Modelling Hail and Convective storms with WRF for Wind Energy Applications

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Abstract. Hail events are relatively rare, but hailstones (solid ice ‘balls’ ranging in diameter from 6 mm (pea) to 110 mm (softball)) have the potential to damage the leading edge of wind turbine blades causing reduced aerodynamic efficiency. Thus, hail is an important component of wind turbine operating conditions. Until recently hail occurrence was poorly (and subjectively) reported, but deployment of dual-polarization RADAR at National Weather Service (NWS) sites across the USA has revolutionized our detection abilities. Implementation of new microphysics parameterizations for the Weather Research and Forecasting (WRF) model have also greatly enhanced model capabilities. Here we present an evaluation of the WRF simulation of hail relative data from the RADAR observations conducted as part of a project with the ultimate goal of quantifying leading edge erosion potential.

1. Introduction
A key and growing source of wind turbine maintenance and repair is excess damage (i.e. material loss) on the leading edge (leading edge erosion, LEE) [1]. LEE can cause significant losses in annual energy production due to degradation of aerodynamic performance [2], caused by roughening of the blade leading edge [3]. Wind turbine blades have the highest failure rate among turbine components [4], and blade wear and failure are associated with long repair times and high cost [5]. Kinetic energy transfer from hail impacts has been identified as a damage vector and thus source of wind turbine blade leading edge erosion. There is evidence that at some sites >99% of the kinetic energy transferred by hydrometeor impacts on wind turbine blades could be from hail [6]. Thus, in order to characterize the potential for wind turbine blade leading edge erosion at sites across the US it is essential to properly characterize the frequency, intensity and characteristics of hail occurrence.

Developing robust estimates of hail frequency, size and intensity has historically been a challenging problem, due to the inherent sources of bias manifest in human-observed hail data sets such as varying population density, uneven training of observers, and under-reporting of non-severe events [7, 8]. NEXRAD, the US National Weather Service RADAR (RAdio Detection And Ranging) network, was upgraded to dual polarization (completed in 2013) and now provides the opportunity to obtain spatially discretized precipitation rates (in mm/hr) every five minutes along with in-cloud hydrometeor type (ice crystals, dry snow, wet snow, rain, heavy rain, big drops, graupel, rain with hail), an index of hail probability and the maximum expected size of hail. While this network covers the majority of the contiguous US [9], there are areas without coverage, mainly in the western US.
2. Data and Methods

Research reported herein is part of a project designed to examine the potential to develop leading-edge erosion potentials to inform wind farm siting, wind turbine selection and operation. The current study focused on a validation of the Weather Research and Forecasting (WRF) model for a test case focused on the southern Great Plains (Figure 1), over an area of frequent hail [7] and widespread wind energy development. As described in more detail below, WRF is applied to simulate a period of relatively high hail activity (June 8 to July 2, 2014) and the inner-most domain (resolved at a grid spacing of 1.3 km) covers an area with nine RADAR stations that can be used for comparison for simulation evaluation. Herein we draw illustrative examples of the model fidelity analysis using WRF output for a 100-km radius areas around the RADAR station KMAF (in Midland, west Texas) and NOAA Storm Data reports [10].

![Figure 1](image-url)

**Figure 1.** Overview of the study area showing the inner-most simulation domain used in WRF, the location of the RADAR stations and the RADAR station (and 100 km radius) from which results are presented. All nine RADAR stations contained in the WRF 1.3 by 1.3 km innermost domain are shown by red circular outlines. Wind turbine locations as of the end of 2017 according to the USGS database (available from: [https://eerscmap.usgs.gov/uswtdb/](https://eerscmap.usgs.gov/uswtdb/)) are shown as grey dots.

2.1. WRF simulation

The WRF model [11] (v3.8.1) is used herein. It is non-hydrostatic model that when applied at convection permitting resolutions (< 4 km) has been shown to reproduce organized storms and convective systems
[12, 13]. WRF has also been used to develop a hail forecast model and evaluate hail size and growth throughout a convective life cycle [14]. The present study focusses on a three week period where RADAR observations and NOAA Storm Data reports indicate repeated hail events over Texas. The simulation period covers 8 June – 2 July 2014. The simulations are conducted for a triple nest:

- d01 has a grid resolution of 12 by 12 km and comprises 320 × 320 cells
- d02 has a grid resolution of 4 by 4 km and comprises 307 × 307 cells
- d03 has a grid resolution of 1.3 by 1.3 km and comprises 502 × 502 cells

There are 41 vertical levels up to a model top of 50 hPa, 18 of these levels are in the first one km of the atmosphere, to suitably capture the planetary boundary layer (PBL). The lateral boundary conditions are updated 6 hourly, with ERA-Interim data [15] and Real Time Global (RTG) SST analyses [16] provide initial conditions. The key physics settings include the Eta microphysics scheme [17], rapid radiative transfer scheme for longwave radiation [18] and Dudhia for shortwave [19], revised Monin-Obhukov similarity scheme for the surface layer physics [20], the Noah land surface model [21], Mellor-Yamada-Nakanishi-Niino (MYNN level 2.5) PBL scheme [22] and the Kain-Fritsch cumulus parameterization [23]. Convection is explicitly resolved in the 4 and 1.33 km domains. Key diagnostics variables; radar reflectivity (as a 3-dimensional field) and hail accumulation at the ground are output from the domains resolved at 4 and 1.33 km grid spacing at 10 minute intervals. Previous research has shown realistic simulations of deeply convective storms and precipitation therefrom are heavily reliant on the microphysics parameterization applied [24, 25]. Simulations presented herein use the Milbrandt-Yau Double-Moment 7-class microphysics scheme [26], which treats graupel and hail as separate species. The scheme has double-moment cloud, rain, ice, snow, graupel and hail, and includes number concentrations of those mass variables. The model time step was 72 seconds, with a grid ratio of three, meaning the time step for the 1.33 km domain was 8 seconds. Convective storm diagnostics are also output for each domain using the NWP diagnostics option in WRF.

2.2. Observational Data
Two observational hail data sets are used herein to validate the WRF hail and reflectivity results. These are described in the following two sub-sections.

2.2.1. RADAR Data
The United States National Weather Service (NWS) operates a weather RADAR network which is a dual polarization system [27], making it an ideal platform for distinguishing hail from other precipitation [28]. NEXRAD RADAR scans a volume of air in a radius up to 300 km from each station, taking measurements at elevation angles between 0.5° and 19.5° with a horizontal resolution of 1°. At each range gate along the RADAR beam a reflectivity value is determined which describes the amount of reflected energy which is determined by the sum of the number of droplets present in the air in each droplet diameter. It is also a function of the phase of the droplets (with solid phase hydrometeors giving higher reflectivity [29]). The temporal resolution of the data used herein is generally 5 minutes, as the RADAR is in storm mode during times of hail (precipitation and clear air modes have longer measurement periods) [30]. Dual-polarization data are publicly available at a resolution of 0.25 km up to a range of 300 km from each RADAR station. Data used herein are restricted to within 100 km of the RADAR station where the lowest beam elevation angles typically intersects the cloud bottoms of convective systems. Two RADAR data products are used in the current work: (1) Hail reports, which include the location of convective storm cells and the maximum hail size (an estimate of the 75th percentile hail stone diameter (D75)) and probability of hail associated with each storm cell, and (2) composite reflectivity, which reports the highest signal return strength measured in each RADAR cell at any elevation angle. Composite reflectivity is used to estimate the spatial extent of hail events (which are associated with reflectivity > 50 dBZ [31]).

2.2.2. NOAA Storm Data.
The NOAA Storm Data database [10] is a set of human-observed hail events, which include location, timing and hail size, and frequently, a subjective description of the storm. While human observations of hail suffer from many biases which make developing a climatology difficult [7, 8], these data are independent from the RADAR data and contribute to an increased certainty that hail occurred, when hail reports are present.

2.3. Analyses

Rare events (such as the occurrence of hail) represent a significant challenge to atmospheric models and forecast evaluation (and verification) of rare events is also extremely difficult [32]. Analyses described herein are focused on evaluation of the accuracy with which WRF simulates hail occurrence with respect to timing, location and intensity. It is noteworthy that, for the purposes of correct characterization of the probability of hail-induced leading edge erosion, it is not necessary per se to correctly forecast the spatial location and extent of each individual event but rather to describe the overall probability and intensity of such events over a specific area (e.g. wind farm). Comparison is made between WRF reflectivity data and observations from human observers and RADAR in a 100-km circle centered at KMAF (see location in Figure 1). As a quantitative measure of the skill of WRF at identifying hours in which hail occurs in this scan region, contingency tables are employed, comparing the WRF output to RADAR observations. The 576 hours of the study are allocated to:

- a, the number of hits (hail event occurred in the RADAR observations and was also ‘forecast’ by WRF)
- b, the number of false alarms (no hail event was reported in the RADAR observations but hail was ‘forecast’ by WRF)
- c, the number of misses (a hail event was reported in the RADAR observations but hail was not ‘forecast’ by WRF)
- d, the number of correct negatives (hail was neither observed nor forecast)

The resulting contingency table is used to calculate three metrics of model skill. The proportion correct, $C$, the hit rate, $H$, and the false alarm rate, $F$ [32]:

$$C = \frac{a + d}{a + b + c + d}$$  \hspace{1cm} (1)

$$H = \frac{a}{a + c}$$  \hspace{1cm} (2)

$$F = \frac{b}{b + d}$$  \hspace{1cm} (3)

We also report the odds ratio, $\theta$, which is less prone to rewarding the under-predicting rare events and represents the ratio of the ‘odds’ of a hit to those of a false alarm [33]:

$$\theta = \frac{\frac{1}{1-H}}{\frac{1-F}{F}}$$  \hspace{1cm} (4)

An odds ratio of $>1$ indicates better-than-random model skill.

3. Results

The occurrence of non-zero hail accumulation integrated to an hourly time step from WRF is compared to the number of hail reports from the NOAA Storm Data and hail occurrence derived from the RADAR data in Figure 2. Qualitatively, WRF correctly captures the diurnal cycle of hail occurrence. In both the WRF output and RADAR observations, hail is most frequent between 20:00 and 06:00 UTC (15:00 to 01:00 local time, CDT). However, there is a clear bias towards excess hail frequency in the WRF simulations. There are four days (June 14 and 20-22) during which WRF simulates non-zero hail accumulations during the hours from 11:00 to 17:00 but there were no reports of hail in either the RADAR observations or from the Storm Data reports (Figure 2). It is possible that deep convection occurred in the vicinity of the KMAF RADAR scan area – particularly given the presence of a dry line (i.e. frontal humidity boundary) [34] to the northwest of KMAF during each of these days [35]. But
either these convective storms were associated with insufficient RADAR reflectivities to be identified as potentially containing hail or they occurred outside the 100 km scan radius.

**Figure 2.** The occurrence of hail during the study period. (a) Number of NEXRAD RADAR hail reports in each hour in the 100-km study area (b), total hourly hail accumulation from the WRF model from model grid cells within the 100 km radius from KMAF (note logarithmic color scale), (c) number of hail reports from Storm Data in each hour.

There is some difficulty in comparing point observations of hail (as in the Storm Report or RADAR hail report) to grid-cell averaged (1.3 by 1.3 km) output from WRF. This problem is well-known in the field of property damage risk [8, 36]. Herein, a first attempt is made to compare the geographic extent and intensity of hail around KMAF as characterized by WRF and derived from the RADAR (Figure 3). From the WRF output, intensity is defined as the total hourly accumulation of hail in the study area (in m$^3$, i.e. the sum of the depth of hail accumulation (reported in mm) in all grid cells multiplied by the area of those grid cells) and the geographic extent of hail is identified by the total area of 1.3 by 1.3 km grid cells with hourly hail accumulation > 0 mm. From the RADAR hail reports, intensity is defined as the total number of 5-minute hail storm reports in the study area for each hour (which takes into account the duration of hail from each tracked storm) For a more direct comparison with WRF, the geographic extent of the RADAR hail reports is characterized using the WRF grid, by the total number of WRF grid cells which contain hail reports. For both the WRF output and RADAR data, the intensity of hail increases monotonically with geographic extent, implying that large hail volumes occur during hours with many hail-producing storms, rather than being driven by a few severe storms. This is supported by the observation that large RADAR maximum hail sizes are not strongly associated with the most intense hours of hail (Figure 3).
Figure 3. Hourly hail intensity and spatial extent (a) total hourly volume of hail vs. the number of 1.3-km × 1.3-km grid cells with hail accumulation (note logarithmic scale) both as modelled by WRF, (b) total number of NEXRAD RADAR hail reports in each hour vs. the number of WRF grid cells which contain RADAR hail reports in that hour. The horizontal, dashed line (50th perc.) in each panel indicates the median intensity value, above which hail events are defined herein as ‘intense’.

Accuracy of the timing of hail as modelled by WRF is illustrated through a contingency table, comparing hail hours in the WRF output to hail derived from RADAR observations. This comparison is made for all hail hours, and for hours with above-median hail intensity (50th perc., shown in Figure 3) in each data set. The proportion correct for WRF modelling the presence of any hail in the study area is 0.73, increasing to 0.85 when only above-median hours are considered. This improvement is driven primarily by the decreased number of false positives in modelling hours of intense hail. The odds ratio increases from 3.14, considering all hail hours, to 4.85, when the only above-median hail hours are considered (Table 1) [33]. This implies that intense, and potentially more damaging, hail events are better simulated. WRF simulates approximately 30% more hail hours than are indicated by the RADAR: 142 from WRF and 109 from RADAR (Table 1).
Table 1. Contingency table results comparing hail events as predicted by WRF to observational-derived estimates from RADAR, for hours with any hail activity (column 1) or hours with hail activity above median intensity (column 2). Each column shows the number of hits (a), the number of false alarms (b), number of misses (c), number of correct negatives (d), proportion correct (C), hit rate (H) the false alarm rate (F), and the odds ratio (θ). Recall θ >1 indicates the model exhibits better forecast accuracy than would be achieved by random chance.

|                  | all hail events | events above median intensity |
|------------------|-----------------|-----------------------------|
| a                | 48              | 19                          |
| b                | 94              | 52                          |
| c                | 61              | 35                          |
| d                | 374             | 471                         |
| C                | 0.73            | 0.85                        |
| H                | 0.44            | 0.35                        |
| F                | 0.2             | 0.1                         |
| θ                | 3.14            | 4.85                        |

Figure 4 shows example hours when WRF, RADAR and Storm Data all indicate the presence of hail. Grid cells from WRF with non-zero hail accumulations overlap with hail reports from RADAR and human observers on June 11, 2300 UTC (Figure 4a). But are displaced in space on June 16, 0000 UTC (Figure 4b). In general, as in these two case studies, hail occurrence from WRF output covers a substantially larger area than is indicated in the RADAR data.

![Figure 4](image_url)

Figure 4. Hourly hail locations for two hours ((a) June 11, 2300 UTC and (b) June 16, 0000 UTC) with hail as indicated by WRF, RADAR and Storm Data. WRF cells with hail accumulation shown in blue, NEXRAD RADAR tracked storms with (red) and without hail (grey). Locations of hail reports from Storm Data are black squares.

Hail occurrence as estimated from RADAR is an indirect measurement of the actual occurrence of hail. Thus, as in previous research, the WRF simulations were also compared with reflectivity (the direct RADAR measurement) to evaluate the degree to which the concentration of hydrometeors in the storms is being correctly simulated [24]. Thus, composite reflectivity (i.e. the highest reflectivity measured at any point in the column) was compared between WRF and the KMAF RADAR for the same time
periods as are shown in Figure 4. As indicated, both WRF and the KMAF RADAR have large areas with high reflectivity (Figure 5, recall values in excess of 50 dBZ are often indicative of the present of hail [31]). Peak composite reflectivity levels from the KMAF RADAR in these two hours exceed those from WRF. Further, WRF indicates the occurrence of hail from storm cells where the composite reflectivities are < 50 dBZ. The areal coverage of regions of high composite reflectivity are similar for the June 11 event. For the June 16 event, WRF simulates much larger areas with high reflectivities than are represented in the RADAR data. This is consistent with the spatial difference in hail estimates from WRF and RADAR for this period (Figure 4).

Figure 5. Composite reflectivity from the RADAR (a&c), and WRF (b&d), for two periods of hail ((a) and (b) June 11, 2300 UTC and (c) and (d) June 16, 0000 UTC). Color indicates reflectivity in dBZ.

When comparing the pseudo-point estimates of hail occurrence from RADAR to the areally averaged grid cell accumulations from WRF, it is useful to have an estimate of the physical size of hail events. Consistent with the meteorological literature that indicates typical isolated storm cells with deep convection have dimension of approximately 10 km, areas of reflectivity > 50 dBZ in the RADAR data tend to be 10 – 20 km in their largest dimension (thus, roughly 80 to 300 km², based in the observations
in Figure 5a&c). A first-order comparison of the spatial extent of hail from WRF and the RADAR reflectivities during widespread hail hours (the top several hail hours in Figure 3) in WRF and RADAR can be made. Assuming an average number of 6 hail-producing storm cells (corresponding to 72 total RADAR hail observations in one hour), covering an average of ~200 km² each, we can estimate the total area of hail as 1200 km². Hours with widespread hail in the WRF output show hail in ~2500 1.3 km × 1.3 km grid cells, or 4200 km².

4. Conclusions and Future Work
Impacts from hail and large rain droplets are a major source of materials stress on the leading edge of wind turbine blades [37]. There is evidence that over much of the continental US hail may be a particularly important source of kinetic energy transfer to the blades and resulting materials stress [6]. Recent information suggests major wind farm owner/operators now envisage increasing operating lifetimes for wind turbines to 30 years [38]. Accumulated materials fatigue and damage from hydrometeor impacts over these extended lifetimes may represent an increasing portion of operating costs and partly offset projected declines in those costs [39]. Thus, there is a need to develop tools that can characterize a priori erosion potentials.

Hail impact on the leading edge of wind turbine blades has been identified as a possibly important source of leading edge erosion particularly in the southern Great Plains. We have simulated a 25 day period with a large number of hail events detected by RADAR using WRF applied at very high resolution for a triple-nested domain centered over Texas. The inner-most simulation domain is discretized into grid cells of 1.3 km by 1.3 km and is thus sufficient to describe deep convection. We present a preliminary comparison of the WRF output via comparison with reflectivity and hail estimates from RADAR and hail observations from human observers.

The WRF simulations exhibit some fidelity in terms of the occurrence of hail. For example, in the comparison of WRF hail output to RADAR observations in a 100-km circle centered at a single RADAR station in west Texas, WRF models the hourly presence of hail with a proportion correct of 0.73, and an odds ratio of 3.14. For the more intense events (i.e. hourly WRF hail accumulation and hourly number of RADAR hail reports above their respective median values), the proportion correct increases to 0.85 and the odds ratio to 4.85. However, the WRF simulations exhibit a positive bias in terms of both (1) the frequency of hail (WRF models the presence of hail in 30% more hours than are estimated from RADAR data) and (2) the spatial extent of hail. During hours of widespread hail, the spatial area over which WRF simulated hail is 3.5 times the area over which hail is indicated by the RADAR output. A larger validation exercise is underway which will include all nine of the RADAR stations contained within the WRF simulation domain. This larger data set will enable a better understanding of the sub-regional variability of the hail climate, and the accuracy of WRF at estimating the frequency and distribution of severity of hail events in this area of the Great Plains.

The current study provides a preliminary evaluation of the hail-modelling capabilities of WRF in the southern Great Plains, a region with high hail frequency and high density of wind turbines. Naturally, more research is needed to examine the simulation sensitivity to, for example, the microphysics schemes. For a long-term hail climatology to be effective with respect to estimating leading edge erosion potential, accurate estimates of the frequency and magnitude of hail events is more important than correctly modelling the exact timing and location of individual events. The ability of WRF to accurately model wind speeds during convective events such as hailstorms is also of primary importance to estimating the closing velocity between the falling hydrometeors and rotating blade and is the subject of ongoing research. If WRF simulation fidelity can be demonstrated in the longer term, the intention is to integrate data from RADAR and WRF to develop an atlas of erosion potential covering the contiguous US for use as a resource in wind turbine selection, the cost-effectiveness of leading edge protection measures and even implementation of operational strategies to mitigate leading edge erosion such as curtailment of rotor speed during severe hail events [40]. This research further enables improved understanding of the atmospheric conditions leading to hail and affords the prospect of developing projections of hail climates in current and possibly future conditions.
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6. References
[1] Keegan, M.H., D. Nash, and M. Stack, On erosion issues associated with the leading edge of wind turbine blades. Journal of Physics D: Applied Physics, 2013. 46(38): p. 383001.
[2] Zidane, I.F., et al., On the role of surface roughness in the aerodynamic performance and energy conversion of horizontal wind turbine blades: a review. International Journal of Energy Research, 2016. 40(15): p. 2054-2077.
[3] Sareen, A., C.A. Sapre, and M.S. Selig, Effects of leading edge erosion on wind turbine blade performance. Wind Energy, 2014. 17: p. 1531-1542.
[4] Zhu, F. and F. Li, Reliability analysis of wind turbines, in Stability Control & Reliable Performance of Wind Turbines. 2018: DOI: 10.5772/intechopen.74859
[5] Shohag, M.A.S., et al., Damage mitigation techniques in wind turbine blades: A review. Wind Engineering, 2017. 41(3): p. 185-210.
[6] Letson, F.W., R.J. Barthelmie, and S.C. Pryor, RADAR-derived precipitation climatology for wind turbine blade leading edge erosion. Wind Energy Science Discussions, 2019. In review.
[7] Cintineo, J.L., et al., An objective high-resolution hail climatology of the contiguous United States. Weather and Forecasting, 2012. 27(5): p. 1235-1248.
[8] Allen, J.T. and M.K. Tippett, The characteristics of United States hail reports: 1955-2014. E-Journal of Severe Storms Meteorology, 2015. 10(3).
[9] NWS. NEXRAD and TDWR Radar Locations. 2017 December 7, 2017 [cited 2019 April 16, 2019]; Available from: https://www.roc.noaa.gov/WSR88D/Maps.aspx.
[10] NOAA. Storm Events Database. 2019 [cited 2019 April 16]; Available from: https://www.ncdc.noaa.gov/stormevents/.
[11] Skamarock, W.C., et al. A Description of the Advanced Research WRF Version 3. NCAR Tech. Note, 2008. 113 pp DOI: doi:10.5065/D68S4MYH.
[12] Weisman, M.L., W.C. Skamarock, and J.B. Klemp, The resolution dependence of explicitly modeled convective systems. Monthly Weather Review, 1997. 125(4): p. 527-548.
[13] Kain, J.S., et al., Examination of convection-allowing configurations of the WRF model for the prediction of severe convective weather: The SPC/NSSL Spring Program 2004. Weather and Forecasting, 2006. 21(2): p. 167-181.
[14] Adams-Selin, R.D. and C.L. Ziegler, Forecasting hail using a one-dimensional hail growth model within WRF. Monthly Weather Review, 2016. 144(12): p. 4919-4939.
[15] Dee, D.P., et al., The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the royal meteorological society, 2011. 137(656): p. 553-597. DOI: https://doi.org/10.1002/qj.828.
[16] Reynolds, R.W. and D.B. Chelton, Comparisons of daily sea surface temperature analyses for 2007–08. Journal of Climate, 2010. 23(13): p. 3545-3562. DOI: https://doi.org/10.1175/2010JCLI3294.1.
[17] Rogers, E., et al. Changes to the NCEP Meso Eta Analysis and Forecast System: Increase in resolution, new cloud microphysics, modified precipitation assimilation, modified 3DVAR analysis. NWS Technical Procedures Bulletin, 2001. 488. 15. Available from: https://www.emc.ncep.noaa.gov/mmb/mm/bulletin/eta12tpb/.
[18] Mlawer, E.J., et al., Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. Journal of Geophysical Research: Atmospheres, 1997. 102(D14): p. 16663-16682. DOI: https://doi.org/10.1029/97JD00237.
[19] Dudhia, J., Numerical study of convection observed during the winter monsoon experiment using a mesoscale two-dimensional model. Journal of the atmospheric sciences, 1989. 46(20): p. 3077-3107. DOI: https://doi.org/10.1007/978-1-935704-13-3_16.

[20] Jiménez, P.A., et al., A revised scheme for the WRF surface layer formulation. Monthly Weather Review, 2012. 140(3): p. 898-918. DOI: https://doi.org/10.1007/s10546-005-9030-8.

[21] Chen, F. and J. Dudhia, Coupling an advanced land surface–hydrology model with the Penn State–NCAR MM5 modeling system. Part I: Model implementation and sensitivity. Monthly Weather Review, 2001. 129(4): p. 569-585. DOI: https://doi.org/10.1007/s10546-005-9030-8.

[22] Nakaniishi, M. and H. Niino, An improved Mellor–Yamada level-3 model: Its numerical stability and application to a regional prediction of advection fog. Boundary-Layer Meteorology, 2006. 119(2): p. 397-407. DOI: https://doi.org/10.1007/s10546-005-9030-8.

[23] Kain, J.S. and J.M. Fritsch, Convective parameterization for mesoscale models: The Kain-Fritsch scheme, in The representation of cumulus convection in numerical models. 1993, Springer. p. 165-170.

[24] Johnson, M., et al., Comparison of simulated polarimetric signatures in idealized supercell storms using two-moment bulk microphysics schemes in WRF. Monthly Weather Review, 2016. 144(3): p. 971-996.

[25] Tao, W.K., et al., High-resolution NU-WRF simulations of a deep convective-precipitation system during MC3E: Further improvements and comparisons between Goddard microphysics schemes and observations. Journal of Geophysical Research: Atmospheres, 2016. 121(3): p. 1278-1305.

[26] Milbrandt, J. and M. Yau, A multimoment bulk microphysics parameterization. Part I: Analysis of the role of the spectral shape parameter. Journal of the atmospheric sciences, 2005. 62(9): p. 3051-3064.

[27] Seo, B.-C., et al., Comparison of single-and dual-polarization–based rainfall estimates using NEXRAD data for the NASA Iowa Flood Studies project. Journal of Hydrometeorology, 2015. 16(4): p. 1658-1675.

[28] NOAA Federal Meteorological Handbook, No. 11 WSR-88D Meteorologic Observations Part C, Products and Algorithms. FCM-H11A-2016. 2016. 25. Available from: https://www.ofcm.gov/publications/fmh/FMH11/fmh11partC.pdf.

[29] Kumjian, M.R., Weather radars, in Remote Sensing of Clouds and Precipitation, C. Andronache, Editor. 2018, Springer. p. 15-63.

[30] NOAA Federal Meteorological Handbook, No. 11 WSR-88D Meteorologic Observations Part A, System concepts, responsibilities, and procedures. FCM-H11A-2016. 2016. 25. Available from: https://www.ofcm.gov/publications/fmh/FMH11/2016FMH11PTA.pdf.

[31] Witt, A., et al., An enhanced hail detection algorithm for the WSR-88D. Weather and Forecasting, 1998. 13(2): p. 286-303.

[32] Wilks, D.S., Statistical methods in the atmospheric sciences. International geophysics series. Vol. 100. 2011, San Diego, Calif: Academic press. 648 pp. ISBN: 0123850223

[33] Stephenson, D.B., Use of the “odds ratio” for diagnosing forecast skill. Weather and Forecasting, 2000. 15(2): p. 221-232.

[34] Ziegler, C.L., T.J. Lee, and R.A. Pielke Sr, Convective initiation at the dryline: A modeling study. Monthly weather review, 1997. 125(6): p. 1001-1026.

[35] NOAA. Daily Weather Map. 2014 [cited 2019 August 6]; Available from: https://www.wpc.ncep.noaa.gov/dailywxmap/index_20140621.html.

[36] Changnon, S.A., Data and approaches for determining hail risk in the contiguous United States. Journal of Applied Meteorology, 1999. 38(12): p. 1730-1739.

[37] Herryng, R., et al., The increasing importance of leading edge erosion and a review of existing protection solutions. Renewable and Sustainable Energy Reviews, 2019. 115: p. 109382.
[38] Wiser, R.H. and M. Bolinger, *Benchmarking Anticipated Wind Project Lifetimes: Results from a Survey of US Wind Industry Professionals*. 2019: Lawrence Berkeley National Laboratory, available from [http://eta-publications.lbl.gov/sites/default/files/wind_useful_life_report.pdf](http://eta-publications.lbl.gov/sites/default/files/wind_useful_life_report.pdf).

[39] Wiser, R.H., M. Bolinger, and E. Lantz, *Benchmarking Wind Power Operating Costs in the United States: Results from a Survey of Wind Industry Experts*. 2019: Lawrence Berkeley National Laboratory, available from [http://eta-publications.lbl.gov/sites/default/files/opex_paper_final.pdf](http://eta-publications.lbl.gov/sites/default/files/opex_paper_final.pdf).

[40] Bech, J.I., C.B. Hasager, and C. Bak, *Extending the life of wind turbine blade leading edges by reducing the tip speed during extreme precipitation events*. Wind Energy Science, 2018. 3(2): p. 729-748.