon line) and nondimensional standard deviations (b) for ASOS network average observations in April 2019 (N=519670). Error bars indicate ±1 standard deviation from the mean quantity for each curve. Dashed lines indicate interpolation between 120 s to 3 s gust duration owing to the lack of observations with higher frequency than 60 s.
Fig 3.8) Distributions of ASOS network average GFs from all observation hours (a), only hours with hourly mean wind speeds $\geq 9$ m/s and standard deviations of wind speed $\leq 5^\circ$ (b), and only hours where the 600-s moving average wind speed and wind direction varied $\leq 40\%$ from the hourly mean (according to Nybo et al. 2019) (c) during April 2019 for select gust durations 3-s (blue), 60-s (cyan), 120-s (green), 240-s (gold), and 600-s (red). Vertical lines (identically colored) denote the average of each distribution.
Fig 3.9) Distributions (a, c) and Q-Q plots, similar to Fig. 3.3 (b, d) of deviations of 60-s (a, b) and 120-s (c, d) average samples from hourly means for all April 2019 ASOS observations. Red lines denote an ideal normal distribution.
Fig 3.10) All observed ASOS network average GFs (a, c) and nondimensional standard deviations (b, d) vs. hourly mean wind speeds for 3-s (a, b) and 120-s (c, d) averaged samples during April 2019. Color coding shows density of neighboring points, with warmer colors indicating higher density and cooler colors indicating lower density. Red lines denote the average of GF or nondimensional standard deviation in 2 m/s wide bins of hourly mean wind speed. Error bars represent ±1 standard deviation about the mean. Values from Durst (1960) are shown in horizontal grey lines.
Fig 3.11) Similar to Fig. 3.10 except for standard deviation of 60-s wind directions within an hour (°, calculated using Yamartino’s 1984 method) vs. hourly mean wind speed.
Fig. 3.12) Similar to Fig. 3.9 except only for hours when the hourly mean wind speed is ≥ 9 m/s and the standard deviation of 60-s (a, b) and 120-s (c, d) wind directions are ≤ 5°.
Fig 3.13) Similar Fig. 3.7 except only for hours when the hourly mean wind speed is \( \geq 9 \) m/s and the standard deviation of wind directions are \( \leq 5^\circ \), leaving 2.1% of the original record (N=10806).
Fig 3.14) ASOS network average GFs in decreasing rank order for hours when the hourly mean wind speed is $\geq 9$ m/s and the standard deviation of 60-s (a, b) and 120-s (c, d) wind directions are $\leq 5^\circ$. 
Fig 3.15) Similar to Fig. 3.7 except only hours where the 600-s moving average wind speed and wind direction varied ≤ 40% from the hourly mean, leaving 1.1% of the original record (N=5931).
Fig 3.16) Scatterplots of NYSM sonic vs. propeller observations of hourly mean wind speed (a) or hourly maximum gust (b) during April 2019. Color coding is indicative of neighboring point density, more points translate to warmer colors while fewer points translate to cooler colors. The linear regression of observations from both anemometers is shown in the red line and the 1:1 line is shown in dashed grey.
Fig 3.17) Similar for Fig. 3.7 except showing gust curves (a) for the mean of all network average GFs (mean of ratios, red and gold lines), the ratio (GF) of network average gust speed and network average wind speed (ratio of means, blue and cyan lines), GF calculated using sonic NYSM observations and Eq. 2.4 from Durst (1960) (maroon line), and nondimensional standard deviations (b) for NYSM sonic (gold and cyan lines) and propeller (red and blue lines) observations in April 2019 (N=71317). Error bars indicate ±1 standard deviation from the mean quantity for each curve.
Fig 3.18) Similar to Fig. 3.8 except for NYSM propeller observations for a wider variety of gust durations: 3-s (purple), 12-s (magenta), 24-s (light pink), 60-s (cyan), 120-s (green), 240-s (gold), and 600-s (red). Additionally, observations are limited to hours with network average mean wind speeds $\geq 0.5$ m/s (to accommodate for the propeller anemometers threshold velocity) (a), wind direction standard deviation maximum value is increased to $\leq 10^\circ$ (b), and deviations from hourly means are based on 3-s samples rather than 600-s (c).
Fig 3.19) Similar to Fig. 3.10 except for NYSM propeller observations during April 2019. Panels (c) and (d) show 120-s gust duration data for comparison to ASOS.
Fig 3.20) Similar to Fig. 3.11 except for all NYSM propeller observations during April 2019.
Fig 3.21) Similar to Fig. 3.17 except focusing only on NYSM propeller observations for hours when the hourly mean wind speed is $\geq 4$ m/s and the standard deviation of wind directions is $\leq 20^\circ$. Note the limitations differ from those imposed on ASOS in Fig. 3.13 due to the overall slower and more variable wind observations in the NYSM record, leaving 21.1% of the original record (N=15028).
Fig 3.22) Similar to Fig. 3.21 except hours when the hourly mean wind speed is \( \geq 9 \) m/s and the standard deviation of wind directions is \( \leq 10^\circ \) for closer comparison to ASOS observations, leaving 0.3% of the original record (\( N=243 \)).
Fig 3.23) Similar to Fig. 3.12 except for NYSM propeller observations for hours when the hourly mean wind speed is $\geq 9$ m/s and the standard deviation of wind directions is $\leq 10^\circ$. Unlike Fig. 3.22 all valid propeller observations are utilized, not just those with valid sonic counterparts, resulting in N=267 hours.
**Fig 3.24** Curves of “maxwind” (average maximum gust of duration $t$ divided by the average maximum 3-s gust) for NYSM network average of all stations and average of stations subset by WMO wind classification (a) and all stations individually (b). Panel (a) curves are color coded by stations composited: all stations (red line), class 1 stations (navy), class 2 stations (blue), class 3 stations (green), class 4 and 5 stations (gold). Panel (b) curves are color coded by each stations average forecast bias verified against HRRR forecasts for April 2019 with greens indicating biases close to zero ($\leq 0.5$ m/s) and reds indicating larger positive biases ($\geq 0.5$ m/s). The network average from panel (a) is duplicated in panel (b) with a thick dashed black line and Durst’s values are shown in the thin black line in both panels.
Fig 3.25) Box and whisker plot of station average wind speed for NYSM delineated by their WMO wind classification. The median, interquartile range, and maxima/minima are denoted by the black center lines, colored boxes, and whiskers, respectively. Average of all station mean winds are shown in the red dots and line. Boxes are colored to be consistent with their maxwind curves in Fig. 3.24a. Note classes 4 and 5 are combined due to the small number of stations in both.
Fig 3.26) Similar to Fig. 3.24 except for ASOS network average and station subsets (a) and all ASOS stations individually (b). Subsets 1 and 2 in panel (a) use all ASOS stations but only for hours when the hourly mean wind speed is ≥ 9 m/s and the standard deviation of wind directions is ≤ 10° (green) and hours when the hourly mean wind speed is ≥ 4 m/s and the standard deviation of wind directions is ≤ 20° (blue), respectively. Panel (b) individual stations are still color coded according to their average HRRR bias over April 2019 by large positive biases (≥ 0.5 m/s) in red, biases close to zero (±0.5 m/s) in green, and large negative biases (≤ -0.5 m/s) in blue.
Fig 3.27) Same as Fig. 2.13c reiterated for convenience. Station average iGF vs. station average bias of forecast wind speed for ASOS (black dots) and NYSM (orange dots) stations. Each dot represents a temporal average over April 2019 for each station. The linear regression is shown in red line.
Fig 3.28) Similar to Fig. 3.10 except just ASOS network average GFs for gust durations 3-s (a), 120-s (b), 300-s (c), and 600-s (d) using only hours when the hourly mean wind speed is $\geq 9$ m/s and the standard deviation of wind directions is $\leq 10^\circ$. 
Fig 3.29) Similar to Fig. 3.28 except for network average iGF instead of GF.
Fig 3.30) The mean curves of average GF (a) and iGF (b) from Fig. 3.28 and Fig. 3.29, respectively. Curves are color coded by gust duration: 3-s (red), 120-s (gold), 300-s (green), and 600-s (blue). Numbers adjacent each point indicates the total samples that constitute the mean. Error bars indicate ±1 standard deviation about the mean.
4. Relating Surface Wind Observations to the Local Environment Using Airborne Lidar

4.1 Introduction

Fovell and Gallagher (2020, hereafter FG20) and Chapter 2 in this dissertation showed a persistent relationship between the forecast bias of surface wind forecasts and observed wind speed at 10 m above ground level (AGL) in the High-Resolution Rapid Refresh (HRRR) model versions 3 and 4. This was shown to be true for both ASOS (Automated Surface Observing System) sites and standard installations of the New York State Mesonet (NYSM). It was established that locations characterized by slower observed wind speeds were more likely to be overpredicted (positive biases) whereas windier sites were underpredicted (negative biases). Furthermore, it was demonstrated that forecast bias was also well correlated with the gust factor (GF) (or inverse gust factor, iGF), being the ratio of gusts to mean winds (or mean winds to gusts). These results are consistent with a body of model verification work (Cao and Fovell 2016, 2018; Fovell and Cao 2017, Fovell and Gallagher 2018) that was focused much more narrowly on high wind speed “Santa Ana” events specific to Southern California.

We have been theorizing that a large GF relative to the network average for a particular location could indicate the presence of obstacles in the local environment. We believe that obstructions that act to slow the wind will have a greater impact on the mean winds, which experience the landscape more, than the more transient gusts, which may have descended from above and thus have spent less time near the ground. This would lead to a larger GF relative to a less obstructed site. One issue, however, is that GF is obviously not independent of the mean wind, and (as shown in particular in Chapter 3) tends to be larger for locations with slower winds. The as-yet-unresolved question is that, for a slower wind location, how much of the
slowness is due to obstructions and how much of it is completely natural – that is, the relatively lower wind speeds would have occurred even in a completely obstruction-free environment?

4.1.1 Background Literature

The World Meteorological Organization (WMO) has standards for measurements of surface winds that strive to minimize the impact of aspects like extreme slopes and nearby obstructions and maximize the representative area of an observation (WMO 2014-2017). However, the real world is rarely nearly flat and comprised of open spaces representative of several square kilometers where obstructions are ten times more than their height away from the observation site (Wieringa 1996). This has created a substantial need to properly classify and quantify the effect the surrounding environment has on numerous atmospheric variables. One of the most common ways the surface environment is characterized, with respect to surface winds, is through surface roughness ($z_0$) (Wieringa 1980). Unfortunately, $z_0$ suffers from the fact it is a one-dimensional variable (in numerical weather prediction models) with no consideration of directional variations in upstream fetch and surface roughness. While there have been a handful of studies that investigated or used directionally varying fetch and roughness (Wieringa 1976, 1980) it still reduces complex information about the positioning and geometry of obstacles in an environment down to a single quantity.

Later studies have worked towards developing a higher-dimensional view of the surrounding environment when considering its effect on atmospheric measurements. Two of the notable contributions towards this end were the works of Fujita and Wakimoto (1982) and Wolfson and Fujita (1989), hereafter referred to as FW82 and WF89, respectively. These studies used panoramic photography from measurement sites to provide both a visual picture of the surrounding environment and also leverage photogrammetry techniques to calculate the angle
above the horizon, referred to as obstruction angle, and the azimuthal width of objects relative to the measurement site. This provided significantly more detailed descriptions of local environments and reframed them in terms of a station relative framework.

FW82 and WF89 aimed to further characterize the effect of obstructions on observed wind speeds through development of transmission factor (TF, \( \psi \)), defined as:

\[
\psi = \frac{V}{U},
\]

where \( V \) is the observed measure wind speed and \( U \) is the maximum potential unobstructed wind speed. In this sense, TF is not dissimilar to GF as it represents the ratio of obstructed winds to maximum potential winds, whereas GF is the ratio of gust (in theory less influenced by obstruction) to mean wind speed, so the ratios are inverted. There are some assumptions built into this methodology. In brief, FW82 and WF89 assumed the maximum wind speed at a given time within a uniform network represented the maximum potential wind speed, given that all stations were subjected to the same mesoscale flow and transmission factors could be calculated for every other station. TF was established as a measure of site exposure by correlating observed TF values to obstruction angles from panoramic photos. They found an exponentially decaying relationship between the two, first expressed in FW82 as

\[
\psi = e^{-k_N \theta} = e^{-0.0948 \theta},
\]

and later refined by WF89 into

\[
\psi = a + be^{-k_N \theta} = 0.42 + 0.35e^{-0.18 \theta}.
\]

Calculations of TF and panoramic photography have subsequently been used in a multitude of studies as an indicator of azimuthally varying obstruction and related to variations in observed wind speed, turbulence, stability, and timing of transitions between phases in the atmospheric

While this methodology is definitely a step forward for classifying the local environment and linking it to observed spatial and temporal variations of atmospheric measurements, it still has some disadvantages. Panoramic photos can only provide information based on objects in the line of sight, there are no direct measurements of the height or distance of obstacles relative to a site, and the horizon identified by the underlying terrain is not always flat. This can result in some environmental factors not being fully represented by this technique.

In this chapter, we attempt to examine the influence of obstacles on winds, gusts, and gust factors by closely focusing on the local landscape and considering winds from given directions in concert with the obstruction angles that characterize those directions. We consider an anemometer in the center of a polar coordinate system, similar to FW82/WF89, and also consider wind direction subdivided into 360 intervals of one degree each. The mean winds and gusts approaching the instrument from each of those 360 directions have a path that may involve obstacles, which can be quantified in terms of their angles above the local horizon relative to the anemometer.

In an extreme case, the obstruction along a particular path may be so tall and impermeable that no wind can reach the instrument along that path. Obviously, the GF is undefined in such a case. In other situations, the winds may be slowed by less formidable obstacles, impacting the mean wind more than the gust, thereby increasing the GF. The obstructions may reside in the immediate vicinity of the instrument, or farther away, and thus were assessed at several scales relative to the station (similar to FW82/WF89). Obstacles of
variable distance and scale might be expected to have different influences on the winds, gusts, and gust factors.

What is needed is a way of measuring obstruction angles in an anemometer-centric coordinate system, along with their distance from the instrument. Ideally, data used to achieve this would be able to distinguish among topography, vegetation, and artificial obstructions, as well as possess sufficiently high resolution to identify the shapes and positioning of these with confidence. Medeiros and Fitzjarrald (2015) stated in their study of effects of sheltering on turbulent mixing that 30 m resolution topographic and land cover data were insufficient to properly identify the clearings some observations sites were sited in and to calculate the curvature of the underlying local scale topography. To accomplish this, we turn to airborne lidar data, a novel and largely unutilized dataset for meteorological purposes. Relating wind information to lidar-derived obstruction angles is the topic of this chapter.

4.2 Data and Methodology

This study is focused on assessing the relationship between surface wind observations and their local environment and as such the data leveraged fall into these two categories. Meteorological data from the NYSM and ASOS networks are utilized, though for the latter only data from stations in and around New York State (NYS) were used for reasons explained in the following section. Information about the local environment is derived from numerous sources including satellite and ground photography but is mainly centered around airborne lidar data. The details of these datasets and their uses are discussed below.

4.2.1 Surface Wind Observations

Observations of surface winds are the backbone of this study and previous chapters. They allow for calculations of gust factor, evaluation of station uniqueness against network averages,
comparisons between networks, assessing the influence of observation methodology on the final observation, and the correlation between observed wind flow patterns and the local environment. While these data have been used and discussed in previous chapters, details relevant to this study are reviewed here.

4.2.1.1 ASOS Observations

We consider ASOS observations the standard for surface meteorological measurements due to their nominal airport locations, anticipated good exposure (at least along runway directions), winds measured using sonic anemometers ostensibly mounted at 10 m above ground level (AGL), and theoretically conforming to WMO standards. While there are more than 850 ASOS stations across the CONUS, this portion of the study starts with the 36 sites in and around NYS, shown in Fig. 4.1, to provide a direct comparison to the NYSM. ASOS data are most easily obtained from NOAA’s Meteorological Assimilation Data Ingest System (MADIS). However, the standard format for MADIS ASOS observations is the Meteorological Terminal Aviation Routine Weather Report (METAR) that unfortunately has been found to seriously compromise the gust record (Gallagher 2016; Harris and Khal 2017; Fovell and Gallagher 2018). Therefore, as in other chapters in this dissertation, we utilize instead the one-minute resolution ASOS observations from the National Center for Environmental Information (NCEI), permitting us access to the complete gust record. As noted in Chapter 2 and 3, ASOS one-minute sustained wind speeds and directions actually represent samples averaged over the two minutes prior to the report.

4.2.1.2 NYSM Observations

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1 Each minute, the one-minute reports also provide the fastest 3-sec sample (i.e., gust) in the last 60 seconds along with its wind direction. These data are not employed in the present analysis.
The NYSM (Fig. 4.1, bottom) is a relatively young observing platform consisting of 126 “standard” stations that span across NYS and as such are much more densely spaced than nearby ASOS stations, often filling in its regional gaps. This higher density coupled with NYS’s complex geography results in a very different siting philosophy as NYSM stations are frequently placed in more forested or otherwise obstructed areas. While this difference between the two networks is not ideal for some applications it provides a valuable contrast and more localized information for other end users. All NYSM stations measure surface winds using both propeller and sonic anemometers mounted at 10 m AGL. For this analysis, we utilize 5-min observations provided by the Mesonet, consisting of 5-min averaged winds and wind directions.

4.2.1.3 Normalizing Wind Observations

There are many useful comparisons that can be made with the combination of ASOS and NYSM networks and the NYSM’s dual-anemometer observations. Unfortunately, there are several factors that make direct comparisons between the available observations difficult and require some processing to eliminate or mitigate. The differences between ASOS, NYSM propeller, and NYSM sonic observations and network configurations are summarized in Table 4.1.

The disparity in averaging interval between ASOS and NYSM -- two minutes and five minutes, respectively -- is the predominant first difference that requires addressing before a direct comparison can be made. Previous works have found that both observed gusts and GFs are sensitive to the averaging interval over which samples are gathered (Monahan and Armendariz 1971; Gallagher 2016; Harris and Kahl 2017). Unlike in Chapters 2 and 3, where we averaged readings over an hour, here observations are aggregated over ten-minute intervals. This shorter interval was selected because in our analysis the direction of the observed wind speed is
important to determining the obstacles that reside immediately upwind of the anemometer and averaging over longer time periods can muddle this. Thus, we opt to use the smallest common multiple of the two base averaging intervals, that being 10 min. Each set of observations are analyzed in their native averaging intervals when comparing stations within each network to each other or to the network average but are normalized to the ten-minute averaging interval when contrasting ASOS with NYSM.

Regrettably, there is an additional complication with the NYSM data that prevent straightforward comparisons between the differing anemometer types. Similar to the ASOS sonic anemometer, the NYSM propeller instrument’s gusts use a three-second average wind (that is reported every three seconds in the complete dataset) in conformance with the WMO standard definition. However, at and before this writing, NYSM sonic anemometers sample once per second but only report every third record, resulting in an incomplete record of ostensibly 1-s gusts. Differing gust durations have been shown in the previous chapter and other bodies of work (Durst 1960; Monahan and Armendariz 1971; Suomi et al. 2015) to have a profound effect on the reported gust (and therefore GF) value. While comparisons between the two NYSM anemometers may provide insight into how hardware influences the measurement of surface winds, we note that such comparisons are contaminated by comparing gusts of differing durations. This is partially compensated for herein via simultaneous, three-way comparisons including ASOS and both NYSM measurements, effectively comparing sonic 3-s gusts, sonic 1-s gusts, and propeller 3-s gusts, respectively.

Once disparities between the configuration of each set of observations has been addressed and eliminated, if possible, a data from the whole of 2017 (January 1st through December 31st) was obtained and utilized. These are the 1-min and 5-min records for the ASOS and NYSM,
respectively. While we recognize that while there are potentially significant seasonal or diurnal variations in how observed winds are related to their surrounding environment (e.g., Acevedo and Fitzjarrald 2001, 2003), we opt to aggregate observations over the entire year to assess the net effect the local environment has on the final observed wind speed and direction.

4.2.2 Airborne Lidar

4.2.2.1 History and Specifications

Airborne lidar data are collected using a sweeping or wide beam lidar unit mounted on the underside of low-flying aircraft flying parallel paths over a designated area to produce a high-resolution 3D cloud of points that can be used to visualize the terrain, vegetation, structures, and the general environment below. Points are identified as energy is emitted and returned to the unit recording their position in terms of X, Y, Z cartesian coordinates at minimum and optionally collecting true color (red, green, blue values, RGB) and return intensity. The vast majority of airborne lidar data are collected as part of the 3D Elevation Program (3DEP), a federal program that aims to provide high quality airborne lidar data across the contiguous US, Alaska, Hawaii, and Puerto Rico (CONUS+) (Dewberry 2012). The vast majority of lidar data available to the public are part of the 3DEP including older historical lidar data and especially data commissioned and collected after 2011 when the project was initiated.

The 3DEP program was designed to provide valuable information for industries like emergency management, transportation, and urban planning, but also has the potential to be extremely useful in understanding surface meteorological observations due to the detailed picture of the environment it provides. One of the major downsides of leveraging these data is its spatial scarcity or inconsistency. Sugarbaker et al. (2016) documented the progress and growth of the 3DEP, noting that approximately 36.4% of the CONUS had available lidar coverage as of 2016
while acknowledging it can be sparse in certain areas. This study focuses on the NYS not only due to the availability of meteorological observations from ASOS and NYSM but also because nearly full lidar coverage is available over NYS. The current coverage throughout NYS is shown in Fig. 4.2a, allowing for analysis of the local environment of 27 of our initial list of 36 ASOS sites and 114 of the 126 NYSM stations. While the proposed lidar projects for the Spring 2021 season (Fig. 4.2b) would fill in most of the gaps within Jefferson, Lewis, Oneida, Hamilton, and Steuben counties, these data are not yet available as of writing and this leaves twelve NYSM stations (largely in the Adirondacks) without lidar coverage. Although there are some lidar projects that cross state lines, the number of ASOS stations with lidar coverage is limited by the fact nine of the “near NYS” stations are actually outside of NYS, eight of which do not have lidar coverage.

The 3DEP program not only promotes expansion of lidar coverage but also guarantees a minimum level of quality assurance. All lidar data that are a part of the 3DEP are assigned to one of three quality levels that are determined primarily by resolution and accuracy (Dewberry 2012). These range in point densities from 0.5-8 points/m² and resulting nominal spacing between points of 1.4-0.35 m from the lowest to the highest quality levels (Q3-Q1). Lidar points have a vertical accuracy of ±0.1 m or ±0.2 m for quality levels 1-2 and 3 respectively. The 3DEP guarantees data with a minimum resolution approximately ten times higher than existing seamless elevation datasets, whose finest resolution is 1/3 arc second or 10 m resolution², allowing us to better assess nearby obstacles, their shape, origin, and potential efficacy in influencing upstream winds.

All 3DEP lidar data have several other additional common quality controls to further ensure their accuracy and consistency (Dewberry 2012, USGS 2021). Data are required to have a field of view (FOV) no greater than 20° from nadir, a minimum of 10% of overlap between flight paths, a minimum of 100 m buffer along target boundaries, no cloud cover between the aircraft and ground, and no snow cover. Additionally, data are typically gathered during spring (March, April, May) after snow cover has melted off, surface vegetation has been revitalized but not overgrown, and tree cover has budded but not fully leafed out. Alternatively, and less optimally, data are collected in the autumn (September, October, November) before snow cover develops but those may be affected by remnant leaf cover or suppression of surface vegetation from blankets of fallen leaves. All of these quality controls aid in ensuring the accuracy of the location data by not overextending the scope of the lidar beam, limiting significant noise or blockage of the beam, and gathering enough overlap to verify the positioning of reference points and structures.

Lidar data are stored online in a tile-based format with each project area broken up into cells in a fixed grid pattern. The size of these tiles differs among lidar projects and while related to the overall size of the project, the resolution of the points contained within them are not consistent. Lidar files are also quite large in terms of data storage, often containing tens or hundreds of millions of points within a single tile. In an effort to keep data storage and organization manageable, the tile in which each station resides was identified and downloaded along with surrounding tiles until a sufficient amount of data to fill the maximum distance of 2 km away was acquired (frequently resulting in a 3x3 square centered on each station). It should be noted a small number of stations were located at the edges of project areas and required the use of multiple lidar sources to provide a more complete picture of the surrounding environment.
in all directions. For these instances, the newest of the lidar sets were treated as truth and prioritized to cover as much area as possible. Older datasets were then used to fill in the gaps around the more current data and stitched together into a mosaic after ensuring the underlying topography from both datasets agree within 0.4 m (twice the vertical accuracy of lidar points) along the entirety of overlapping boundaries (100 m wide).

4.2.2.2 Standardizing Lidar Data

Similar to WMO standards for wind observations, lidar data have a nominal configuration but in reality, are highly heterogeneous, with individual project areas (seen in Fig. 4.2) having unique aspects that make them difficult to compare directly. Lidar data require a projection to serve as a framework for its positional data. Nominally, lidar data are measured using the Universal Transverse Mercator (UTM) projection and coordinate system. The UTM projection is a Mercator (cylindrical) style projection that splits the globe up into sixty north/south zones, each of which are 6⁰ longitude wide. The coordinates are measured in meters as Northing (y) and Easting (x), starting at zero at the equator for the former and at 500,000 at the central meridian of each zone (known as a “false easting” to force all positive values) for the latter. It should be noted Mercator projections distort areas at high latitudes and may experience some warping at mid-latitudes where NYS is situated but are considered adequately accurate for our study. NYS spans from approximately 79.75-71.94⁰W and UTM Zones 17-19 (west-east), with the majority of NYS located within Zone 18. It is a relatively common practice for lidar projects in NYS to be flown using an “extended” Zone 18, especially when the project area crosses or nears the borders between two zones, and this is the frame of reference we utilize in this study keep coordinates congruent.
While the UTM coordinate system is the nominal projection and meters the standard unit for lidar projects across the CONUS there are many projects that utilize alternative configurations. Some lidar data use the UTM projection but record position data using feet (including the “false easting”) while others use entirely separate geometric projections and reference systems. The most common variants (within NYS) are the State Plane Coordinate System (SPCS) and Albers Conical Equal Area (ACEA), both of which are ostensibly measured in feet but are occasionally listed in meters. The SPCS alternates between using Transverse Mercator (TM) and Lambert Conformal Conical (LCC) projections according to the aspect ratio of the state where the project is flown. While NYS typically uses a LCC projection for projects flown using SPCS there are numerous exceptions due to its nearly square aspect ratio. The ACEA is a relatively new variation of LCC used for limited area projects and leverages specialized reference coordinates. These projections differ greatly not only from UTM projection but also internally, with several project areas utilizing non-standard and unique true latitudes and/or standard longitudes.

Additionally, there are a wide variety of file formats the data can be recorded in. Lidar are ostensibly recorded in “.las” (LASer) format and contain all position, color, intensity, and classification data for each point. However they can also be archived in “.xyz”, “.xyzi”, “.pts”, “.txt” formats, each with their own subsets of data contained within the file and structure.

Altogether, this heterogeneity in available lidar data makes them difficult to work with, especially when performing analysis over larger regions that spans multiple project areas. For our analysis we aim to standardize lidar data to use the UTM extended Zone 18 projection with coordinates in meters stored in the “.xyz” (position data is priority but classification is appended whenever available) format whenever possible. This conversion was simplified and performed
using Corpscon v6.0 (US Army Corps of Engineers 2009) and FugroViewer v3.3 (FugroViewer 2021) to first convert the projection and units and secondly the file format and data structure, respectively. Unfortunately, there are some project areas that could not be standardized due to highly irregular SPCS and ACEA projections. After retaining only locations for which standardized lidar data were available, we are left with 112 NYSM and 20 ASOS NYS-area stations.

4.2.2.3 Quality Controlling Location Data and Reference Points

While the high-resolution 3D nature of lidar data makes it incredibly novel and useful it remains difficult to quantitively relate effectively 2D wind observations to each point in a 3D space simultaneously. We take an approach similar to that of FW82 and WF88 by focusing on the angle of each potential obstruction relative to the station. This approach allows us to concentrate on 2D quantities (direction and angle above/below horizon) making them easier to compare to wind observations while still retaining information regarding the 3D nature of the environment, since these obstruction angles are dependent on both height and distance from the station.

This station-relative methodology necessitates precise coordinates for the location of each station so the obstruction angle of each surrounding lidar point can be accurately calculated. Small shifts in the relative positioning can inflate or suppress the angles of terrain and other obstacles surrounding the anemometer. To that end the latitude and longitude coordinates for the NYSM and ASOS stations were imported and converted into UTM Zone 18 coordinates to match the standardized lidar files. The coordinates were then reconverted back into lat/lon and checked against available satellite imagery (Google Earth) and ground-based photography to ensure the accuracy of the reference coordinates. ASOS stations required significant adjustment,
on the order of 100 m, after conversion due to the limited precision of ASOS coordinates (hundredths of decimal degrees) but installations were relatively easy to identify from satellite imagery. The surface and aerial photography (ortho imagery) available on the NYSM website were quite helpful for gauging the position of the stations relative to their surrounding obstacles and assisted in the making of several small adjustments, on the order of 10 m, to the reference points.

Lastly the lidar point classified as ground (terrain) nearest each ASOS and NYSM station was identified, and its elevation (Z) coordinate recorded. Obstruction angles relative to each station were calculated using:

$$\theta_i = \tan^{-1}\left(\frac{Z_i - Z_{ref}}{\sqrt{(X_i - X_{ref})^2 + (Y_i - Y_{ref})^2}}\right)$$

(4.4)

for all lidar points within 2 km the station; where $X_i, Y_i, Z_i$ are the easting, northing, and elevation of each lidar point within the file; $X_{ref}, Y_{ref}, Z_{ref}$ are the easting, northing, and elevation of the lidar point identified as the reference point for the station; and $\theta_i$ is the resulting obstruction angle of the lidar point where positive/negative values indicate an obstruction above/below the horizon relative to the station. These points were separated according to their classification (when available) into these categories: ground (terrain), unclassified non-ground (vegetation, artificial structures, etc.), water, low level noise, and other unclassified. Only ground and unclassified non-ground points were retained and further stratified by their distance from the station.

We borrow the overall approach and terminology from FW82/WF88 relating patterns in wind observations such as average mean/gust speed, directional frequency, and GF (used here as a substitute for transmission factor) to the angle of obstructions above the horizon at three
different scales. Our analysis differs in that we consider not only the maximum angle above the horizon (restricted by line of sight) but also how the average obstruction angle, density of obstructions, and depth of obstacles vary in each direction. Additionally, we opt to redefine the radii of the three ranges to accommodate both the limited area of typical lidar projects and the data storage requirements accordingly: 0-50 m mososcale, 50-500 m misoscale, and 500-2000 m mesoscale.

4.2.2.4 Removing Noise and Unwanted Structures

Despite all the preprocessing performed, some of the lidar data were still not ready for comparison to surface wind observations due to the presence of residual noise, unwanted or unrealistic obstacles, or other errors. While the lidar point clouds were quality checked before archiving there are still some instances where points that do not exist in reality can be retained. Many of these issues are related to high-reflectance ground objects (smooth water surfaces, large glossy metallic objects, etc.), poor air quality (high density of smog or other particulates), or excessive clutter (swarms of birds, insects, blowing debris), all of which can interfere with the return of energy back to the lidar unit. These can generate points with abnormal intensities and/or positions.

Lidar files were checked for potential noise, which are typically designated as unclassified if they persisted through processing, by comparing the obstruction angle of each point to its ten closest neighboring points and its elevation against the elevation of the station reference point. If the obstruction angle of the point is greater than 30° above or below the horizon, or the elevation difference is more than 304.8 m (1000ft, the minimum safe altitude of small aircraft in congested areas, Federal Aviation Administration 2021) compared to the station elevation, then the point was flagged. Suspect points were subjected to a visual check using
satellite and ground photography (where available) to confirm if the point was realistic or represented noise. These thresholds were chosen to identify isolated noise points relative to neighbors or those located at the flight level of the aircraft. Notable examples where noise was identified and removed using this method are NYSM stations BURT (Fig. 4.3c,d) and WARW (Fig. 4.3e,f) which contain flight parallel noise (potentially from elevated lidar overlap) and reflective surfaces (from a nearby pond), respectively. Furthermore, each station is checked for large, potentially reflective objects using satellite imagery and, if identified, a stricter elevation test was performed for areas with these objects (involving comparison only to nearby ground points with an elevation threshold of 15 m). Further removal of potentially reflective points was hampered by the fact not every lidar project recorded the intensity of points making it difficult to separate low lying noise that can be introduced by dust, flocks of birds, and swarms of insects.

In addition to actual noise (i.e., points that do not exist in reality), there are objects and features we need to remove despite being real. Because of the high resolution of the lidar data it is often able to resolve features we considered to be too small to have much influence on the wind speed owing to a narrowness of width, depth, or vertical extent. Some of the most notable features identified in the lidar data that fit within this category are power lines, phone lines, and guy wires from nearby radio towers, as can be seen to the east of HART (Fig. 4.3a,b). These types of objects do not extend down to the ground like trees and buildings identified in the lidar data and thus should not exert the same degree of obstruction despite their apparent high angles above the horizon. Removing these actual but irrelevant objects can be difficult due to the fact that their heights are similar to obstacles such as trees. These problem objects were identified visually using top-down heat maps of obstruction angle, which were inspected for the presence of long parallel lines possessing similar angles above the horizon.
Occasionally, the equipment and fencing of the station itself can be identified in the lidar data, depending on if they were collected after the station’s installation and resolution of the data. This can result in the appearance of the station obstructing itself relative to the reference point. With the assumption that the setup of the station does not obstruct itself, we disregard all points within 10 m of the reference point. This radius was determined based on the width of the fencing and area where local vegetation is trimmed around NYSM stations. This has the added benefit of removing obstacles near the station location that may exist in the lidar data that pre-date some NYSM stations but were removed during the construction of the station.

Lastly, a handful of stations were discarded due to issues with the anemometer mounting. There is one ASOS station, KMTP, whose anemometer is reported online\(^3\) as at being mounted at only 5.8 m above ground level but site imagery suggests it may be mounted even lower. Either way, this non-standard height makes direct comparisons with 10 m standard winds complicated and can contaminate composites of ASOS observations. While NYSM does not have stations with non-standard anemometer mounting heights, there are five stations sited in and around New York City (NYC) (STAT, MANH, QUEE, BKLN, and BRON) that were all installed on rooftops. These are not true 10 m AGL winds. To ensure uniformity amongst observations, these stations were excluded from any additional analysis, resulting in a final total of 107 NYSM and 19 ASOS stations leveraged for further study.

4.3 Results

4.3.1 Comparison of Wind Observations

4.3.1.1 ASOS vs NYSM Observations

\(^3\) [https://www.weather.gov/media/asos/ASOS%20Implementation/windtower.xls](https://www.weather.gov/media/asos/ASOS%20Implementation/windtower.xls)
As noted previously, the ASOS and NYSM networks have fundamental differences in their siting philosophy and measurement methodology. This needs to be assessed before a fair comparison of wind observations to their respective environments can be performed. Figure 4.4a,b show the ASOS and NYSM (sonic anemometer) network average mean wind and gust speeds compared to each other in the native averaging intervals every ten minutes for a full year (N=50464). These were created as subsets from the 1-min ASOS and 5-min NYSM datasets, consisting of every other 5-min NYSM observation and every tenth 1-min ASOS reading, for 10-min periods in which both networks had valid data from at least 60% of their stations. The regression line shows that while there are some instances where the network average winds were more or less equivalent, mean wind speeds observed by the NYSM were on average 27.8% slower than those recorded at ASOS stations. This is not an issue since few of the networks’ stations are collocated and they sample the landscape differently (see discussion in Chapter 2) and thus there was no reason to believe the network averages would be equivalent.

However, the average gusts of the two networks agree more closely, with NYSM gusts being on average just 4.8% slower than ASOS. Yet, this is misleading owing to the difference in their reporting intervals, being 5-min for NYSM observations and 2-min for ASOS. We put the observations from each network on more even footing by taking the average wind and maximum gust of pairs of NYSM 5-min observations to get a 10-min mean wind speed and gust, respectively. Similarly, we averaged wind speed and took the maximum gust of five non-overlapping 1-min ASOS observations to produce equivalent 10-min mean wind speeds and maximum gusts. This transforms both dataset into 10-min mean winds and 10-min maximum gusts. After normalizing the averaging interval between the two networks (Fig. 4.4c,d), we
detect essentially no change in the hourly mean wind relationship (NYSM still being 27.8% weaker) but now the NYSM gusts are 13.2% slower than their ASOS counterparts.

The change in the relative gust magnitudes is due to increase of the ASOS network average gusts outpacing that of NYSM network average gusts. The average gust speeds increase within both networks due to the lengthening of the temporal window which increases the number of samples included within it and thus enhancing the probability of finding a larger gust value. Average gusts increase more for the ASOS network than NYSM because of the additional widening of the time window to create a 10-minute mean wind and gust, doubling of interval length for NYSM but quintupling it for ASOS. The important result, however, is that we still see that NYSM gusts are closer in magnitude to their ASOS counterparts than the NYSM sustained winds.

Next, a crude method was employed to compensate for the siting philosophies of the two networks by only considering stations in the NYSM that are considered by the Mesonet to be WMO class 1 or 2 with respect to wind observations (as well as retaining the normalized averaging intervals), shown in Fig. 4.4e,f. Using only the “best” sited NYSM stations helps closes the gap between NYSM and ASOS but does not completely eliminate it, with NYSM mean winds and gusts on average 20.3% and 8.3% slower, respectively. The relative discrepancy between relative winds and gusts between the two networks remain.

One of the potentially important differences between the ASOS and NYSM observations that helps to drive the disparity between their average mean wind speeds is the percentage of low wind speeds at stations. Here we define low wind speeds as those less than 1 m/s, which is not dissimilar to the 0.7 m/s threshold speed for the NYMS propeller anemometer (R.M. Young Company 2000). These low wind speeds are typically less impactful in terms of their associated
weather, have more variable or less consistent wind directions, and are difficult for NWP models
to predict (as shown in previous chapters). Approximately 40% and 60% of all NYSM stations
record low wind speeds more than 10% and 5% of the time, respectively, whereas only 5% of all
ASOS stations record low wind speeds more than 2.5% of the time. Furthermore, even the WMO
class 1 and 2 NYSM stations report low wind speeds for an average of 7.5% and a maximum of
17% of all observations.

Since even the best exposed NYSM stations are not exempt from frequent low wind
speeds, we further restrict the comparison between the networks to WMO class 1 and 2 NYSM
stations for observations greater than or equal to 1 m/s, shown in Fig. 4.4g,h. This restriction
again helps reconcile the two networks but does not completely eliminate the differences
between them, with the NYSM still 15.1% slower on average than ASOS and the gusts now
being nearly one-to-one, only 2.1% slower. This leads us to the conclusion that if we can assume
that ASOS stations are on average better exposed than NYSM stations, both mean wind and gust
speeds are slowed by obstructions but gusts are affected to a weaker degree than sustained wind
speeds.

4.3.1.2 NYSM Sonic vs. Propeller Observations

In the previous chapter, we showed that as gust duration (sample averaging interval)
increases, observed gusts and GFs decrease as intense short duration gusts are smoothed by
shouldering samples. Because of this, we can expect the gust and GF values of the NYSM
propeller anemometer to be on average lower than those from the sonic anemometer owing to
their use of 3 s and 1 s gust durations, respectively. Keeping this in mind, there are still
differences expected between the two instruments due to the mechanical aspects of how they
measure the wind, and their precision and threshold wind speeds. The propeller anemometer has
a threshold velocity of 0.7 m/s, precision of 0.166 m/s, and accuracy of ±0.3 m/s (R.M. Young Company 2000), whereas the sonic anemometer has no threshold velocity (except > 1 m/s is required for accurate wind directions), precision of 0.1 m/s, and accuracy of ±0.3 m/s (G. Lufft Mess und Regeltechnik GmbH 2021).

The binned distribution of differences between propeller and sonic readings drawn from 5-minute observations from all locations and times when both anemometers were reporting simultaneously are shown for both mean wind (blue) and gust (red) speeds in Fig. 4.5a. We can see that the propeller anemometer has a significantly higher percentage of readings in the slowest bin (4.2% and 2.5% for mean wind and gust speeds, respectively), likely due to its higher threshold velocity resulting in more calm or near calm observations. The propeller anemometer also reports relatively more mean wind speeds between 1-2 m/s and gusts between 1-4 m/s, which means the sonic anemometer records more mean wind speeds above 2 m/s and gusts greater than 4 m/s. This tendency for higher mean wind and gust speeds recorded by the sonic anemometer may in part due the drop off in high frequency signals captured by the propeller anemometer resulting from frequency truncation and higher response times and lengths (McBean 1972; Horst 1973; Francey and Sahashi 1979).

Another noticeable feature is the apparent sawtooth pattern in the gust difference distribution that reflects the fact there are far fewer propeller observations every third bin (every 0.75 m/s), (Fig. 4.5a). This is due to a discrepancy in how the precisions of each anemometer line up with the bin width of 0.25 m/s and changes shape depending on the bin size. This pattern is not seen in the mean wind speed because of the averaging of many samples together blends the discrete observations from the instrument. It is important to note that, for gusts, the sawtooth behavior obscures the apparent wind speed at which the gust differences shift from positive to
negative (meaning gusts at those speeds become more frequent in the sonic record). The first drop in frequency at 0.5-0.75 m/s is an artifact of the sawtooth pattern and does not represent the point at which the gust preference actually switches (at about 5 m/s).

The speed at which the difference frequency shifts from more propeller observations to more sonic observations is much lower for mean winds than gusts. The pattern of this shift can be better seen in the distribution differences of individual station observations. Figure 4.5b,c shows the same type of distribution differences for PENN and CROG, being WMO class 1 and 5 stations for wind, respectively, which represent the best exposed and most sheltered stations in the NYSM. At PENN, the frequency flips from more frequently propeller to sonic at 3 and 3.5 m/s for mean winds and gusts, respectively. In contrast, at CROG the frequencies flip at 0.75 m/s for the mean winds and 2.5 m/s for the gusts. This signal is a bit muddled for locations with slower average wind speeds due to the threshold velocity of the propeller anemometer forcing more slow but not calm wind speeds to shift towards the calm side, creating a switch back and forth between more and fewer propeller observations compared to the sonic. However, if we disregard frequency differences between 0.25-1 m/s, it becomes easier to properly identify the actual threshold where anemometer probability flips.

Overall, we can see that the sonic anemometer favors faster recorded mean wind and gust speeds than the propeller instrument. The average difference between the sonic and propeller anemometers is +0.23 m/s and +0.46 m/s for mean winds and gusts, respectively. While these differences are relatively small, they can be quite large at locations where wind speeds are on average slower (i.e., closer to our low wind speed threshold, 1 m/s). When we disregard low wind speed observations, the average difference between the two anemometers grows, increasing to +0.35 m/s and +0.7 m/s for the winds and gusts, respectively. The greater disparity in average
gust speed may be in part due to the gust duration difference between the anemometers but the preference for higher recorded wind speeds from the sonic anemometer we expected remains clear.

4.3.1.3 Directional Variation of Observations

Surface heterogeneities, whether they be large scale topographic features on the order of 100 km, smaller scale depressions and hills on the order of 1 km, or local obstructions <100 m, can have a strong influence on both observed wind speed and direction (Medeiros and Fitzjarrald 2015; Weerasuriya et al. 2018; Uchida and Ohya 2003). All these obstacles can channel, divert, split, and reverse wind flows depending on the geometry of the obstacle, its size, and the position of an observation point relative to the upstream wind direction (Liu et al. 2011). Thus, we theorize that sudden shifts in wind direction frequency or speed can be indicative of obstacles in the surrounding environment. However, as we stated previously in Chapter 2, it is difficult to determine the degree to which an observation is modified by its surrounding environment versus representing the natural unobstructed wind climatology. This is extremely problematic for observations in isolation with no other points of reference to compare variations in observed wind and surrounding environment. While imperfect, we aim to compare several NYSM stations of differing exposure and pairs of NYSM and ASOS stations in relative proximity to each other, to assess how obstacles can influence the variability of wind speed and direction.

For this section the local environment and presence of upstream obstacles are identified through the use of orthoimagery available through the New York State Digital Orthoimagery Project (NYSDOP, NYS Department of Cyber Security 2013). Presently only the existence upstream obstacles are considered to relate them to directional changes in wind. Airborne lidar
will be leveraged in the following section to compare to orthoimagery and quantify the degree of obstruction each obstacles imposes.

Orthoimagery confirms that PENN is a very exposed station (Fig. 4.13a) and its wind rose (Fig. 4.6a,b) reveals it has a clear preference for winds between the SSE and NW. We note the cut off in observations on the NW end is more gradual whereas the drop off in frequencies on the SE end is much more rapid and drastic. All the directions frequently observed at PENN appear to be from a general downslope perspective as wind flow in a general west to east direction is toward the lower elevation at the edge of Seneca Lake. With the exception of the sharp cutoff in wind observations to the SE, this fairly even “fan” pattern is thought of as a typical climatological wind influenced by large scale terrain and weather patterns. HART is a well exposed, WMO class 2 station that has some further removed trees and nearby radio towers that provide obstacles of unknown influence (Fig. 4.13c). The wind (Fig. 4.c,d) roses look fairly similar to those of PENN with the majority of winds coming from between S-to-NW directions, but also with a smaller frequency spike to the north and more gentle drop-offs in frequency on both sides of the “fan”. It makes sense for HART to have a similar wind rose to PENN as they are both well exposed and reside in the Finger Lakes region of NYS, likely sharing a similar large-scale weather climatology.

We consider GFAL (Fig. 4.13e) as having average exposure for an NYSM station (i.e., using GF as a proxy for station exposure, this station has an average GF) and is designated WMO class 3 with regards to wind exposure, although the average WMO classification of NYSM stations is 2.05. In Figure 4.6e,f we start to see a transition from the “fan” of preferred wind directions to a narrower fan with a few peaks in frequency concentrated into certain directions. The strong preference of southerly winds at GFAL is a result its location within the
Hudson River Valley, specifically at the northern end of a sharp westerly bend in the river valley that can promote up-valley southerly winds. From these three stations we can see a general trend of wind directions becoming more limited as WMO class increases and exposure decreases, thus far in keeping with our hypothesis that greater degrees of obstruction will result in more noticeable shifts in wind speed and direction.

While differing in their WMO classification, these three stations are all fairly well exposed, using GF as a proxy for station exposure, for each of their respective WMO classes. In contrast, WBOU (Fig. 4.13d) and SARA (Fig. 4.13f) are WMO class 2 and 3 stations whose GF would indicate a higher degree of obstruction, and DUAN is a class 4 station. The wind rose at WBOU (Fig. 4.7a,b) has three preferred wind directions: from the WSW, NNW, and ENE. Unlike the previous stations there is no prominent wide swath of commonly occurring wind directions, but it is suspected that the weak webbing of frequencies between the WSW and NNW directions (255-335°) would have more closely resembled the broad fan of better exposed stations if not for the tree line that encroaches on the station from the WNW (discussed in the following section shown in Fig. 4.10). These present a barrier to winds coming from these directions and while the winds are not significantly slower from the WNW compared to the surrounding peaks the frequencies are much smaller promoting the idea that winds are being diverted around the obstacles nearest the station.

We can see similar features at SARA (Fig. 4.7c,d) including a peak in wind direction frequency from three distinct directions and a “webbing” of reduced frequencies that span between two of them. Here winds are most likely to be observed from the WNW, NW, and ESE, with the gap between 300-315° having fewer observations than the bookending peaks but are relatively more common than compared the remainder of the wind rose. SARA is located near
Saranac Lake and is in the northeast corner of the Adirondack Park along a fairly steep NW/SE terrain gradient. This would suggest that the predominant flow is actually bimodal at SARA, being generally out of the WNW/NW or ESE as winds flow downslope or upslope, respectively. The gap in wind frequency between 300-315° is potentially caused by a nearby obstacle similar to WBOU, albeit with a much thinner azimuthal width, that causes winds to be diverted to the NW and slowed considerably before reaching the anemometer.

At DUAN (Fig. 4.7e,f), winds are distinctly bimodal with the vast majority of winds coming from either the WNW or ESE, two opposing directions. It is difficult to say if wind directions are oriented this way because of its proximity to the Mohawk River Valley and flow parallel to it, the local terrain SE/NW terrain gradient and winds flow up/down slope perpendicular to it, some local channeling from obstructions, or a combination of these. Overall, while there are stations that prove to be an exception to the rule like OLDF (not shown), it appears that as the degree of obstruction at a station increases the more selective wind directions tend to be.

ASOS stations located near NYSM stations can provide insight into the relative contribution of weather climatology, large scale environmental forcing, and local environmental exposure by contrasting the two. The ASOS stations KPEO (Fig. 4.14a), KELZ, and KGFL (Fig. 4.14b) are located 5.5 km, 27.5 km, and 0.72 km away from PENN, HART, and GFAL, respectively. The wind roses for these ASOS stations are shown in Fig. 4.8. The winds at KPEO (Fig. 4.8a,b) at first glance appear quite different to those at PENN, given they are much more constrained to the SSW direction. However, while winds are not as frequent between 225-315° they are still 2-3 times more likely than the NE sector at both PENN and KPEO. Despite the close proximity of these two stations the difference in their preferred wind directions is likely
due to their locations relative to the large-scale environment. The NYSM station PENN is situated on the western shore of Seneca Lake while KPEO is located on the SE of the northern tip of Keuka Lake. This means that at PENN the most prevalent wind directions come from over land whereas the dominant wind direction at KPEO is aligned with the long fetch of Keuka Lake which provides a very long and smooth fetch, promoting strong winds in line with its orientation.

The wind roses of KELZ (Fig. 4.8c,d) and HART, despite being the furthest apart, are surprisingly similar. Both generally favor winds between 135-315° with a slight preference for winds from the SW. There are a few differences like the larger prevalence of winds from the southeast and a lack of northerly winds at KELZ compared to HART. The former of which is likely due to the airport KELZ is sited at being on a localized hill/plateau with a relatively strong NW/SE terrain gradient sloping down away to the SE promoting upslope winds from that direction.

Lastly, KGFL (Fig. 4.8e,f) appears quite similar to GFAL (Fig. 4.6e,f) with a few small exceptions. This resemblance is unsurprising considering KGFL and GFAL are the closest pair of ASOS and NYSM stations, being sited on opposing sides of the same airport. Both stations have a strong preference for southerly winds coming up the Hudson River Valley and a weaker peak of wind from the NE that runs parallel to the smaller stream and terrain gradient to the SE of the airport. Compared to GFAL, KGFL has a weaker tendency for winds between 225-270° and a stronger preference for NNW winds. This is the result of the 720 m displacement of KGFL to the SSW of GFAL, moving it closer to trees surrounding the airport on the west side but exposing it to the longer unobstructed fetch to the north along the nearby runway (Fig. 4.14b).

Overall, we can start to see how smaller, more localized features influence the variation of wind directions and speeds at stations. Generally, the more well exposed a station is, the larger
the directional range and variation of wind observations are. Large scale terrain features such as major mountains, foothills, rivers, and valleys can restrict or dominate the wind flow at a station but in the absence of these features sharp or sudden changes in wind direction frequency and speed can reveal potential obstruction, diversion, or channeling of winds by the local environment.

4.3.2 Characterizing the Local Environment with Airborne Lidar Data

Previous mentions of the environment and its influence on the observed wind patterns at specific locations were assessed through satellite imagery and coarser topographic maps, which are helpful for identifying larger-scale topographic gradients and the presence of potential obstacles. Airborne lidar data allows us to resolve finer objects in the local environment better identifying small terrain changes and providing quantitative 3D information for each object unlike the 2D top down or panoramic perspectives that photography gives us. The only drawback is that it is difficult to fully visualize 3D environmental data (especially in a non-interactive medium), thus we elect to represent the lidar data in terms of top-down heat maps of obstruction angle. This method preserves information pertaining to each points height relative to its distance from the station and simplifies the 3D nature of the data. These heat maps can be compared to orthoimagery to see how well the airborne lidar data captures the presence and positioning of obstacles.

Figure 4.9 shows heat maps, with red/blue indicating objects above/below the horizon relative to the reference elevation and position for each station, for two NYSM stations, PENN (left column, a-c) and OTIS (right column, d-f), at three ranges away from the station. These stations are both WMO class 1 but differ in their GF values\(^4\), 1.38 and 1.94 respectively.

\(^4\) GF values were calculated using the NYSM data in its native 5-min averaging interval.
suggesting PENN is better exposed than OTIS. Both stations do not have many if anything in the way of obstacles within the closest 50m (mososcale, Fig. 4.9a,d). At this range, only the immediate local topography is visible with the exception of some farming equipment 10 m to the south of PENN and a few sparse shrubs at OTIS (three small clusters of 2⁰ to the NW, NE, and SE). The terrain at PENN is gently sloping downwards from west to east at about ±2⁰ relative to the station, while the topography at OTIS shows the station situated on the south end of a small hill to the north and opposite another small hill to the south, but slopes are still small at about ±3⁰ relative to the station.

There are significantly more features to observe within the 50-500 m (misoscale, Fig. 4.9b,e) range (comparable to Fig. 4.13a,b). At PENN there are still very few non-terrain obstacles with the most notable objects being a couple barns and sheds 200 m to the east and a farmhouse surrounded by a few trees to the 440 m to the SSE. Unlike PENN, the misoscale environment surrounding OTIS is rife with obstructions and is completely surrounded by trees in all directions, albeit at varying distances away with the closest being about 85 m to the west and northeast and the furthest 340 m to the SSE. The heights of these trees combined with their varying distances give them obstruction angles ranging from 3-11⁰ above the horizon and pose a much higher degree of obstruction than any obstacle seen at PENN. Even if there are gaps between the edge of the tree line and the anemometer to allow for winds to be vertically mixed down to the surface or for horizontal wind speeds to recover some momentum, it is highly unlikely that the observed wind at OTIS is unaltered by its surroundings.

What is rather surprising -- other than the fact both of these stations are classified as WMO class 1 -- is how the lidar suggests that OTIS does not meet the WMO criteria for a class 1 designation. The WMO guidelines state that a class 1 wind station should have no obstacle with
an angular width greater than $10^\circ$ within thirty times of its height of the station, which translates to an obstruction angle no greater than $2^\circ$ above the horizon. Just taking the $45^\circ$ sector residing southwest and west of OTIS, the tree line is on average $8.8^\circ$ above the horizon, not only well above the limitations for a class 1 station but also even failing to meet the requirements of a class 2 station (i.e., no objects with obstruction angles under $6^\circ$). Further away, 500-2000 m from the stations (Fig. 4.9c,f), obstructions angles grow smaller as objects are increasingly distant and not correspondingly higher to compensate. This means most objects more than 500 m away are not typically visible and are often blocked by closer objects or the horizon itself if the terrain drops away from the reference point.

While PENN and OTIS showed us that there could be significant disparities in the prominence of surrounding obstacles within the same WMO classification, we still expect obstacles to become more numerous, taller, and located closer to each site as WMO classification increases. Figure 4.10 shows the environments around HART (GF=1.47, left column, a-c) and WBOU (GF=1.88, right column, d-f), stations with the second lowest and highest GF among WMO class 2 NYSM stations. HART was shown previously in Fig. 4.3a,b as an example of a station with an object whose degree of obstruction was over inflated by the lidar data. The radio tower to the east of HART has been partially but not completely removed by our methodology for eliminating unwanted objects because the base of the radio tower, the fence guarding it, and the anchors for several guy wires are still visible as larger obstruction angles to the east and northwest, respectively. Apart from the radio tower other unwanted objects such as power and phone lines can be seen. These can be identified by the N/S trail of slightly positive and $0^\circ$ running N/S just east of the station that cross the location of the radio tower (providing power), and also the evenly spaced solitary points of larger positive obstruction angles (poles of the
power/telephone lines) that run approximately W/E just north of the station. These points lower to the ground were not removed for fear the algorithm would start to eliminate other obstacles with similar obstruction angles within the mososcale and misoscale ranges. The intention is for these angles to not appear significantly larger than the maximum obstruction angle from other objects that are more effective at slowing wind speeds, which will become the focus of this study in later sections.

We are more concerned with are the trees surrounding HART in each direction (Fig. 4.10b, comparable to Fig. 4.13c). These tree lines each vary in their distance to the station and their angle above the horizon, with the eastern line being the closest (175m), tallest (5°), and unbroken lines of trees. The trees to the west are very similar in their density and height but are further removed and therefore closer to the horizon. Trees to the north tend to be more scattered and do not form a solid line, while the trees to the south while denser and thicker are kept closer to the horizon by downward sloping terrain.

The immediate environment around WBOU (Fig. 4.10d), unlike HART, is completely clear with only fairly steeply sloping terrain, -7.5° (SE) to 5° (NW), visible. Further away at the misoscale range (Fig. 4.10e, comparable to Fig. 4.13d) numerous obstacles fill the environment, including several tree lines and the NYS Department of Corrections’ Sullivan Correctional Facility. The correctional facility can be seen in the circular shape that represents the surrounding fencing to the SW of the station and fairly small positive and negative obstructions are seen because of the downward sloping terrain. The forest clearing WBOU is situated in provides the station some long open, albeit skinny and winding, fetches. The fetch to the southwest is actually fairly wide and long but contains the correctional facility which may present an obstacle despite its low obstruction angles. Whereas the fetch to the ENE is thinner
and clear of obstacles but the topography slopes up noticeably from the south to north, so the fetch is not flat. Despite these openings, the forest encroaches on WBOU from the NW and SE, obstructing both sectors rather heavily. The trees to the northwest are the most prominent relative to the station reaching up to 15° above the horizon to the west and north where the tree line curls inward towards the station raising the obstruction angle by shortening its distance to the station. Similar to PENN and OTIS we can see a clear disparity between the degree of obstruction expected at stations with the same WMO classification but diverging GFs. Similar to HART and WBOU, GFAL and SARA (Fig. 4.11) are the second lowest and second highest GF NYSM stations, 1.61 and 2.09 respectively, except for the WMO class 3 stations instead of class 2. Because of their classification, we expect there to be a larger abundance of taller obstacles in their surrounding environment. The immediate environment around GFAL (Fig. 4.11a) resembles the nearby environment of the class 1 stations with no non-terrain obstacles and only the local southeast-to-northwest slope of the terrain visible. The lack of points in a path 28 m to the northwest is a drainage creek for the nearby airport and appears this way because we discarded any points that were identified as water. This creek varies between 3-5 m wide and is difficult to discern on satellite imagery or typical topographic maps (≈10m highest resolution), highlighting the level of detail airborne lidar data can provide. Unlike GFAL, SARA has a significant number of obstacles within 50 m of the station (Fig. 4.11d). These are largely small trees or shrubs that range between 5-13° above the horizon due to their proximity to the station rather than their height. Some are as close as 15 m to the north, while others are slightly more distant, 20 m and 30 m to the southwest and west, respectively. While no direction is perfectly open, the direction with the fewest and most isolated obstacles lies between 45-180°, NE-S. These represent only small clusters or lone standing
obstacles, and thus may be considered “thin” according to the WMO siting standards, but the same cannot be said of the major tree line that encroaches on the station from the southwest, coming within approximately 33 m of the station and rising 20° above the horizon.

Similar to the NY SM examined earlier, GFAL and SARA have markedly more obstructions in the misoscale range. At GFAL (Fig. 4.11b, comparable to Fig. 4.13e), we can see the airport buildings 200 m to the west, a cluster of trees 280 m to the north, closer clustered vegetation 70-200 m to the south, what appears to be a cluster of trees or other vegetation 200 m to the east, and the underlying terrain still sloping from the southeast to northwest. The most prominent of these obstacles are the vegetation to the south and east for which obstruction angles vary between 7.5-10° above the horizon. However, it is important to note that after comparing the obstructions indicated to the east to station imagery, and comparing their obstruction angles to the underlying terrain, it was determined this apparent obstacle to the east is merely low-lying vegetation that was not classified as such, as its obstruction angles of about 7.5° barely differ from the underlying terrain. This is an important aspect to consider in the analysis of lidar data, that non-terrain obstructions inherently depend on the background topography that can act to inflate the perceived degree of obstruction of short objects or suppress the influence of taller objects, like the airport to the west whose obstruction angles are only 2-3° above the horizon because of the lower elevation in that direction.

The misoscale environment at SARA (Fig. 4.11e, comparable to Fig. 4.13f) is nearly completely saturated by forest with trees surrounding the station in all directions with a few notable pockets. The tree line to the southwest that crossed into the mososcale range has the largest obstruction angles of 15-19° above the horizon but all of the surrounding trees present significant obstructions dropping no lower than 10° above the horizon. The only exception to this
is the E-SE directions where there is a gap in the tree line (for road and personnel access) and the line of sight does not intersect with the forest until 100-180 m away, resulting in obstruction angles of only 5° above the horizon. Because of the general uniformity of the obstacles surrounding SARA, their obstruction angles slowly decrease the farther away from the station they get, resulting in a sort of “hot spot” closest to the station.

As with the previous station pairs, the mesoscale environment (Fig. 4.11c,f) does not reveal any more prominent obstacles that were not visible in the misoscale range. At this spatial scale it is highly unlikely for an object to be sufficiently tall to pose a larger threat of obstruction than those within 500 m of the station. Rather, the mesoscale obstructions can provide a good idea of larger-scale fetch similar to what a numerical model may be able to resolve. We anticipate that problems can arise when verifying forecasts to observations if there are significant disparities between the relative exposure at these two scales.

The airborne lidar provides us the opportunity to better examine the prominence of obstacles in the local environment that we previously hypothesized were the cause of observed differences in wind speed and direction between pairs of NYSM and ASOS stations. Figure 4.12 shows the lidar heat maps of obstruction angles at all three ranges for ASOS sites KPEO (left column, a-c) and KGFL (right column, d-f). Like most of the stations we assessed before, the misoscale environment shows little besides the immediate slope of the terrain around the stations. The ground slopes downward from southeast to northwest at KPEO (Fig. 4.12a), as elevation decreases towards the nearby lake, and gently falls away in all directions but north around KGFL (Fig. 4.12d) owing to its location just to the south of one of the runways.

The misoscale environment at both ASOS stations looks quite different compared to their NYSM counterparts. There are numerous prominent tree lines observed at KPEO that span from
0-135° and 270-315° that are 70 m and 135 m away respectively (Fig. 4.12b, comparable to Fig. 4.14a). While the obstruction to the northeast side of the station may be inconsequential if winds are already much less likely to originate from those directions as indicated by the wind rose at PENN, northwest winds are far less common at KPEO than PENN, likely due to the cluster of trees to the northwest (compare Fig. 4.9b with Fig. 4.12b). It is less clear if the lack of southerly and southeasterly winds at KPEO compared to PENN is due to the presence of farther removed buildings and lines of trees associated with the airport or such winds would instead be shifted and channeled from the southwest due to the larger scale forcing from Keuka Lake.

Contrary to the case of PENN/KPEO, the misoscale environment at KGFL (Fig. 4.11b comparable to Fig. 4.14b) is much less complicated than that of GFAL (compare Fig. 4.11b with Fig. 4.12e). The ASOS station is located near the intersection of the runways, which are visible as straight lines of small positive obstruction angles. Overall, the environment is devoid of any notable obstacles or elevation changes between 290-180° (WNW-S) except for the surrounding forest that is most prominent to the southwest-west of the station. This is the likely cause for the smaller prevalence of southwest and westerly winds at KGFL compared to GFAL and further highlights that scattered trees about 215 m away and 3° above the horizon on nearly flat terrain are more effective at slowing or diverting winds than man-made buildings approximately 160 m away and 2.5° above the horizon but on terrain that slopes down away from the station.

Similar to stations previously examined, obstruction angles in the mesoscale environment tend to be smaller than those in the misoscale range since objects are farther away from the station but not significantly higher to compensate (Fig. 4.12c,f). The mesoscale environment around KPEO shows the size and scale of a few obstacles whose tips fall inside the misoscale range, including multiple N/S oriented buildings and tree lines that run parallel to the airport.
runway to the south, and the tip of Keuka Lake 1500 m to the west. The environment within 2000 m of KGFL appears very similar to that of GFAL showing the overall footprint of the airport within the surrounding forest. While the obstruction values of the surrounding trees may be different due to the small displacement between the two stations, they are both generally less than 4° above the horizon. The more significant difference is the positioning of the ASOS station near the runway, aligning it better with the large open fetch to the north and south and helping favor those wind directions.

4.3.3 Relating Wind Observations to the Local Environment

4.3.3.1 Qualitative Analysis

Previous sections showed that while WMO wind classifications provide a general idea of station exposure they often have significant variability with respect to the prominence, distance, and ubiquity of nearby obstacles within each class. Furthermore, we showed that airborne lidar can be utilized to create high-resolution 3D snapshots of the local environment and provide a much more detailed assessment of the local environment and how it relates to observed wind patterns. Thus far, our initial comparison of lidar heat maps and observed wind roses showed how the presence of obstacles can divert, weaken, or channel surface winds. Our larger goal is to test our hypothesis that GF can be used as a simple proxy for site exposure and relate both GF and observed wind speeds to obstructions identified in the airborne lidar with higher precision and detail than in previous works.

Our approach is similar to that of FW82 and WF88 in comparing azimuthal variations in obstruction angles to GF (instead of their transmission factor $\psi$) both qualitatively and quantitatively. Utilizing the lidar data gives us the distinct advantage of being able to document more of the environment than just line of sight allows, letting us see above and below the horizon.
and calculate the maximum ($\hat{\theta}$), minimum ($\check{\theta}$), and average ($\bar{\theta}$) obstruction angles, from all sources (ground and non-ground), along a sight line with a given width away from the station. 

**Figure 4.15** shows the azimuthal variation of $\hat{\theta}$, $\check{\theta}$, and $\bar{\theta}$ in the misoscale range every 1° azimuth around the station, and average GF every 5° azimuth, for NYSM stations OTIS, WBOU, and SARA. From here on out in our analysis we elect to ignore observation times from both networks and all stations that report wind speeds less than 1 m/s (“low wind speed”). This was done to prevent extraordinarily high values of GF (approaching infinity as wind speeds become calm) from contaminating average quantities due to observed prevalence of low wind speed observations in the NYSM. Obstruction angles are all calculated relative to the individual station reference point with flat being along the horizon (0°) and GFs are gauged relative to the overall station average GF -- both indicated by thicker black circles.

As we discussed earlier, OTIS is a WMO class 1 NYSM station that, while completely clear in its immediate environment (mososcale), is entirely surrounded by trees in the misoscale environment (**Fig. 4.9e**). These trees are the source of the large maximum obstruction angles that vary between 2.5-11° above the horizon (depicted by the red path seen in **Fig. 4.15a**). The average obstruction angles (blue path) of all points along each direction at this range are overall much smaller, between -1-3°, and the minimum obstruction angles (magenta path) are all less than zero (below the horizon) due to the gentle sloping away of the terrain away from the station. The maximum obstruction angles are largest between 225-295° (SW-WNW) and 0-45° (N-NE) while the average obstruction angle peaks between 210-260° (SSW-WSW).

These peaks in obstruction angle match up well with higher GF values (**Fig. 4.15b**), relative to the station average, of 2.18-2.19 to the north-northeast and west. The most prominent depressions in GF, relative to the station average, of 1.6-1.8 to the south and east of the station
are well matched with lower values of maximum obstruction angle. The agreement in the spatial patterns of maximum obstruction angle and GF support the idea that the maximum obstruction is the dominant and limiting factor for observed wind speeds at a station, and these tend to reach a maximum within the misoscale environment.

We can see a similar agreement between the azimuthal patterns of maximum obstruction angle and GF at both WBOU (Fig. 4.15c,d). Unlike OTIS, the tree lines surrounding WBOU are broken and segmented, encroaching closest to the station to the west and north while leaving long, skinny, and nearly open fetches to the SSW and ENE. These directions match up well with corresponding maxima and minima in both maximum obstruction angle and GF from those directions. The closest tree line that spans from the west to north of WBOU has a nearly constant maximum obstruction angle of 10° above the horizon but shows two small local maxima at 280° and 5° of about 14° and 13° above the horizon, respectively. This matches well with the GF pattern in the NW sector where GF increases starting at the average value of 1.9 from the W, rising to 2.4 from the WNW, decreasing back down to 1.95 from the NNW, and increasing back to 2.3 from the north. This wave pattern, while potentially out of phase by a few degrees of azimuth, agrees with the structure of the tree line reflected in the obstruction angles as GF increases/decreases as the tree line approaches/recedes away from the station and the maximum obstruction angles increase/decrease. Additionally, maximum obstruction angles fall as low as 0° and 2.5° along/above the horizon in the directions of the longer more exposed fetches to the SSW and ENE where GFs are also at a local minimum value of 1.4.

In contrast to the previous two sites, there is still a large degree of concurrence between maximum obstruction angles and GFs at SARA (Fig. 4.15e,f) but there are also a few places that appear out of phase or not fully in agreement with each other. SARA, like OTIS, is completely
surrounded by forest in all directions (Fig. 4.11e) but experience local minima and maxima in distance from the station from the SW/NE and NW/SE, respectively. These directions match up with local maxima and minima in average GFS with values of 2.4 and 2.2 to the SW and NE, and 1.55 and 1.6 to the NW and SE. The GF pattern follows the maximum obstruction angles quite well to the SW and SE with the enhanced GF values spanning the area between 180-270° (S-W), similar to the maximum obstruction angles, and both reaching a minimum around 110° (ESE).

However, maximum obstruction angle and GF disagree somewhat over the precise width and placement of the maximum and minimum to the NE and NW. The swath of larger GFS to the NE of SARA span from 0-90° (N-NE) whereas maximum obstruction angles only maintain their local maximum value of 15° between 45-60° (NE-NNE), dropping steadily more towards the north and rapidly towards the east down to 10° and 5°, respectively. Lastly, the local minima of maximum obstruction angle and GF are slightly misaligned from the NW, located at 305° and 315°, respectively. This offset in direction may be, in part, due to obstructions in the mososcale environment to the northwest of the station. We theorized earlier that gap in these clusters of trees could result in channeling and redirection of wind speeds, thus the misoscale minimum in obstruction angle may not align perfectly with the direction mososcale obstructions divert winds before they ultimately reach the station.

Despite ASOS stations in general being better exposed and having fewer and less prominent obstructions than NYSM stations, similar relationships between maximum obstruction angles and GFS can be seen at KPEO and KGFL as shown in Fig. 4.16. The area around KPEO is on the whole very flat, given its proximity to Keuka Lake, and this is revealed through the relatively tight spacing among the maximum, average, and minimum obstruction angles surrounding it (Fig. 4.16a). Major deviations occur when the maximum obstruction angle
increases away from the minimum and average (which is typically around \( -2-0^\circ \)) before returning back towards it, in contrast to other stations for which maximum obstruction angles are almost always above the average. These peaks in maximum obstruction angle occur to the WNW, NE, SSE, and SSW, and are associated with prominent clusters and lines of trees as well as smaller lines and clusters and lines parallel to the nearby runway as we previously discussed (see Fig. 4.12b). The more notable obstructions to the WNW and NE reach maximum obstruction angles of \( 6^\circ \) and \( 5-10^\circ \), respectively, and are accompanied by rises in GF to 1.4 and 1.6, which are large relative to the station average of 1.32 (Fig. 4.16b).

Maximum obstruction angles at KGFL (Fig. 4.16c) are small compared to stations we have previously looked at, but what few deviations above the horizon there are match well with observed average GFs. Between the southwest and west of KGFL, the surrounding forest starts to appear closer to the station in the misoscale environment (see Fig. 4.12e), resulting in maximum obstruction angles between 2-3.5\(^\circ\) above the horizon. While relatively small, these obstructions do represent a notable increase in the maximum obstruction angle from the average which rests almost exactly on \( 0^\circ \) and coincide with larger GFs between 225-285\(^\circ\). These GFs peak around 1.35 and exceed the station average of 1.27 (Fig. 4.16d). There is another peak in GF, albeit much narrower and weaker in magnitude, of 1.3 to the south of the station that cannot be explained by obstructions within the misoscale environment and may instead be related to the mesoscale environment.

4.3.3.2 Quantitative Analysis

4.3.3.2.1 NYSM Analysis

Our analysis thus far has shown that there are significant azimuthal variations in both maximum obstruction angle and GF that are often in phase with each other, reinforcing the idea
that obstruction and GF can be related. In FW82/WF88, it was found transmission factor ($\psi$) had
an exponentially decaying relationship with obstruction angle above the horizon. We aim to see
exactly how GF, mean wind speed, and gust speed all quantitatively depend on maximum
obstruction angle. Additionally, we further seek to differentiate the relative contributions of the
surrounding terrain and non-ground obstacles on wind observations from each other.

Figure 4.17 shows scatterplots of the maximum obstruction angles from ground (left
column, a,c,e) and non-ground (right column, b,d,f) sources in the misoscale environment
plotted against average GFs every 1° around NYSM stations OTIS, WBOU, and SARA. Average
GFs were calculated by taking the average of all GFs with wind directions within 0.5° azimuth of
each whole 1° around the station, resulting in 360 average GFs to match with obstruction angles.
We opt to focus our analysis at the 50-500 m range as that appears to be where maximum
obstruction angles peak most frequently but acknowledge that obstructions can be more
prominent at mososcale and mesoscale ranges at specific locations and will show or note that
whenever that occurs. Despite their differing WMO classifications (1, 2, 3) and station average
GF values (1.92, 1.88, 2.09), we can see similar patterns in the relationship between maximum
obstruction angle and average GF at all three stations. For each station, the correlation between
average GF and maximum obstruction angle from non-ground obstructions (trees, vegetation,
buildings, etc.) is much stronger compared to obstructions from terrain. At all three stations,
there is a positive relationship between the maximum obstruction angle from a given direction
and that direction’s observed average GF, so as obstructions rise higher above the horizon, the
observed GF grows larger. The amount of scatter around each regression line varies among
stations with OTIS (Fig. 4.17b) having the least amount of scatter and SARA (Fig. 4.17f)
showing the most. The reason SARA shows more scatter than other stations may be due to
obstructions in the mososcale environment we discussed previously that further obstruct or channel winds before they reach the anemometer.

The relationship between maximum terrain obstruction angles and average GF varies much more among the sites. Both OTIS (Fig. 4.17a) and WBOU (Fig. 4.17c) appear to have a weak but positive relationship between terrain obstruction angle and average GF. At OTIS, this is driven by a few dozen points whose obstruction angle is greater than 1° above the horizon whereas GF at WBOU has an almost curved figure-eight pattern that results in GF generally increasing as the terrain slopes above or below the horizon. Lastly, there is almost no discernable relationship between maximum terrain obstruction angle and average GF at SARA despite the observed wind tending to flow parallel to the general NW/SE terrain gradient, and we note the range of terrain angles is also limited. This inconsistency leads us to believe that obstructions that rise above the ground are more effective at controlling the value of GF and potentially modifying observed wind speeds (with the exception of stations whose obstructions are heavily dependent on steep changes in the underlying terrain such as Whiteface Mountain Base, WFMB not shown).

However, this strong relationship between maximum obstruction angle and average GF is not present at every NYSM station. Figure 4.18 shows scatterplots similar to those in Fig. 4.17 except for NYSM stations GFAL, DUAN, and OLDF, which are classified as WMO class 3, 4, and 4, with station average GF values of 1.61, 1.77, and 2.56, respectively. At GFAL (Fig. 4.18a,b) it is difficult to determine if there is any relationship between maximum obstruction angle and average GF due to the significant amount of scatter. This may be in part due to one of the most prominent obstructions identified by the lidar data being inflated by the underlying terrain, as we discussed previously. In reality, this low-lying vegetation likely exerts little effect
on wind speed, but it appears as a much more significant obstacle in the lidar imagery. This vegetation comprises a cluster of points with maximum obstruction angles between 5-7.5° and average GFs of 1.45-1.61, without which there is a much more noticeable positive relationship between maximum obstruction angle and average GF.

Both DUAN and OLDF are rather unique locations. At DUAN (Fig. 4.18c,d), obstruction angles peak within the mososcale environment due to trees close to the station, resulting in maximum obstruction angles greater than 35° within 50 m of the anemometer. While there is a fair amount of scatter along the regression line and the squared correlation coefficient is relatively small, $R^2=0.195$, there is general trend for average GF to increase as the maximum obstruction angle increases. The reason for the significant scatter is how quickly the maximum obstruction angle drops off as the direction moves 1° away from the peak of any given obstacle, especially at such a close range, but winds coming from those directions may still be significantly slowed or potentially channeled causing a disparity between the maximum obstruction angle and average GF value.

Unlike DUAN, where there are a few tall clusters of trees close to the station, OLDF (Fig. 4.18e,f) is sited in the middle of a dense surrounding forest. The distance between the station and the tree line varies between 28-60 m (median distance is 40 m), crossing the threshold between the mososcale and misoscale environments at several points. While the majority of the tree line is located within the mososcale environment, an analysis of obstructions at this range would result in several false gaps in the surrounding forest in directions where trees lie just outside the mososcale range. We instead opt to assess surrounding obstructions on the misoscale, despite the presence of obstacles in the mososcale range, to better represent the ubiquity of the surrounding forest. Another unique feature of OLDF is that observed average
GFs have relatively little variation and are also very large, with most values between 2.35-2.7.

Both the omnipresence of the surrounding forest and the lack of variation in average GF value contribute to the absence of relationship between maximum obstruction angle and average GF. This suggests that while there are minor variations in the maximum obstruction angle of the trees surrounding OLDF in all directions, they all serve to obstruct the observed winds nearly equally.

Each station has its own individual environment, obstacles, and complexities, and as we have seen some support our hypothesis that local obstruction and GF are related while others show no correlation between the two owing to unique circumstances. The question remains, when taken as a whole, do the 107 NYSM stations with lidar data show and support the theory that GF can be used a proxy for obstruction? To answer this, we composited all 360 1° azimuthal increments from all 107 NYSM stations and compared their maximum obstruction angles to both their average GFs and average mean wind speeds, to see explicitly if increasing degrees of obstruction acted to slow wind speeds and increase GFs. Because the correlations were generally much stronger in the stations that we assessed (and consistent with the majority of stations, not shown), our analysis of the network as a whole focuses on the relationship between wind observations and the maximum non-ground obstruction angle, rather than those from terrain. However, because several NYSM are known to have obstructions in their mososcale environments, our analysis looks at both the mososcale and misoscale ranges where obstruction angles are most likely to be maximized.

Composites of all 38520 available 1° azimuth increments comparing maximum obstruction angle from the surrounding mososcale environment to average GF and average mean wind speed are shown in Fig. 4.19. As a reminder, each point in these composites represent a single 1° azimuth direction from a single station. We then color code each point by the number of
wind observations (≥1 m/s), within the full year, reported from that direction that are used to calculate the average GF and mean wind speed, normalized by the number of observations from all stations throughout the year. What is immediately apparent is, regardless of how GF and mean wind speed change with maximum obstruction angle, the majority of points, especially those with a higher observation count, exist at obstruction angles within 5° of the horizon. This point clustering is encouraging since it means the majority of NYSM stations have no or few sizable obstructions within 50 m of the station.

That being said, there are still a fair number of points, albeit ones with overall smaller fractions of the total observations within the network, that have maximum obstruction angles exceeding 10°. We can see in the sections that extend past the ±5° range that average GF increases while average mean wind speed decreases as the absolute value of the maximum obstruction angle gets larger. This pattern is mainly evident by the increasing/decreasing of the minimum/maximum GF/mean wind speed with growing obstruction angle acting to decrease the overall range of possible values and enlarge/shrink the average value (Fig. 4.19a,b).

This is evident if we further bin and average all points based on their maximum obstruction angle in 0.5° increments to see how the mean within these composites changes with obstruction, as shown in Fig. 4.19c,d. In these mean trend composites each point represents an average of a multitude of 1° azimuth directions from a number of stations whose maximum obstruction angle falls within a 0.5° wide bin. The color coding now indicates the sum of all wind observations from directions that fall within each bin, normalized by the number of observations from all stations throughout the year. Although variability, as depicted by the vertical lines indicating ±1 standard deviation, is not small, it is clear that GF increases and average wind speed decreases as the obstruction angle becomes more positive. These mean trends reinforce
our assessment that average GF is minimized when obstructions are absent and increases as obstacles rise farther above or below the horizon. Interesting behavior also appears for negative obstruction angles on the mososcale. We note GF rises as the maximum mososcale obstruction angle decreases from $0^\circ$ whereas mean wind speed remains relatively constant (and essentially at its maximum values). What is most certain, though, is the range that the majority of observations contribute to and gives us confidence to draw conclusions about, that being $\pm 4^\circ$ relative to the horizon.

Figure 4.20 shows the same combination of composites of all points and their subsequent binned means but for the misoscale environment around NYSM stations. There is a much more immediately recognizable relationship between both average GF and average mean wind speed with maximum misoscale obstruction angle. While the overall range of maximum misoscale obstruction angles is smaller, with fewer points less than $-5^\circ$ or greater than $30^\circ$, the remaining points follow a much clearer direct/inverse relationship with average GF/mean wind speed.

In the mososcale analysis, the increase of mean GF with obstruction angle is largely a consequence of the progressive disappearance of low gust factors as angles became greater. In contrast, on the misoscale, both the maximum and minimum GF values increase in tandem as the maximum obstruction angle rises farther above the horizon. However, the shape of the mean wind speed with respect to maximum obstruction is similar in both the mososcale and misoscale environments, albeit more compact in the latter (Fig. 4.20a,b).

It is important to note that maximum obstruction angles near zero, indicating small or a complete lack of obstructions, do not guarantee faster observed average wind speeds. Some locations observe weak average wind speeds from certain directions regardless of upstream obstructions due to preferences in the natural wind climatology. This highlights that fact
obstructions act predominantly to reduce the maximum probable observed wind speeds resulting in the converging cone shape we see in both the mososcale and misoscale environments. The mean trends of both average GF and mean wind speed are smoother and steeper in the mesoscale analysis (Fig. 4.20c,d) compared to their mososcale counterparts (Fig. 4.19c,d), with the minimum average GF 0.2 lower and maximum average mean wind speeds 0.85 m/s higher at 0° but increasing/decreasing to the same values, 2.5 and 2 m/s, respectively, when maximum obstruction angles exceed 20° above the horizon. Additionally, because obstruction angles tend to peak in the misoscale environment, there are more observations spread across a variety of maximum obstruction angles, giving us confidence in the trends of the mean quantities between -2-15° off of the horizon.

The bottom line is that, among these NYSM stations, the relationships between obstruction angle and both gust factor and mean wind speed are sharper and more robust on the misoscale, suggesting that it is this scale that may be most useful for diagnosing the effects of obstacles on wind characteristics.

4.3.3.2.2 ASOS Analysis

While we have observed a strong relationship between observed GF and mean wind speed with obstruction angle in the NSYM it is not guaranteed this is a robust or universal correlation that can be applied to other networks and observations. As we have discussed, the ASOS network has an inherently different siting philosophy than the NYSM and, as a result, the environment surrounding ASOS stations are characterized by obstacles of differing types, prominence, distances, and ubiquity. We perform the same type of analysis for ASOS stations and network as with the NYSM to see if these relationships hold true across networks in different environments.
Figure 4.21 shows scatterplots of maximum obstruction angles from terrain (left column) and non-terrain (right column) sources versus average GF similar to Fig. 4.17, except for a handful of ASOS stations KPEO, KGFL, and KELZ. While the maximum obstruction angles at ASOS stations are generally much lower than at NYSM sites -- the maximum is about 11° at KPEO (Fig. 4.21a,b) whereas KGFL (Fig. 4.21c,d) and KELZ (Fig. 4.21e,f) do not exceed 5° -- the tendency for average GF to increase with maximum obstruction angle is apparent. The relationships between average GF and maximum obstruction angle at the three ASOS stations are the most similar to those observed in the NYSM but are rather unique among themselves. In general, KPEO most closely resembles WBOU, KGFL is visually similar to OTIS, and KELZ appears most similar to GFAL. Of the three stations KPEO has the most visually noticeable positive relationship between maximum obstruction angle and average GF (Fig. 4.21b). This is in part due to the range of maximum obstruction angles at KPEO being more similar to NYSM than other ASOS stations, and the nearby NYSM station PENN (5.5 km to the east), which contributes to this larger range of observed GF values, 1.26-1.69, and more noticeable relationship between the two.

However, a small range of maximum obstruction angles does not translate to a lack of a strong or noticeable correlation between average GF and maximum obstruction angles. The ASOS station KGFL is a prime example of this (Fig. 4.21d). The range of both maximum obstruction angles, -0.5-3.5°, and average GF, 1.2-1.37, are fairly small compared to other stations but there is still a distinguishable positive trend between the two. This puts it in stark contrast to its neighboring NYSM station GFAL that showed no discernable dependency of average GF on maximum obstruction angle (Fig. 4.18b). The misoscale environment around KGFL is largely flat to accommodate the nearby runway, with angles ranging between -1 and
+1° relative to the station, unlike GFAL where the terrain changes somewhat drastically owing to valleys around creeks and nearby hills, resulting in angles varying between -5-6° (shown in the Fig. 4.11b and Fig. 4.12e heatmaps). This highlights the importance the underlying terrain can play via constructive or destructive interference with non-ground obstacles.

The last ASOS station in this set, KELZ, presents a complicated environment to assess using lidar data. At first glance the scatterplots of maximum obstruction angles and average GF (Fig. 4.21e,f) would indicate that there is no clear dependency of average GF on either maximum terrain or non-ground obstruction angles. While this is nothing particularly unusual, especially for maximum terrain angles that exhibit a loop-like pattern similar to other stations like KPEO, GFAL, DUAN, and WBOU, this pattern with respect to maximum non-ground obstruction angle is somewhat suspicious. Upon closer examination there are number of similarities between the maximum terrain and non-ground obstruction angles. There are nearly parallel lines of average GF of approximately 1.3 and 1.385 that span from maximum terrain angles of -4-0.5° and a tight cluster of average GFs that range from 1.21-1.35 around a maximum terrain angle of 1°. These patterns show up again in the maximum non-ground obstruction angles, albeit shifted towards slightly more positive values of obstruction angle, raising doubt as to whether these are truly non-ground obstructions. Figure 4.22a,b shows heat maps similar to Fig. 4.12b,e, except that ground and non-ground classified points are plotted separately. These heat maps show that the ground and non-ground points are almost perfectly identical with a few additional objects like a cluster of trees to the north, fence surrounding the airport to the west, and a large amount of cluttered vegetation dotting the area where terrain slopes away from the station to the south.

This similarity is further shown in the rings of azimuthal minimum (magenta), average (blue), and maximum (red) obstruction angles (Fig. 4.22c,d). The minimum and average angles
for ground and non-ground points are indistinguishable from each other and while there are deviations between the two classifications with respect to their maximum obstruction angles, they follow a very similar pattern. This creates a two-fold problem. Firstly, there are directions where there are no actual obstructions, and our analysis of maximum obstruction angle is instead relying on ground (or near-ground noise) that has been misclassified by the post-processing algorithm that classifies lidar points after collection. Secondly, similar to the situation we observed at GFAL, the majority of non-ground obstructions are being obscured by the downward-sloping terrain. Combined, these issues make it more difficult to identify any relationship between average GF and maximum obstruction angle.

This issue could be potentially mitigated by performing secondary checks to ensure lidar points are appropriately classified or meet a minimum height requirement above the ground. Unfortunately, this process would be time- and computationally-consuming. Proper differentiation of ground and non-ground points would require elevation checks against a multitude of neighboring ground points and can quickly grow exponentially expensive computationally, given the mososcale, misoscale, and mesoscale ranges contain on average 62,832, 6,283,185, and 100,530,965 points, respectively. A quick and dirty method would be to use the difference between the maximum obstruction and maximum terrain angles, but this oversimplifies the problem and eliminates some of the advantages the 3D environment provides us. This could be problematic if the maximum obstruction angle and the maximum terrain angle do not occur at the same distance from the station and can result in the object being seen as smaller/shorter than it is in reality. This exemplifies the difficulty of considering a fully 3D environment but simplifying and extracting the most essential components for comparison to 2D wind observations from a singular point.
This issue of misclassifying low-level noise, ground clutter, or low-lying vegetation as generalized non-ground points is somewhat prevalent with approximately half of stations from both networks containing non-ground points that closely follow or perfectly mimic the surrounding terrain. Luckily, this does not affect our analysis of maximum obstruction angles, with a few exceptions. Misclassified low-lying points that are more representative of the topography are largely ignored by focusing on the maximum obstruction angle for a given direction. These points contaminate the average and minimum non-ground obstruction angles but are not identified as the maximum obstruction angle as long as a taller object is present along the sight line for a given direction. This proved problematic at KELZ due to the lack of any non-ground obstacles at 105 of the 360 possible directions, forcing the misclassified points to be identified as the maximum obstruction angle. As stated previously this was compounded by the fact the terrain slopes down away from the station in the 225 of the azimuthal directions where actual obstacles are located obscuring their presence and magnitude. While other stations have misclassified points none are problematic to the same degree as we have seen at KELZ where only 30 of 360 azimuthal directions had uncontaminated estimates of maximum obstruction angle.

Similar to the NYSM, each station within the ASOS network has its own unique environment and relationship between surrounding obstructions and observed wind values. Composites of all 19 usable NYS-area ASOS stations may represent a much smaller sample size compared to NYSM but still provide a valuable assessment of how quantities like average GF and mean wind speed generally change with surrounding obstructions. As we have discussed at length, the siting philosophies of the two networks differ greatly from each other and, as a result, there are far fewer locations and directions from ASOS stations that have notable obstructions in
their mososcale environment, which can be seen in Fig. 4.23a,b. Of all 6840 points (360 1° azimuth increments from 19 stations) only 17 are characterized by obstruction angles greater than 15° above the horizon while the vast majority of points lie between ±2° with largely flat or open surrounding environments. This means that the observed trends (Fig. 4.23c,d) where average GF decreases and mean wind speed increases with larger mososcale obstruction angles cannot be trusted. There are simply not enough observations nor ASOS stations located in environments with significant mososcale obstructions to be able to draw conclusions about how observed winds related to the mososcale environment. This is not surprising given that ASOS stations strive to be as exposed as possible and be representative of larger areas for the purposes of aviation.

The misoscale environment around ASOS stations, while subjected to fewer and smaller obstructions than NYSM stations on average, does have enough variety in its degree of obstruction to observe meaningful relationships between obstruction angles and average GF and mean wind speed, as shown in Fig. 4.24. Just as with the NYSM, the tendency for average GF to increase and mean wind speed to decrease with increasing maximum misoscale obstruction angle is clear in the network composites. There is significantly less scatter of average GF and a much steeper drop off of mean wind speed with respect to maximum obstruction angle compared to the misoscale pattern seen in NYSM (Fig. 4.20), due to the smaller number of stations and range of maximum obstruction angles. This leaves some uncertainty as to the perceived leveling off of GF and mean wind speed as obstruction angles increase greater than 8° above the horizon. What can be said confidently is that in both the ASOS and NYSM networks we see mean wind speeds decrease, and consequently average GF increases, as the maximum degree of obstruction increases above the horizon.
4.3.3.2.3 Network Comparisons

We have seen that both the NYSM and ASOS have similar trends in how their wind observations vary with respect to differing degrees of obstruction but have yet to determine how similar or different these variations are. We now directly compare the mean average GFs for every 0.5° interval of maximum obstruction angle of both the NYSM and ASOS networks, as shown in Fig. 4.25 (left column, a,c,e). We start with the data in their native (incommensurate) averaging intervals (Fig. 4.25a) for the ASOS and NYSM sonic instruments. As seen previously, the average GF of both networks has a direct positive relationship with obstruction angle, increasing as obstacles rise higher above the horizon. What becomes apparent is these trends are nearly parallel to each other between 0-8°, the range for which there are sufficient data to have confidence in the change of average GF but are slightly offset from each other with an average GF at 0° obstruction angle of 1.5 and 1.25 for NYSM and ASOS, respectively.

Because GF is only bounded at its lower limit of 1 (maximum gust cannot be smaller than mean wind speed), it can increase very rapidly and skew the perceived rate of change as wind speeds decrease. We compensate for this by assessing how inverse GF (iGF) changes with maximum obstruction angle (Fig. 4.25b). We considered iGF in Chapters 2 and 3. Unlike GF, iGF is bounded between 0 and 1, approaching unity when gusts and mean wind speeds are nearly equal and zero when gusts are extremely large or mean winds approach calm. This range compression helps highlight the fact that the relationship between obstruction angle and inverse gust factor, while similar, is not perfectly parallel. The iGF for ASOS decreases slightly faster than for NYSM before leveling off as observations become sparse.

This gap between NYSM and ASOS average GFs at similar maximum obstruction angles is not surprising given our initial comparisons were based on the surface observations in their
native averaging intervals which previous studies (Monahan and Armendariz 1971, Gallagher 2016, Harris and Kahl 2017) have shown that GF is sensitive to. Because of this, we next normalize the ASOS and NYSM sonic observations to a uniform ten-minute averaging interval, as was done in an earlier section (Fig. 4.25c,d). When the networks use the same averaging interval, the NYSM and ASOS GFs and iGF almost perfectly align. With the lengthened averaging interval, gust factors have increased and iGF values have decreased but NYSM values shifted more as its gust sampling rate (1 s) was shorter. All of this is expected. There is still a small gap between the two networks when obstructions are closest to the horizon -- GFs of 1.5 and 1.7 for NYSM and ASOS respectively -- that shrinks as obstruction angle increases, so the small disparity in slope that we saw earlier remains. Despite this gap, the average ASOS GF and iGF now fall within the error bars of the NYSM average (representing ±1 standard deviation about the mean).

This comparison attempts to eliminate as many differences as possible between the ASOS and NYSM observations to better assess how the various environments surrounding the observations contribute to disparities between the two networks. While we can unify the averaging interval of the two networks, and they both use sonic anemometers, a difference we can neither control nor ignore is their differing gust durations. The previous chapter (Chapter 3) and past literature (Durst 1960, Suomi et al. 2015) showed that gusts and therefore GFs are sensitive to gust duration, with long gust durations decreasing maximum gust values by smoothing peak records with shouldering samples. The shorter (1 s) gust duration used by the NYSM sonic anemometer observations acts to inflate reported gust and GF values and might be partly responsible for the small gap remaining between the two networks. To test this, we also make the same type of comparison with ASOS, normalized to a 10-minute averaging interval,
except we now use the NYSM propeller observations instead, as shown in Fig. 4.25e,f. While this potentially introduces issues stemming from differences in anemometer type, the propeller anemometer observations from the NYSM report a WMO standard 3 s gust. We see that the GF and iGF curves are now closer, but only very slightly, and thus we can conclude that the shorter gust sampling rate used by the NYSM sonic instrument is not contaminating the comparison after normalization to the ten-minute interval.

With these comparisons we have addressed several of our main questions: does GF have a strong relationship with obstruction angle and therefore contain information about the local environment, is this relationship robust across different observation platforms, and can GF be used as a proxy for site exposure. However, to finalize our answers to these questions, we have to address the underlying theory for why GF is related to site exposure and test our explanation that obstacles act to slow mean wind speeds to a greater degree than gusts. Our analysis thus far has shown that mean wind speeds are indeed influenced by obstacles, slowing down rather abruptly as obstructions rise above the horizon.

To come to our final conclusions, the dependency of both mean wind speeds (left column, Fig. 4.26a,c,e) and gusts (right column, Fig. 4.26b,d,f) on maximum obstruction angle are investigated concurrently. As we have seen in previous portions of our analysis, mean wind speed decreases quickly as maximum obstruction angle departs from zero for both networks. It is interesting to note that ASOS and NYSM mean wind speeds follow each other very closely, with their average values overlapping almost perfectly, for all three forms of the comparison: using their respective native formats (Fig. 4.26a), NYSM sonic 10-minute normalized winds (Fig. 4.26c), and NYSM propeller 10-minute normalized winds (Fig. 4.26e). This suggests to us that the main driver of the systematic difference in mean wind speed between the NYSM and ASOS
networks (recall Fig. 4.4) come from observations from directions that have an obstruction angles larger than 15° above the horizon. The ASOS network does not have any locations with obstruction angles this large (except the solitary point at 39° but this was determined to be noise not removed in the previous steps) and thus its network average does not incorporate the low wind speeds associated with these angles. We believe these mean wind observations are slow because they have been affected by large obstructions and incorporation of these slow readings result in the NYSM appearing on average 27.8% slower than ASOS. This also explains why the NYSM is generally 15.1% slower than ASOS even when considering WMO class 1 and 2 NYSM stations, because as we’ve seen there are stations in those classes like OTIS and WBOU that have significant obstructions in their misoscale (as opposed to mososcale) environments that can influence winds measured at their location.

Comparisons of composited average gusts (Fig. 4.26b,d,f) reveals that gust speed, like mean wind speed, also decreases rather quickly as obstructions deviate from flat with the horizon. Before we consider how gust speed changes relative to mean wind speed, we assess how gust speed depends on the configuration of observations. The comparison of average gusts from the NYSM and ASOS networks in their native format (Fig. 4.26b) is reminiscent to that of GF with a notable gap between the two despite their similar trends for decreasing as obstruction angle increases. We noted earlier that the gap between NYSM and ASOS GFs shrunk and almost completely disappeared when the averaging interval and gust duration of observations were unified, eliminating any possible differences between the two networks. This convergence of average GFs is driven by the diminishing gap between the average gust speeds, seen in Fig. 4.26d,f, since mean wind speed composited over long periods is not sensitive to averaging interval.
At first glance, it would appear our theory that gusts are less sensitive to local obstructions is false but closer examination suggests otherwise. While both mean wind speed and gust slow down as obstacles become more prominent, the rates at which they do so are subtly different. Mean wind speed are around 4 m/s when there are no obstructions, or they are even with the horizon, and on average decreases to 2.5 m/s when obstructions rise to 5° above the horizon, 2 m/s at 10°, and 1.5 m/s by 15°. In contrast, average gust speed starts at approximately 5.75 m/s at 0° and decreases to 4.75 m/s at 5°, 4.5 m/s at 10°, and 4.25 m/s at 15°. So, although average gust speed is decreasing in tandem with mean wind speed as obstruction increases, the rate that gusts slow down is smaller, resulting in a growing disparity between the two or, equivalently, a growing gust increment (defined as \( GI = \bar{U} - \bar{U} \)).

For a moment, let us consider Suomi et al.’s (2013) definition of GF to better understand how relative changes in the gust and mean wind speed affect the resulting value:

\[
GF = \frac{\bar{U}}{\bar{U}} = \frac{\bar{U} + GI}{\bar{U}} = 1 + \frac{GI}{\bar{U}}.
\]

With this, we can see that GF is dependent on the gust increment (GI) and the mean wind speed. Hypothetically, if gust speeds and mean wind speeds were to decrease at the same rate, perfectly parallel to each other, then GI would remain constant (although this becomes increasingly unlikely as the mean wind continues to decrease towards the hard bottom boundary of zero) while the mean wind speed continues to drop, resulting in growing GF values. So, if GI were to increase, even slightly, as mean wind speed decreases, GF would increase at an even faster rate.

We roughly estimated that GI is increasing as gust speeds are not quite as sensitive to obstructions as mean wind speeds are, but now show this explicitly in Fig. 4.27. This figure displays the average GI composited every 0.5° by maximum obstruction angle similar to our analyses of GF, mean wind speed, and gust speed. The GI increases for both networks as
maximum obstruction angle increases, in a relatively smooth manner while there a sufficient number of observations contributing to the average (greater than roughly 2% for ASOS and about 1% for NYMS). The range for which there are enough observations to be confident in estimates of average GI are smaller for ASOS than NYMS, 0-5° and 0-12°, respectively, so it is difficult to determine how quickly GI increases with obstruction. However, what remains clear is that GI is increasing at the same time mean wind speeds decrease. This explains the relationship we see between GF and maximum obstruction angle, why GF increases so sharply as obstacles rise farther up off the horizon, and supports our theory that gusts are less sensitive to local obstacles than mean winds.

4.4 Discussion and Conclusions

Several studies and Chapter 2 of this dissertation have continually noted there is a robust relationship between bias of surface wind forecasts and observed wind speed. This correlation is has been noted across a multitude of model resolutions (0.667-3 km), physics parameterizations (planetary boundary layer and surface layer schemes, and land surface models), observation platforms (ASOS, NYMS, San Diego Gas & Electric), and both operational (HRRRV3 and HRRRV4) and reforecast models (Cao and Fovell 2016, 2018; Fovell and Cao 2017; Fovell and Gallagher 2018, 2020). Collectively these studies showed that forecasts were more likely to overpredict wind speeds at sites characterized by lower wind speeds and underpredict winds at windier locations, resulting in persistent positive/negative biases for the calmest/fastest winds. Additionally, these patterns in bias were also shown to be correlated with GF (or iGF), which could ideally be used as a predictor for these systematic biases and has been theorized to be indicative of unresolved or represented obstacles in the local environment surrounding observation sites. This potential utility is complicated by the fact that GF is inherently dependent
on the observed mean wind speed (shown in Chapter 3; Davis and Newstein 1968; Ashcroft 1994) and as such is not independent of bias. This leaves the unanswered questions of; to what degree are slow wind a result of obstructions or natural climatology and is there an explicit link between GF and obstructions in the local environment?

Past studies that have related the environment surrounding surface observations to observed quantities have done so with limited data in regard to the number of sites, length of surface records, and characterization of the local environment (Wieringa 1980; FW82; WF88; Acevedo and Fitzjarrald 2001, 2003). This motivated our use of airborne lidar data to characterize the local environment. Lidar data provided us a high-resolution fully 3D snapshot of the environment surrounding surface observations at several scales (mososcale 0-50 m, misoscale 50-500 m, and mesoscale 500-2000 m) allowing for the identification of individual and groups of obstacles that could be directly related to trends in observed winds. This coupled with a full year of observations from the NYSM and ASOS networks allowed us to thoroughly analyze and compare the environment and observed wind patterns among stations in a network and between two networks.

Chapters 2 and 3 of this dissertation showed a consistent tendency for NYSM stations to report lower mean wind speeds than those recorded by ASOS stations, and it was suspected this was due to their differing siting philosophies and requisite degree of obstruction typical within each network. To test this, we first compared the network average mean wind and gust speeds from NYSM and ASOS over a period of a year addressing differences in the configuration of their observational setups. Our findings support those in Chapter 2 showing that even in their native format (without compositing observations into hourly intervals) the network average mean wind speeds for the NYSM are on average 27.8% slower than those of ASOS. Even when we try
to eliminate as many differences between the networks as possible by normalizing observations to 10-min averaging intervals, ignoring low wind speed observations (<1 m/s), and utilizing only WMO Class 1 and 2 NYSM stations (in a crude attempt to eliminate network exposure issues), NYSM network average winds are still, on average, 15.1% slower than ASOS. This led us to conclude that there were either systematic disparities in exposure between ASOS and the “best” exposed WMO Class 1+2 NYSM locations or NYSM stations were sited in naturally low wind environments.

Because upstream obstructions are expected to slow or divert winds before they are recorded by anemometers, we also performed comparisons of wind roses among several NYSM stations of varying WMO classification of exposure indicated by satellite imagery (later confirmed by lidar data) and pairings of NYSM and ASOS stations in relative proximity to each other. Overall, the range and variability of observed wind directions were larger for stations that had fewer or less ubiquitous obstacles surrounding them, which did not necessarily translate to a lower WMO classification. Stations like GFAL had a much wider range of preferred wind directions than WBOU, which appeared more trimodal despite their WMO classifications of 3 and 2, respectively. While there were several instances where sharp cutoffs in wind frequency or drop-offs in maximum wind speed from a specific direction appeared to be collocated with objects that could be identified from satellite imagery or site photography it is still uncertain if these are the result of the upstream obstructions or coincidentally the naturally preferred wind directions from climatological weather patterns. Our comparisons between nearby ASOS and NYSM stations helped increase our confidence in the former theory given pairs of stations in proximity to each other are more likely to be subjected to the same background preferences for wind direction and speed and disparities between the two resulting from the effects of local
influences. This is especially compelling for pairs like GFAL/KGFL that are separated by only 720 m but have notable differences in their preferred wind directions owing drastic changes in upstream fetch.

Utilizing airborne lidar data across large areas or comparing multiple locations from a variety of lidar project areas can be very difficult given the high degree of heterogeneity among lidar sources. Even when disparities in projection, reference coordinates, and units are compensated for there are still potentially complications from inescapable factors like noise and unwanted or misclassified points that may require further post-processing before the data is ready for use. Once extraneous points were removed, we borrowed from the methodology of FW82/WF88 and reframed each lidar point as an obstruction angle relative to its respective station, allowing us to consider the relative height and distance of an obstacle from the measurement site simultaneously. Heat maps of these obstruction angles revealed objects and terrain changes on the order of approximately 1 m, the most prominent obstructions surrounding each site, and how each of these change with respect to distance from the anemometer (i.e., increasing spatial scale). Because obstruction angle of a point is sensitive to its distance from a station, obstruction angles generally reach a maximum above the horizon (large positive values) the closer they are to a station. While objects within the mososcale range tend to have higher obstruction angles due to their proximity, the vast majority of stations have few to no obstacles within 50 m due to siting or clearing of the environment during installation. As a result, obstructions tend to be the most prominent in the misoscale range.

An unintended consequence of visualizing the environment around NYSM stations is a questioning of the WMO classifications they are given. Our analysis assessed NYSM stations in pairs of WMO Class 1, 2, and 3 stations and found the proximity, prominence, and density of
obstacles within the misoscale range varied drastically within each classification. These variations in exposure were closely related to station average GF. Stations with a relatively lower average GFs (PENN, HART, GFAL) had far fewer, smaller, and more distance obstructions compared to stations with higher average GFs (OTIS, WBOU, SARA) in the same WMO class. This suggests that WMO classification may not reflect the true exposure of a station. Even more worrisome is the lidar data shows that obstructions surrounding stations like OTIS and WBOU actually exceed the maximum obstruction angle threshold for WMO class 1 and 2, respectively (WMO 2014-2017). While this is troubling it does highlight the use of airborne lidar data for accurately assessing (or reassessing) exposure classifications.

We began to explicitly test if GF was related to surrounding obstructions with a qualitative analysis comparing azimuthal variations of average GF to maximum, average, and minimum obstruction angles along azimuthal sight lines. Maximum obstruction angles were generally associated with non-ground objects rising above the horizon whereas average and minimum obstruction angles are strongly representative of the underlying terrain due to the sheer number of ground points influencing the average. While the azimuthal variation of maximum obstruction angle tended to be noisier than average obstruction angle, average GF was much more in phase with maximum obstruction angle. When maximum obstruction angle reached relative maxima/minima average GFs larger/smaller relative to the overall station average were observed in the corresponding directions. These patterns match the best at the center of azimuthally wide obstacles and are occasionally out of phase in the direction of narrow obstacles or at the edges of objects where obstruction angle changes quickly.
This apparent relationship was tested further in our quantitative analysis where average GFs and maximum obstruction angles\textsuperscript{5} were directly compared for all 360 $1^\circ$ azimuthal increments to see how strong the correlation was and how the two varied together. Additionally, points were separated based on their classification as ground (terrain) and non-ground to assess GFs dependency on surrounding topography versus obstacles such as trees, buildings, etc. Overall, when directly compared to each other average GF has a weak and poorly defined relationship with maximum terrain obstruction angle that can vary widely in shape and slope. Three common shapes of the relationship between maximum terrain obstruction and average GF are uniform scatter of GF independent of terrain obstruction angle, a “loop” or “figure eight” pattern, or a linear inverse relationship which tend to have the highest correlation coefficients (KGFL, $R^2 = 0.473$).

In contrast, average GF was found to have a much stronger, positive, more consistent relationship with maximum non-ground obstruction angle. The presence and prominence of this correlation varies from station to station but appears at both NYSM and ASOS locations with $R^2$ values as large as 0.707 (WBOU). This supports our theory that GF contains information regarding site exposure since higher GFs tend to be associated with larger more positive maximum obstruction angles while lower GFs cluster closer to small obstruction angles near the horizon. Instances where there this correlation was weakest or completely absent were characterized by few or small obstacles, ubiquitous or invariable obstacles, and topographical changes that negatively interfere with the presence of non-ground objects in their surrounding environments.

\textsuperscript{5} Maximum obstruction angles were collected from the misoscale range unless otherwise specified (for example, the analysis of DUAN focuses on mososcale obstruction angles).
Because each station has its own individual environment and complexities, we separately composited all stations within the NYSM and ASOS networks to assess how GF relates to obstructions across all stations in a given network. Composites of both networks, while differing in their typical values of GF and range of maximum obstruction angles (e.g., ASOS has fewer and less prominent obstacles), show that both average GF and mean wind speed have notable relationships with maximum obstruction angle. Average GF from a given station and wind direction tends to be larger as the absolute value of maximum obstruction angle increases, but as we are assessing maximum obstruction angle the majority of values are largely positive above the horizon. Mean wind speed displays a similar pattern with respect to maximum obstruction angle, albeit being the inverse of average GF, with typical mean wind speed decreasing rather significantly as the absolute value of maximum obstruction angle grows larger. These patterns are best exemplified by the mean trends within each network composite and support our theory that larger upstream obstacles act to slow mean wind speeds and inflate GF. Furthermore, while these trends are visible for mososcale obstruction angles (within NYSM), they are more gently sloped and generally less reliable due to the lack of sites and directions with varying mososcale obstructions, reinforcing our conclusion that wind observations are most sensitive to non-ground obstacles in the misoscale environment.

Comparing mean values of average GF, iGF, mean wind speed, and gust speed from both networks conjointly with respect to maximum obstruction angle show that stations in both networks follow nearly parallel rates of change with only a small offset separating NYSM and ASOS mean trends. When we accounted for difference in their native formats, such as averaging interval and gust duration (addressed using NYSM propeller anemometer observations), it became apparent that the ASOS and NYSM networks are actually quite similar with their mean
trends layered directly on top of each other. The driving factor behind the systematic differences noted in Chapter 2 and earlier in this chapter are the larger obstruction angles experienced by many of the NYSM stations that ASOS sites are not often subjected to. This lowers the network average mean wind speed and inflates the network average GF, but for sites and directions with similar ranges in upstream exposure the networks are nearly equivalent.

Lastly, we evaluated the underlying theory that GF is correlated with local obstacles because mean wind speeds are more sensitive and slowed a larger degree by surrounding obstructions than gust speeds. Mean trends from both networks showed that average gust speed is not independent of maximum obstruction angle and follows a similar pattern to mean wind speeds, decreasing as the absolute value of obstruction angles increases. Further analysis of the gust increment GI (the difference between maximum and mean wind speeds) revealed that the gap between average gust speed and mean wind speed actually increases in tandem with maximum obstruction angle. This indicates that while average gust speed is not independent of maximum obstruction angle, it drops off at a gentler rate, reinforcing our theory that mean wind speeds are more sensitive to exposure than gusts. The trend of average GF to increase with larger maximum obstruction angle can then be attributed to the dual effects of diminishing mean wind speeds (smaller denominator) and growing GI (numerator from an expanded definition of GF, see Suomi et al. 2013). Finally, we can conclude that GF can be used as a simple proxy for site exposure because of its persistent and explicit relationship with local obstructions.
<table>
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<th>NETWORK</th>
<th>Near NYS ASOS (CONUS)</th>
<th>NYSM (propeller)</th>
<th>NYSM (sonic)</th>
</tr>
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<tr>
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<td>126</td>
<td>126</td>
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<td>Geographic Area</td>
<td>NYS (CONUS)</td>
<td>NYS</td>
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<td>2016-present day</td>
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<td>Sonic</td>
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<td>10 m</td>
</tr>
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<td>5 minutes</td>
<td>5 minutes</td>
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<tr>
<td>Gust Duration (sample averaging interval)</td>
<td>3 seconds</td>
<td>3 seconds</td>
<td>1 s (sampled every 3 s)</td>
</tr>
</tbody>
</table>

Table 4.1 Configuration of near NYS ASOS, NYSM propeller, and NYSM sonic observations used in this study. Relevant quantities for the entirety of the ASOS network are denoted in parentheses for reference. ASOS mounting heights are listed as “nominal” due to stations like KMTP where the anemometer is mounted at 5.8 m (AGL). Record length for ASOS is listed according to the date when the network fully transitioned to sonic anemometers for consistency. Record length for NYSM sonic observations is listed as beginning in 2017 due to significant data dropout and corruption during the mesonet’s first year in operation.
Fig. 4.1) Locations of Near NYS ASOS (black) and NYSM standard (red) stations.
Fig. 4.2) Existing lidar project areas as of November 2020 (a) and proposed lidar data collection areas between November 2020-November 2021 (b). Color coding indicates each unique lidar project area, commissioning department, and year of collection.
Heat maps of lidar points around NYSM stations with noise and unwanted obstacles

Fig. 4.3) Top-down heat maps of all (terrain, non-terrain, other) obstruction angles at NYSM stations HART (a-b), BURT (c-d), and WARW (e-f) smaller (left column; 0-50m HART, 50-500m BURT and WARW) and larger (right column; 50-500m HART, 500-2000m BURT and WARW) scales. Terrain and obstacles above/below the horizon are shaded red/blue. Noise and unwanted objects are highlighted in deeper reds indicating they are much higher above the surface.
Comparison of NYSM and ASOS network average winds and gusts

(a) NYSM vs. ASOS Native Network Avg Mean Wind Comparison
N=50,464
Slope=0.7223
R²=0.4885

(b) NYSM vs. ASOS Native Network Avg Gust Comparison
Slope=0.9521
R²=0.4753

(c) NYSM vs. ASOS 10min Norm. Network Avg Mean Wind Comp.
N=50,476
Slope=0.7221
R²=0.4859

(d) NYSM vs. ASOS 10min Norm. Network Avg Gust Comp.
Slope=0.8677
R²=0.4649

(e) NYSM Class 1+2 vs. ASOS 10min Norm. Net Avg Mean Wind Comp.
N=51,305
Slope=0.7974
R²=0.5046

(f) NYSM Class 1+2 vs. ASOS 10min Norm. Net Avg Gust Comp.
Slope=0.9174
R²=0.4867

(g) NYSM Class 1+2 vs. ASOS 10min. NoLow Net Avg Mean Wind Comp.
N=30,357
Slope=0.8490
R²=0.3851

(h) NYSM Class 1+2 vs. ASOS 10min. NoLow Net Avg Gust Comp.
Slope=0.9791
R²=0.3496

Fig. 4.4) Comparisons of ASOS (x-axis) and NYSM (y-axis) network average mean wind speeds (left column) and gusts (right column) for all matching observation times throughout 2017 in their native formats (a-b), normalized to a 10min averaging interval (c-d), using only WMO Class 1+2 stations for NYSM with a 10min averaging interval (e-f), using only observations greater than 1m/s from WMO Class 1+2 NYSM stations with a 10min averaging interval (g-h).
NYSM propeller minus sonic anemometer frequency difference distributions

Fig. 4.5) Histograms of difference in mean wind speed (blue) and gust (red) observation frequency between the propeller and sonic anemometers (Propeller-Sonic) for all NYSM observations (a), PENN (b), and CROG (c). Note the bin size for gusts is wider (0.5 m/s compared to 0.25 m/s) owing to the mismatch in anemometer precision (0.5 m/s is the least common multiple of sonic and propeller precisions of 0.1 m/s and 0.166 m/s, respectively).
Fig. 4.6) Mean wind speed (left column) and gust speed (right column) wind roses (fraction of total observations) for NYSM stations PENN (a-b), HART (c-d), and GFAL (e-f), binned every 5°.
NYSM station wind and gust roses

Fig. 4.7) Similar to Fig. 4.6 except for NYSM stations WBOU (a-b), SARA (c-d), and DUAN (e-f).
Similar to Fig. 4.6 except for ASOS stations KPEO (a-b), KELZ (c-d), and KGFL (e-f).
Heat maps of lidar points around NYSM stations, WMO Class 1

Fig. 4.9) Similar to Fig. 4.3 except for PENN (left column) and OTIS (right column) for the micoscale (0-50m, a,d), mioscale (50-500m, b,e), and mesoscale (500-2000m, c,f) environments around each station.
Heat maps of lidar points around NYSM stations, WMO Class 2

Fig. 4.10) Similar to Fig. 4.9 except for HART (left column, after noise processing) and WBOU (right column).
Heat maps of lidar points around NYSM stations, WMO Class 3

Fig. 4.11) Similar to Fig. 4.9 except for GFAL (left column) and SARA (right column).
Heat maps of lidar points around near NYS ASOS stations

Fig. 4.12) Similar to Fig. 4.9 except for KPEO (left column) and KGFL (right column).
Fig. 4.13) NYS Ortho-imagery centered over NYSM stations (a) PENN, (b) OTIS, (c) HART, (d) WBOU, (e) GFAL, (f) SARA. 500m radius is indicated by a red ring.
Fig. 4.14) Same as Fig. 4.13 except for ASOS stations (a) KGFL and (b) KPEO.
Fig. 4.15) Azimuthal rings of maximum (red), average (blue), and minimum (magenta) obstruction angles in the misoscale environment every 1° looking outward from the station (left column) and average GF for wind observations binned every 5° color coded by direction frequency (fraction of total observations) for OTIS (a-b), WBOU (c-d), and SARA (e-f). The black circles indicate an obstruction angle of 0° (flat) and the total station average GF for the left and right columns, respectively.
Near NYS ASOS station misoscale obstruction and average GF rings

(a) KEPO Total Obstruction Angle Rose, 1° Width
(b) KEPO Average GF Ring, 5° Width
(c) KGFL Total Obstruction Angle Rose, 1° Width
(d) KGFL Average GF Ring, 5° Width

Fig. 4.16) Similar to Fig. 4.15 except for KPEO (a-b) and KGFL (c-d).
NYSM station misoscale obstruction vs. average GF analysis

(a) OTIS 500m Max Terrain Obstruction Angle vs Avg GF

(b) OTIS 500m Max Non-Ground Obstruction Angle vs Avg GF

(c) WBOU 500m Max Terrain Obstruction Angle vs Avg GF

(d) WBOU 500m Max Non-Ground Obstruction Angle vs Avg GF

(e) SARA 500m Max Terrain Obstruction Angle vs Avg GF

(f) SARA 500m Max Non-Ground Obstruction Angle vs Avg GF

Fig. 4.17 Scatterplots of maximum terrain (left column) and non-terrain (right column) obstruction angles within the misoscale environment vs. average GF every 1° (N=360) around OTIS (a-b), WBOU (c-d), and SARA (e-f). Zero degrees, flat, off the horizon is indicated in vertical black lines and linear regressions are shown in red lines.
**NYSM station misoscale* obstruction vs. average GF analysis**

(a) GFAL 500m Max Terrain Obstruction Angle vs Avg GF

(b) GFAL 500m Max Non-Ground Obstruction Angle vs Avg GF

(c) DUAN 500m Max Terrain Obstruction Angle vs Avg GF

(d) DUAN 500m Max Non-Ground Obstruction Angle vs Avg GF

(e) OLDF 500m Max Terrain Obstruction Angle vs Avg GF

(f) OLDF 500m Max Non-Ground Obstruction Angle vs Avg GF

Fig. 4.18) Similar Fig. 4.17 except for GFAL (a-b), DUAN (c-d), and OLDF (e-f).
Fig. 4.19) Scatter plots of maximum non-terrain obstruction angle within the mososcale environment vs. average GF (left column) and average mean wind speed (right column) every $1^\circ$ azimuthally around all NYSM stations. Top row shows each 360 $1^\circ$ directions at all 107 stations ($N=38520$). Bottom row shows GFs/mean winds averaged by their maximum obstruction angle binned every $0.5^\circ$ with grey lines indicating $\pm 1$ standard deviation of observations from the mean. Color shading indicates the fraction of observations (frequency) from a given direction with the corresponding maximum obstruction angle.
NYSM network composite misoscale obstruction vs. average GF and mean wind

Fig. 4.20) Similar to Fig. 4.19 except for the misoscale environment around all NYSM stations.
Near NYS ASOS station misoscale obstruction vs. average GF analysis

Fig. 4.21) Similar to Fig. 4.17 except for ASOS stations KPEO (a-b), KGFL (c-d), and KELZ (e-f).
KELZ misoscale lidar point heat maps and obstruction rings

(a) KELZ Terrain Obstruction Angles Heat Map 500m
(b) KELZ Non-Ground Obstruction Angles Heat Map 500m
(c) KELZ Terrain Obstruction Angle Rose 500m, 1° Width
(d) KELZ Non-Ground Obstruction Angle Rose 500m, 1° Width

Fig. 4.22) Top-down heat maps similar to Fig. 4.9 except of terrain (a) and non-ground (b) obstruction angles within the misoscale environment surrounding KELZ. Azimuthal rings of maximum (red), average (blue), and minimum (magenta) obstruction angles similar to Fig. 4.15 (left column) except from terrain (c) and non-ground (d) sources.
Fig. 4.23) Similar to Fig. 4.19 except for all available ASOS stations (N=6840).
Fig. 4.24) Similar to Fig. 4.23 except for the misoscale environment.
Fig. 4.25) Scatter plots of maximum non-terrain obstruction angle within the misoscale environment vs. average GF (left column) and average iGF (right column) composited similar to Fig. 4.19 by maximum obstruction angle binned every 0.5° for NYSM (blue) and ASOS (red) networks. Top row shows sonic anemometer data in their networks native averaging intervals, middle row shows sonic anemometer data using normalized ten-minute averaging intervals, and bottom row shows NYSM propeller and ASOS sonic data using normalized ten-minute averaging intervals. Error bars indicate ±1 standard deviation of observations from the mean.
NYSM and ASOS average mean wind and gust misoscale mean trend comparison

Fig. 4.26) Similar to Fig. 4.25 except for average mean wind speeds (left column) and average gust speeds (right column).
Fig. 4.27) Similar to Fig. 4.25 except for average gust increment and shaded by the percentage of observations composited into each 0.5° bin. NYSM is shaded in cooler colors (green/blue) and ASOS in warmer colors (yellow/red).
5. Conclusions

5.1 Summary and Discussion

This dissertation critically examined patterns in forecasts and observations of mean wind and gust speed using under utilized datasets. Previous work has established a pattern of systematic underlying bias of individual locations even when forecasts appear skillful due to small or near zero average biases (Cao and Fovell 2016, 2018, Fovell and Cao 2017, Fovell and Gallagher 2018, FG20). These biases can be quite large at individual locations and show that overall forecast skill can be deceptive and hinder addressing the rudimentary causes that are responsible for these disparities between forecasts and observations. While there are variations in the scope and focus of these works, they all share the principle finding that average bias of individual locations is strongly correlated to the average observed wind speed.

This prompted the theory that observations themselves could be “biased” and may be subjected to modifying effects that are not properly resolved nor are resolvable as a practical matter for most numerical weather predictions. The theory posited those stations with lower average mean winds were being subjected to obstruction not resolvable in most numerical models and observed wind speeds were slowed resulting in positive forecast biases. Alternately, those stations with faster mean winds may be better exposed or subjected to unresolved channeling and observed wind speeds were enhanced relative to forecasts resulting in negative forecast biases. In turn this lead to the idea that GF could be used as a simple proxy for site exposure due to its codependence with forecast bias. Additionally, Cao and Fovell (2018) and Fovell and Gallagher (2018) found that GF, particularly GF\(_{net}\), could potentially be used as a simple gust predictor and produce unbiased gust forecasts from compromised wind speed forecasts.

There motivated the following research questions listed in Chapter 1, aimed at critically evaluating and expanding the scope, applicability, and confidence of previous findings:

Q1) What are the systematic errors and weaknesses of a skillful operational model like HRRR? Can observations from multiple unique observations platforms be used to expand
understanding of existing errors? And can patterns and sources of these persistent errors be identified to put other verifications in a fairer light and direct future model improvements?

Q2) How strict are the assumptions and restrictions Durst 1960 used in the construction of his gust curve and how robust is the resulting gust curve compared to gust curves generated from other high frequency data spanning a variety of geographic areas and environments.

Q3) Can variations in observed wind speed, gust, and direction be linked to obstacles in the local surrounding environment? Can novel airborne lidar data be used to assess the relative degree of obstruction winds at a location are subjected to? And can GF be used as a simple proxy for site obstruction?

Q1 is composed of a series of questions that were left by FG20, which was relatively exploratory due to its novel data usage and methods, whose answers were the aim of Chapter 2. Our results supported those of previous studies confirming the presence of systematic biases of individual locations, verified against ASOS observations, even when average model bias is incredibly close to zero (-0.2 m/s for HRRRV3 and 0.0 m/s for HRRRV4). Consistent with previous works the average bias for a site was found to have no dependency on forecast wind speed and strong correlations with the average observed mean wind speed, GF (and thus iGF), and new to this study the difference between forecast and observed standard deviation of wind speed. This pattern of biases was found to be persistent when considered across the entirety of the CONUS (compared to the smaller regional focus of previous works on Santa Ana winds), version of the operational HRRR (V3 vs. V4), and verified using alternative observations from the NYSM (despite its network average bias of +1.04 m/s). Additionally, gust forecasts produced using GF_{net} were shown to be quite skillful with notable scatter in their bias but, similar to mean wind speed forecasts, were centered along the 1:1 line and near zero bias. Unfortunately, this also results in a correlation between gust forecast bias and observed gust akin to that of mean wind speed.
The relationship between standard deviation difference and bias prompted further examination of the relative shapes of wind speed distributions of forecasts and observations. Our analysis shows a notable mismatch between the two winds speed distributions with the forecasted distribution much narrower with a larger peak at middling wind speeds compared to the distribution of observed wind speeds. This disparity is the driver of the systematic overprediction of low wind speeds and underprediction of the fastest wind speeds, noted previously, as the model struggles to reproduce the low- and high-end tails of the distribution and is particularly troublesome with respect to the later.

Subsetting the verification by landuse type and local time of day revealed strong relationships between both and the precise pattern of bias. It was shown that specific landuse categories are associated with consistent forecast biases. Landuse assignments of urban, grasslands/open shrublands, and croplands were found to be persistently underpredicted with the model failing to capture moderate to fast winds performing worst for wind speeds between 4-8 m/s. Whereas all forested categories were found to be routinely overpredicted due to the forecasted wind speed distribution being less skewed and shifted to the right relative to observations. The relative contribution of each category is dependent on the number of stations classified as each within the network and helps explain the large average forecast bias for the NYSM network which is more commonly sited in forested areas than ASOS.

Our analysis with respect to local time revealed disparities between observed and forecasted wind speed distributions are smallest during daytime hours, despite missing the high wind speed tails, and worst at night when the forecasted distribution is both offset and too narrow. This highlights the poor handling of the nocturnal stable boundary layer and how it can result in both over- and under-prediction of wind speeds. It was shown the distribution differences for all landuse categories were more notable for nocturnal hours than daytime regardless of their overall bias, stressing the importance of properly representing the stable boundary layer.
Lastly, while there are notable shifts in landuse classification, whose full effects require more study, and improvements in capturing the high wind tail of distributions, our results show little over difference in the verification with respect to HRRRV4.

Q2 was inspired by the use of GF\textsubscript{net} as a simple gust forecasting tool and motivated by a desire to put its use in historical context. Chapter 3 was designed to answer these questions once the shortcomings of past literature in critical evaluating both Durst (1960) and its subsequent gust curve became apparent.

Reconstructions of gust curves from ASOS 1-min and NYSM 3-s data show that the typical GF, for all gust durations of \( t \) seconds, were much larger in comparison to the original Durst curve. The NYSM network GFs in particular are much higher than both Durst and ASOS for all gust durations reaching up to 2.4 for the shortest gust duration of \( t = 3 \)-s. Gust curves that more closely resemble Durst’s we produced by imposing limitations on the minimum hourly average wind speed and hourly maximum wind direction standard deviation. These restrictions lower ASOS and NYSM GFs by increasing the mean wind speed in the denominator of average GF and also result in samples about the mean wind speed being more normally distributed and in line with Durst’s assumptions. However, the filters required to generate comparable gust curves result in data that represents a very small percentage of the total record and highlight that Durst’s curve is not robust across a variety of atmospheric conditions as has been shown in previous works (Krayer and Marshal 1992 and Yu and Gan Chowdhury 2009).

Similarly, we have shown there to be significant deviations of maximum wind curves constructed from ASOS and NYSM data compared to equivalent curves from Durst’s data. These maxwind curves relate iGF to averaging interval and as a result are much easier to assess relative differences in their slope due to its mathematical constraint between 0 and 1. Maxwinds were found to drop off more quickly with increasing averaging interval for locales with higher WMO wind classification and subsequently station obstruction, again highlighting the importance of mean wind speeds in determining the shape of these curves.
Based on the increasing variability of GF and iGF for slower wind speeds we posit that these results may be used thusly. For a given mean wind speed, which may be derived from a top of the hour forecast of wind speed, a range of GFs could be collected to estimate the largest 3- to 600-s gust that could be expected within that hour. This could be presented as a useful tool for gauging wind threats of variable duration when high frequency data is unavailable.

Q3 was motivated by a common through line of the Chapters 2 and 3 being mean wind speeds are highly correlated to deviations from model forecasts and other forecast tools like the Durst curve, and a necessity to explicitly link fluctuations in observed wind speed to exposure of the local environment. Chapter 4 opens with comparisons of raw and adjusted ASOS and NYSM observations, showing that even when observational methods like averaging interval and calm wind percentage are taken into consideration there are still systemic differences between the two networks. A crude method to address exposure using WMO classification fails to make observations from the two networks fully comparable to each other suggesting WMO may precisely represent all the complexities in environments surrounding observation sites.

Our analysis relies heavily on the use of airborne lidar data, a novel, incredibly heterogeneous, and highly complex dataset that requires a significant effort to utilize properly. After sufficient quality control airborne lidar data is shown to be able to reconstruct the environment surrounding observations sites to a high degree of accuracy and precision. This data allows for detailed analysis of the relative position, height, angle above the horizon, shape, and density of both terrain and non-terrain obstacles. Heat maps of the environments around NYSM stations revealed significant variability in the prominence, density, and proximity of obstacles, particularly in the misoscale range. This confirms our concerns that WMO may not be representative of the true or total exposure of a station and in fact these variabilities are better correlated with station average GF.

Azimuthal comparisons of between obstruction angles (average, max, and min) and average GF show the highest degree of agreement between average GF and the maximum obstruction angle, with the two being almost completely in phase. This reinforces the idea that
while the density and depth of an obstruction may play a factor in slowing wind speeds the dominant driver is the angle of an object relative to the measurement location. The directional variations of maximum obstruction angle and average GF match up the best at ranges where obstruction angle peaks, again representing the most prominent obstruction in the environment, which for the majority of stations is in the misoscale range, between 50-500 m away from a station.

Analysis of individual stations showed non-terrain obstructions appear to be the most prominent and consistently correlated with average GF due to the typically small variation of topography around stations (i.e., not typically sited on steep slopes) and tendency for non-terrain obstructions to stick up above the surface. Even with respect to non-ground obstructions individual stations have highly variable correlations between maximum obstruction angle and average GF with some stations exhibiting strong steep relationships between the two while other have significant scatter or no discernable relationship.

Network composites are used to smooth over the complexities of individual environments that may obscure or muddle a potential relationship between obstruction and GF. When considered as a whole both network display notable tendencies for the average GF from any given location and direction to be larger as the maximum obstruction angle deviates from even with the horizon. At the same time, it is shown that as maximum obstruction angles diverge from flat along the horizon the average mean wind speed is expected to decrease dramatically, especially within the first ±10⁰ off the horizon. These relationships are most visible when considering averages of all stations and azimuthal directions binned by their maximum obstruction angle (0.5⁰ were used here).

One of our most notable findings was the similarity between ASOS and NYSM observations when assessed relative to obstruction angle. While ASOS is not subjected to as prominent obstruction angles as some NYSM stations are, for those they have in common the trends of average GF, iGF, mean wind speed, and gust speed are all almost perfectly identical (when factors such as averaging interval and gust duration are uniform for both networks). This
not only increases our confidence in the robustness of our conclusions across observing platforms but calls back to our initial comparisons, explaining the source of the systematic differences between the networks are driven entirely by locales and directions outside of the range of obstruction experienced in the ASOS network.

Lastly, our initial hypothesis that gusts were less affected by surface obstructions was verified. While average gust speeds decrease in a manner similar to those of mean wind speed as obstructions deviate from the horizon, we showed that they in fact drop off as a slower rate. Thus, we can affirm that gusts are less sensitive to local obstructions (if not to the degree anticipated) compared to mean wind speeds and GF therefore contains information pertaining to the surrounding environment and may be used as a simple proxy for exposure.

5.2 Future Work

There are a multitude of details, complexities, and unanswered questions remaining in this body of research that may be explored in future endeavors. Based on the results of Chapter 2 additional research may be warranted in further exploring the root causes of systematic biases with respect to landuse assignment. This may be performed using a sensitivity study of surface characteristics introducing noise or directly altering their values and evaluating resulting differences with a HRRR like re-forecast WRF configuration. For Chapter 3 additional high temporal resolution data could be sought out to further evaluate the robustness of gust curves like Durst’s and expand the record to increase confidence for highly filtered or restrictive conditions.

The amount of work that can be built upon Chapter 4 is prolific given its basis on an under-utilized, novel, and presently growing dataset. Environments from different observation networks over larger areas can be evaluated as lidar coverage increases and reinforce confidence in our observed relationships. Alternately, surface meteorological data can be subset by local time or other measure of stability (flux measurements) to assess the relative effectiveness of obstructions when the atmospheric boundary layer is well mixed, highly stable, or transitioning, similar to the body of work by Acevedo and Fitzjarrald 2001, 2003 and Medieros and Fitzjarrald 2015.
Finally, we noted previously that these conclusions do not necessarily translate from the surface throughout the surface and boundary layer. The work done in each chapter of this dissertation could be built up and improved by incorporating and validating vertical measurements of the atmosphere to see how surface quantities and vertical variations are related to each other in the context of model skill, gust variations, and sensitive of vertical structure to fine scale surface features.
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