

Article

Toward a More Robust Filtering Algorithm for Radar-Derived Wind Speed Data

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Highlights

What are the main findings?

- High biases in radar-derived wind speed measurements from the American WAKE Experiment were traced to averaging and quality control of non-atmospheric data.
- A new filtering algorithm was implemented to better extract low-quality data and account for the presence of presumed biological activity, and a novel spatiotemporal averaging technique was developed to conduct comparisons with reprocessed data that account for instrument-specific probe volume and sampling frequency.

What are the implications of the main findings?

- Radar data can more confidently be used to diagnose flows in and around wind farms for wind energy purposes, for research and industry applications and future measurement campaigns.
- Radars demonstrate the capacity to detect biological signatures near wind farms, which upon verification could be used to inform operation and curtailment decisions.

Abstract

Given its large range and spatial footprint, radar remote sensing has been met with increased interest in the wind energy community. Paired radars can yield complete wind speed and direction measurements over this large spatial footprint, an invaluable asset for wind farm operators, and also the main responsibility of the Texas Tech University X-band radars installed for the American WAKE Experiment (AWAKEN). However, care must be taken in how these measurements are quality-controlled and understood. This study examines the data filtering algorithms used in AWAKEN, and how their refinement can characterize atmospheric flows around wind farms differently. The original filtering method employed in AWAKEN was found to allow some non-atmospheric measurements to remain while also expunging other, higher-quality measurements, yielding a high bias in radar wind measurements. Closer inspection of the filtering process and its output in a separate field experiment led to the discovery of biological or non-atmospheric tracers influencing radial velocity fields, and to the development of a new algorithm that more effectively removes low-quality and non-atmospheric data while preserving high-quality data. When applied to the AWAKEN dataset, comparisons between radar data processed with the new algorithm and a ground-based lidar in the radars' overlapping scanning areas show substantial reduction in the previously noted radar bias, demonstrating the utility of the new algorithm and the sensitivity of radar measurements to processing techniques.

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1. Introduction

The main goal of the American WAKE Experiment (AWAKEN) was to better understand flow modulation around wind farms, by documenting and analyzing farm-to-farm interactions with measurements from several types of instruments [1,2]. The project was focused in north-central Oklahoma, a region of densely-packed wind farms in the United States Wind Belt.

Extensive remote sensing instrumentation was employed in AWAKEN to measure wind speeds (WS) at range, including two scanning X-band radars operated by Texas Tech University (TTU-X1 and TTU-X2; together, TTU-X) as well as a WindCube v2.0 lidar (Vaisala; Louisville, CO, USA) through the Fraunhofer Institute for Wind Energy Systems (IWES). These systems were strategically positioned such that the lidar wind profiles were recorded at the orthogonal intersection of the radars' scanning paths.

Earlier analytical studies using data from AWAKEN noted that TTU-X WS measurements tended to be higher than those of other instruments [3–6]. However, the generalization of these studies is limited by one or more factors, as these earlier studies: (a) restricted comparison datasets by atmospheric stability and/or wind direction; (b) compared measurements valid for different geographic areas; (c) employed Cartesian-gridded radar data, which undergoes objective analysis (OA) processes that can introduce averaging effects; or (d) compared measurements from collocated instruments, preventing an analysis of the accuracy of radar data at long ranges.

To overcome these limitations, the present study conducted a less restricted comparison of remote sensing instruments, using longer ranges targeting the same geographic location and with minimal data modifications, to determine if systematic biases existed in TTU-X measurements. The results are necessary to assess the nuance of the TTU-X data, and to verify the strengths and limitations of remotely-sensed WS as a whole. Since lidars and radars can measure WS over large onshore and offshore areas, through various depths, with finer resolution, and often at lower cost than anemometers and towers, they are increasingly used in the wind power industry for resource assessment, siting, and power forecasting [7–9]; thus, there is motivation both from academic and industry perspectives to obtain the most accurate, consistent measurements possible.

As in previous studies, differences in radar and lidar WS measurements were observed in the initial analysis of this study. These differences were later traced to the quality-control and editing processes performed on the radar data. Subsequent revisions to the employed techniques, specifically addressing the handling of outliers, ground clutter, and non-atmospheric tracers, have yielded positive results, greatly reducing the previously observed differences in WS between the instruments and bringing mean WS bias within the window of measurement uncertainty of the lidar. The new methods employed herein have the capacity not only to retroactively improve long-range WS measurements in AWAKEN, but also to be implemented in future campaigns or in industry applications to garner the most consistent, precise results for use in research and practical contexts.

2. Materials and Methods

2.1. Instrument Configuration

2.1.1. TTU X-Band Radars

TTU-X were programmed in the AWAKEN campaign to collect data over 140° sector areas at 18 elevation tilts, at an along-beam resolution of 9 m and to a maximum range of

35 km. This configuration creates three-dimensional “volumes” of data that exist in polar space, where each range-azimuth-elevation coordinate triad contains data for four main variables, described below. The measurement revisit time, from the first azimuth of the lowest tilt to the last azimuth of the highest tilt, was approximately two minutes, and steady state was assumed over this period [10]. Table 1 summarizes the TTU-X technical specifications.

Table 1. TTU-X technical specifications for the AWAKEN campaign.

Parameter	TTU-X1 Value	TTU-X2 Value
Latitude	36.3035°N	36.3972°N
Longitude	97.6714°W	97.725°W
Elevation (Mean Sea Level)	363 m	372 m
Frequency	9330 MHz	9430 MHz
Power	10,495 W	10,447 W
Pulse Width	10 μ s	10 μ s
Pulse Repetition Frequency	4280 Hz	4280 Hz
Maximum Range	35 km	35 km
Nyquist Velocity	34.026 m s ⁻¹	34.026 m s ⁻¹
Scan Speed	30° s ⁻¹	30° s ⁻¹
Sector Area	340–125°	5–145°
Elevation Range	[0.1:0.1:1.8]°	[0:0.1:1.7]°
Range Resolution	9 m	9 m
Azimuth/Elevation Resolution	0.5°	0.5°
Azimuthal Oversampling	0.35°	0.35°
Elevation Oversampling	0.1°	0.1°

In AWAKEN, TTU-X collected data for four variables: total power (ZT, dBZ); radial velocity (VR, m s⁻¹); spectrum width (SW, m s⁻¹); and signal quality index (SQ, dimensionless). As the radars pulse energy into the atmosphere, ZT measures the proportion of energy returned, while VR describes the rate at which air moves toward or away from the radar along its instantaneous line of sight (LOS). SW quantifies the variability of the VR measurements within a particular polar bin, and the final moment, SQ, ranges from 0 to 1 and describes the strength of the return signal against background noise. High-quality data typically exhibit high SQ values and low SW values (i.e., a strong return signal with spatially consistent velocity measurements), while the reverse is true for low-quality or noisy data (i.e., a weak return signal with velocity measurements that are not spatially consistent). Examples of high- and low- quality scans are shown in Figures 1 and 2, respectively.

TTU-X were deployed in the southwest region of the AWAKEN domain, with the aim of fully characterizing wind behavior in, around, and between three wind farms: Breckinridge to the north, King Plains to the east, and Armadillo Flats to the south (Figure 3). Of particular interest was any farm-scale waking in the central region of the three farms, considering their proximities make direction-dependent impacts common; as a result, WS was the key variable of interest for which the TTU-X radars were responsible.

From the perspective of a single radar, VR is limited in its ability to quantify WS because it describes only the motion of the air along that radar’s instantaneous LOS. As a result, unless the wind and the radar’s beam are perfectly aligned, there is a nonzero component of the wind that is neither resolved by the radar nor described in its reported VR measurement. This unresolved component grows larger with the angular offset between the beam and wind vectors, peaking in regions where the two are perpendicular—a zone known as the “zero isodop.” In these cases, none of the true wind vector is resolved, and

VR is reported as zero regardless of the true WS (Figure 4). It is also important to note that, via this same principle, low elevation angles—those in AWAKEN being less than 2° —limit the resolved vertical component of the wind, meaning VR measurements mainly characterize only horizontal, not three-dimensional, winds.

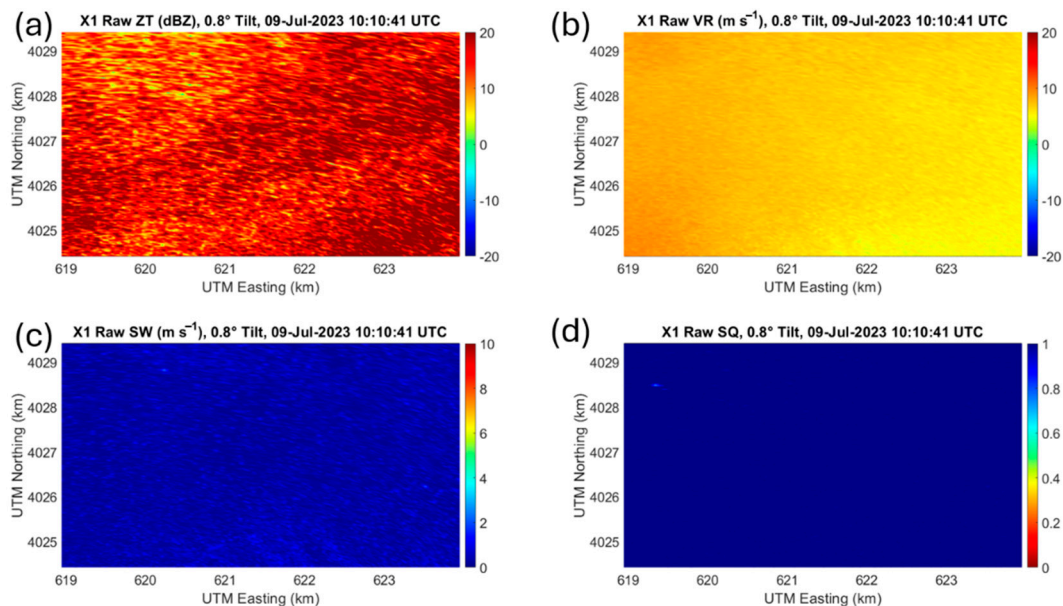


Figure 1. Example high-quality TTU-X1 data, valid for the 0.8° elevation tilt at 10:10:41 UTC, 9 July 2023, displaying (a) a broadly high return/ZT field; (b) a smooth VR field featuring a steady gradient, as expected with steady changes in azimuth/LOS; (c) a smooth SW field with values close to zero; and (d) a nearly uniform SQ field with values approximately equal to 1. Data were collected during a period of stratiform precipitation featuring ample atmospheric tracers (hydrometeors).

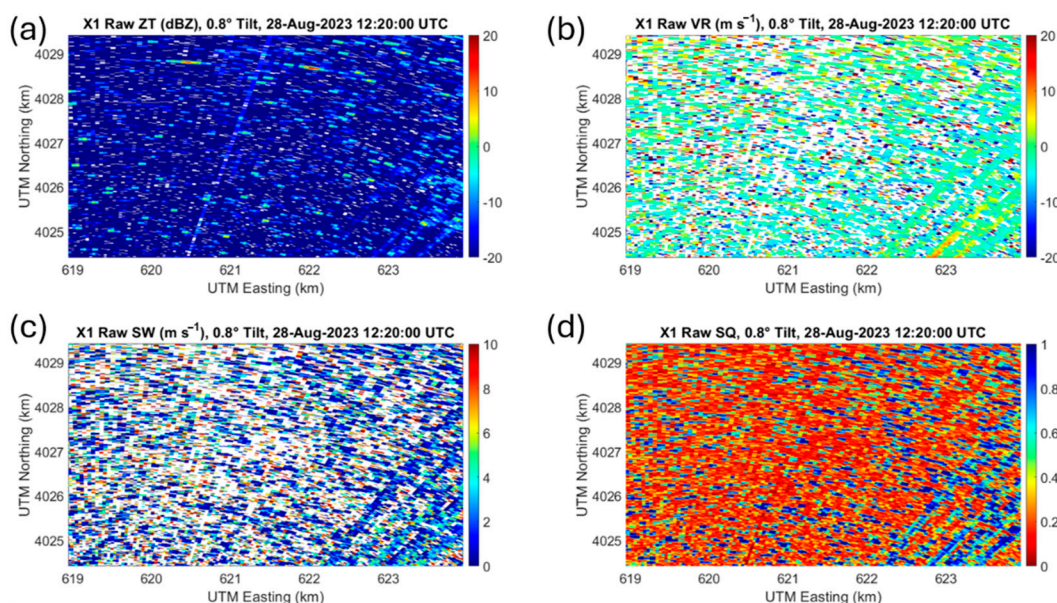


Figure 2. Example low-quality TTU-X1 data, valid for the same 0.8° elevation tilt but at 12:20:00 UTC, 28 August 2023, displaying (a) a broadly low return/ZT field; (b) a noisy, speckled VR field with scattered non-physical values, no noticeable gradient, and gaps with insufficient data for a reported value; (c), a noisy SW field speckled with high values and gaps with insufficient data for a reported value; and (d) a noisy SQ field with virtually all values below 0.5. Data were collected during a clear-air period with comparatively few atmospheric tracers.

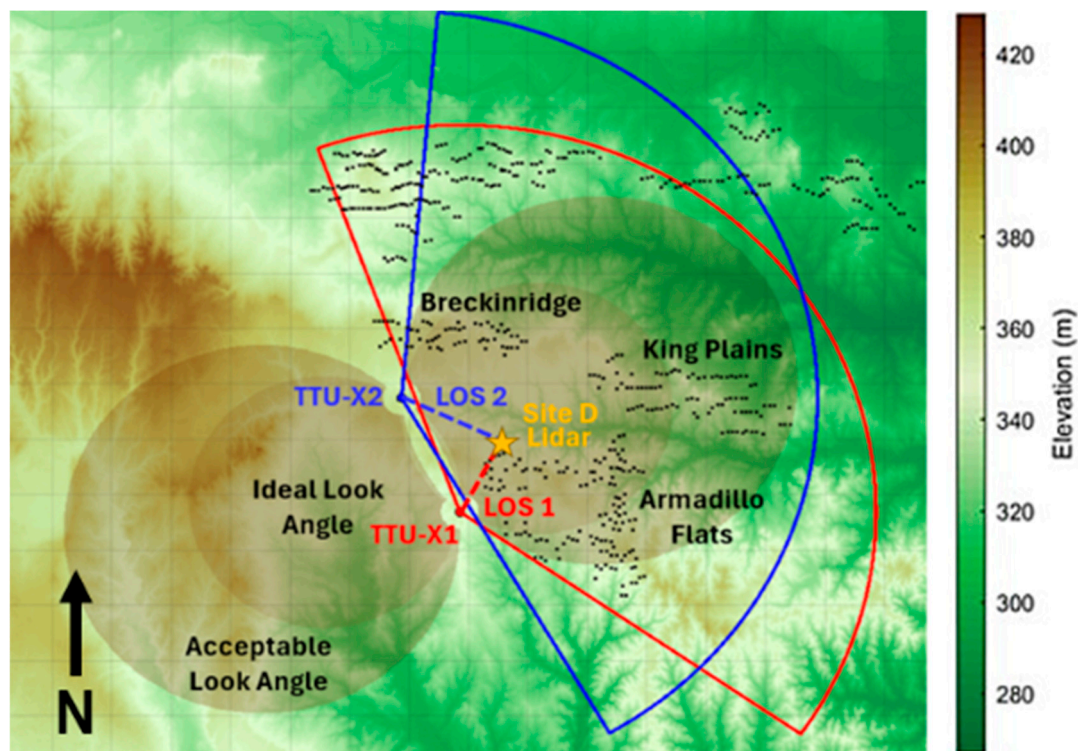


Figure 3. Situation and scanning area of TTU-X1 and TTU-X2, and the Site D lidar at their orthogonal beam intersection. LOS 1 and LOS 2 (dashed red and blue lines, respectively) indicate the azimuths along which radar VR data are collected, and the red (blue) arc shows the range of the TTU-X1 (TTU-X2) radar. Black dots indicate the locations of wind turbines, and the larger (smaller) brown shaded lobe marks the area of acceptable (ideal) look angles for DD synthesis.

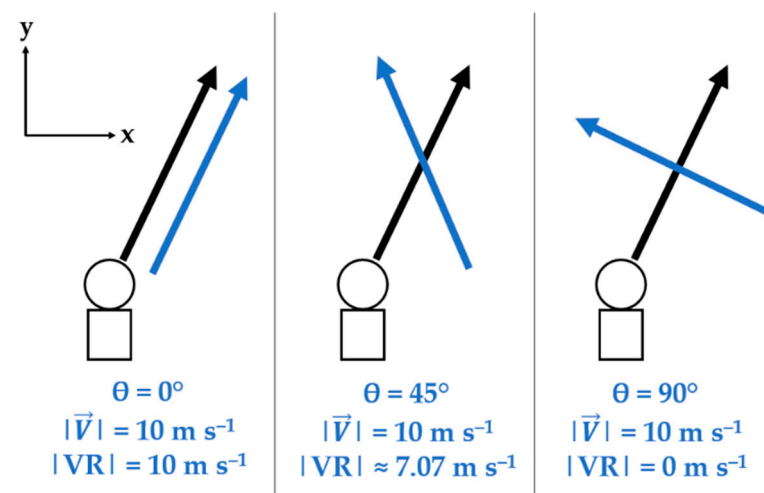


Figure 4. Visual depiction of the VR limitation and zero isodop. In each setting, the wind vector (blue) has a magnitude of 10 m s^{-1} ; however, depending on the angle θ between the wind vector and the radar beam (black), the full wind magnitude may not be resolved. Unless $\theta = 0^\circ$ or 180° , some component of the wind vector is lost. The lost component is maximized where $\theta = 90^\circ$ at the zero isodop, where no inbound or outbound velocity is measured regardless of the WS.

Addressing this inherent VR limitation is the main reason two radars were used in AWAKEN. In regions where data from two radars overlap, VR measurements from each radar can be combined to resolve a full wind vector via a method known as dual-Doppler (DD) synthesis [11]. This technique matches VR volumes from each radar in time and employs beam geometry to reconstruct full wind vectors, though is thus limited by the

crossing or “look” angle between the two radar beams. Those areas suitable for DD synthesis are shaded in brown on Figure 3: the pair of larger, lighter brown circular domains shows where the minimum look angle qualification (20° to 160°) is met, while the nested darker brown circular domains show where the ideal look angle qualification (30° to 150°) is met. These ranges are based on prior studies making use of the same principle [12,13].

The shaded regions, having VR measurements from each radar at optimal look angles, can thus resolve a full DD WS and wind direction (WD). However, the exact locations of each radar’s data bins within these regions differ from scan to scan, and from radar to radar. In order for DD synthesis to take place, VR measurements from each radar must exist in identical coordinate spaces so that they can be geometrically combined. To achieve this, data from each radar are traditionally interpolated from their native polar space onto a common Cartesian grid via an OA scheme. As mentioned in Section 1, however, this interpolation and averaging can create erroneous signatures or “artifacts” in the data that are not truly present in the atmosphere. Routine and unavoidable phenomena like radar beam spread, missing data points, the passage of time within individual volume scans, and the inherent shape and orientation of the raw VR measurements as compared to a uniform Cartesian grid can, when mathematically interpolated, cause distortions like radial streaks, hot spots, and over-smoothing of fine-scale features, in all compromising the veracity of the Cartesian field. Fortunately, these artifacts are not a concern in this study, as it opted not to make use of DD data obtained using gridded OA fields (see Section 2.3).

2.1.2. Fraunhofer IWES Profiling Lidar

Within the scan area of TTU-X is AWAKEN Site D, the location of the profiling Fraunhofer IWES lidar (FIL). The lidar generates, at 10-min intervals, vertical profiles of 11 variables, including WS and WD, at 12 vertical analysis heights, [40:10:100, 100:20:200] m above ground level (AGL). Measurements are obtained through continuous five-point scans (vertical, north, east, south, west). Non-vertical beams are aimed from ground in their respective cardinal direction at an opening angle of 28° from zenith, creating a cone-shaped probe volume slightly wider than it is tall, and horizontal homogeneity is assumed to compute the WS and WD values at the aforementioned analysis heights. The FIL along-beam resolution is 27 m [14,15], and provided wind speed uncertainty bands of 1.4–2.6% for 40 to 80 m AGL, 0.6–1.4% for 80 to 120 m AGL, and 0.6–0.8% for 120 to 135 m AGL are listed in its data sheet [16].

Distance measurements from vertically profiling lidars in particular have found extensive use in the wind energy industry for, e.g., resource assessment, analysis of turbulence intensity and across-rotor wind shear, and wake development and dissipation [7,17,18]. In this study, the IWES lidar provides a valuable perspective for two reasons: first, it is substantially closer to the volume being measured than the two radars (which are between 7 and 9 km away); second, it is well within the ideal look angle domain for DD synthesis, positioned strategically at the point where TTU-X1 and TTU-X2’s beams intersect at a right angle. The lidar can thus act as a valid point of comparison to understand and diagnose any systematic biases in the radar data, should those exist, and its location allows VR measurements to be combined into a full WS via simple trigonometry rather than through OA and spatial interpolation

2.2. Data Filtering

2.2.1. TTU X-Band Radars

In previous campaigns, raw VR measurements have historically undergone a real-time quality assurance/quality control (QAQC) editing process as they are collected. This process attempts to eliminate inter-scan jitter (small azimuthal offsets), remove ground clutter (e.g., buildings, power lines, wind turbines, trees), and search for ZT and VR

outliers to apply moment-specific thresholds and remove low-quality data or data associated with non-atmospheric phenomena. It also makes use of a data “mask” to systematically filter out values from zones with consistently high ZT [19].

As described in Section 1 as well as in greater detail in Sections 3.1–3.3, this legacy algorithm was found not to be fully adept at removing non-atmospheric measurements from the radar VR fields, leading to disagreements in velocities reported by TTU-X and the FIL. A revised algorithm, also detailed in Sections 3.1–3.3, was developed as part of a separate measurement campaign taking place in Germany, wherein similar signatures and biases were initially observed and were later rectified by the revised algorithm [20]. This new methodology was then applied as-is to the AWAKEN dataset (with the exception of a removed sea clutter filter, which was relevant to the location of the Germany campaign due to its proximity to the North Sea but not to the landlocked domain of AWAKEN), to test its applicability and utility in other datasets.

2.2.2. Fraunhofer IWES Lidar

The lidar data are filtered only by carrier-to-noise ratio (CNR); data associated with CNR values lower than -23 dB are discarded, as is common for WindCube v2.0 models. While some applications vary this threshold, with some allowing values as low as -26 dB to increase data availability (thereby simultaneously increasing noise), -23 dB was chosen for this study because (1), for the cases chosen, data availability was not a persistent issue, so a more stringent threshold did not cause an excessive lack of data; (2), work within the context of AWAKEN has consistently used a threshold of either -22 or -23 dB [3–6]; and (3), manufacturer guidance lists -23 dB as a standard threshold [21]. Other recent work on AWAKEN instrument intercomparison has found that lidar CNR, as a variable, does not have a significant effect on the sign or magnitude of difference between lidar and radar measurements [6], so the thresholding applied herein exists more as a method of maintaining consistency than of substantially altering the comparison dataset.

It is also worth noting that the FIL’s location makes it subject to the presence of wind turbine wakes, especially for southerly and south-easterly WDs (Figure 3), which may at times violate the homogeneity assumption it makes to generate its wind profiles under certain WDs. While other recent studies have reported no such dependence of instrument difference on WD [6], a signature is evident in Table 2, wherein negative biases are present in the 135 – 225° quadrant for both radars, especially for TTU-X2.

Table 2. TTU-X bias statistics binned by FIL wind direction. Square brackets indicate inclusive bounds on WD, while parentheses indicate exclusive bounds. Case-cluster bootstrap confidence intervals (CI, $n = 10,000$) are computed to account for the correlated nature of measurements within a single profile and the autocorrelated nature of measurements adjacent in time.

WD Sector ($^\circ$)	TTU-X1 Bias (m s^{-1})	TTU-X1 95% Case-Cluster Bootstrap CI (m s^{-1})	n_1	TTU-X2 Bias (m s^{-1})	TTU-X2 95% Case-Cluster Bootstrap CI (m s^{-1})	n_2
[0–45)	0.282	[0.067, 0.416]	881	0.030	[−0.017, 0.137]	847
[45–90)	0.012	[−0.095, 0.143]	1417	0.136	[−0.086, 0.297]	1304
[90–135)	0.072	[−0.027, 0.093]	874	−0.104	[−0.301, −0.072]	835
[135–180)	−0.192	[−0.381, −0.006]	1112	−0.696	[−0.905, −0.410]	1001
[180–225)	−0.142	[−0.220, 0.030]	508	−0.343	[−0.433, −0.271]	497
[225–270)	−0.608	[−0.801, 0.665]	20	−0.737	[−0.954, −0.223]	20
[270–315)	0.776	[0.665, 0.999]	37	0.137	[−0.193, 0.292]	37
[315–360]	0.656	[0.185, 0.724]	239	−0.481	[−0.857, 0.026]	239

2.3. Measurement Methodologies and Data Standardization

One difficulty in comparing WS measurements between TTU-X and the FIL is the difference in their respective probe volumes, as informed by their locations and scanning strategies. While both the lidar's conical probe volume and the radars' range gate spacing are fixed, the radars' probe volume size varies depending on beam spread, which increases with range in both the horizontal and vertical dimensions. Thus, there are typically not valid radar measurements perfectly collocated with the lidar's ground position and analysis heights, and some degree of spatial averaging must take place to perform a comparison of the two measurements.

Since the FIL assumes horizontal homogeneity, its measurements were considered representative of the full cross-sectional width of the FIL probe volume, and since the FIL along-range resolution is 27 m, non-vertical beams oriented at 28° off zenith create a probe volume depth $\Delta z = 27\cos(28^\circ) \approx 23.8$ m. This horizontal homogeneity assumption and the FIL along-range resolution yield a frustum-shaped probe volume, essentially a horizontal slice of a cone opening upward from the ground (illustrated by the black bounds on Figure 5). For reference, at 200 m AGL, the FIL cross-sectional radius is about 106.3 m, yielding a diameter of about 212.6 m in width

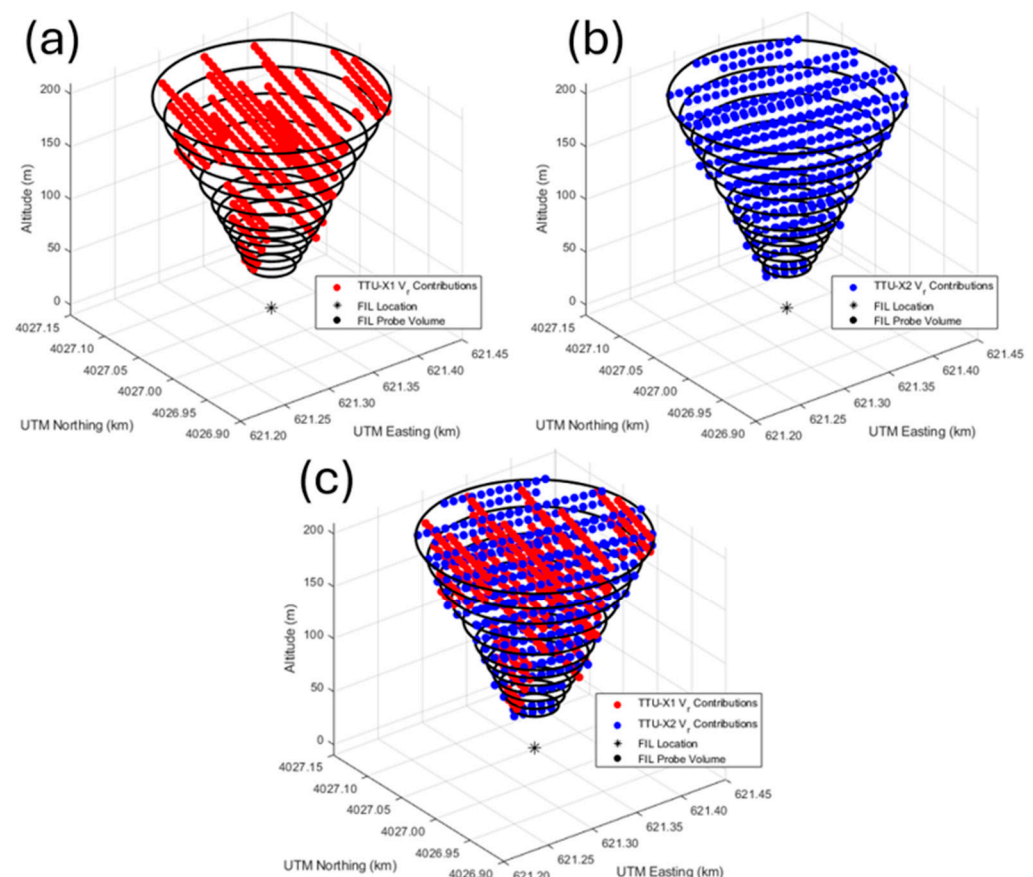


Figure 5. Locations of contributing VR data points for a single volume for (a) TTU-X1, valid 12 September 2023, 00:00:26 UTC; (b) TTU-X2, valid 12 September 2023, 00:00:21 UTC; and (c) TTU-X1 and TTU-X2 in aggregate. Circular black bands show FIL probe volume radii at analysis heights between 40 and 200 m AGL; lidar location at ground level is marked with a black asterisk.

Ordinarily, a full WS would be the metric of interest when comparing instruments like TTU-X and the FIL, and several studies have done so to varying degrees and with varying approach [3–6]. However, the OA required to transform VR data from polar to Cartesian space to obtain this WS can, as described in Section 2.1.1, introduce artifacts and

smooth out smaller features in the VR data itself. Additionally, since DD WS combines measurements from multiple radars, any systematic biases or trends that may be present in just one radar are no longer solely attributable to that radar. For these reasons, the comparison conducted in this study was one concerning only VR measurements, as the raw data are not spatially altered in any way and the individual radars' perspectives can be more closely analyzed.

Since the FIL reports a full WS and WD while the radars report only LOS velocities, for a physically consistent comparison the lidar wind vector must be broken into two components: one along the line of sight connecting each radar and the FIL (i.e., the blue and red dashed lines in Figure 3), and another along the axis perpendicular to that line of sight. Essentially, for each radar's perspective, each 10-min lidar wind vector is broken into an along-beam and across-beam projection; thus, the radar VR values and the along-beam projections describe the same physical phenomenon—the motion of air along an identical azimuth. For TTU-X1 location (R_{1x} , R_{1y}), TTU-X2 location (R_{2x} , R_{2y}), Site D FIL location (D_x , D_y), FIL WS W , and FIL WD β , the FIL along-beam projections FIL_1 and FIL_2 can be expressed as the dot products of (a) the unit vectors connecting TTU-X to the FIL and (b) the full FIL wind vector:

$$FIL_1 = \left\langle \frac{D_x - R_{1x}}{\sqrt{(D_x - R_{1x})^2 + (D_y - R_{1y})^2}}, \frac{D_y - R_{1y}}{\sqrt{(D_x - R_{1x})^2 + (D_y - R_{1y})^2}} \right\rangle \cdot \langle -W \sin \beta, -W \cos \beta \rangle, \text{ and} \quad (1)$$

$$FIL_2 = \left\langle \frac{D_x - R_{2x}}{\sqrt{(D_x - R_{2x})^2 + (D_y - R_{2y})^2}}, \frac{D_y - R_{2y}}{\sqrt{(D_x - R_{2x})^2 + (D_y - R_{2y})^2}} \right\rangle \cdot \langle -W \sin \beta, -W \cos \beta \rangle. \quad (2)$$

To best match the lidar probe volume described above, all (and only) those radar VR bins that are located within the frustum-shaped probe volumes corresponding to each analysis height q_z (i.e., [40:10:100, 100:20:200 m AGL]) are considered. Gaussian weighting applies with horizontal ($d_{h,i}$) and vertical ($d_{v,i}$) distance from the center of each frustum at (D_x , D_y , q_z), such that radar VR bins VR_i at ($r_{x,i}$, $r_{y,i}$, $r_{z,i}$) further in the horizontal dimension from the lidar's vertical beam and further in the vertical dimension from the particular analysis height receive less weight:

$$d_{h,i} = \sqrt{(r_{x,i} - D_x)^2 + (r_{y,i} - D_y)^2} \quad (3)$$

$$d_{v,i} = r_{z,i} - q_z \quad (4)$$

$$w_{h,i} = \exp\left(-\frac{d_{h,i}^2}{2\sigma_h^2}\right) \quad (5)$$

$$w_{v,i} = \exp\left(-\frac{d_{v,i}^2}{2\sigma_v^2}\right) \quad (6)$$

$$w_i = w_{h,i} w_{v,i} \quad (7)$$

The weighted-mean VR for a particular radar volume number r , at analysis height q_z and given i valid contributing VR bins, is then:

$$\overline{VR}_{r,q_z} = \frac{\sum_1^i w_i VR_i}{\sum_1^i w_i}. \quad (8)$$

Based on the opening angle and along-beam resolution of the lidar and the desired edge weighting (reduced but nonzero for points near the extremities of the frustum), σ_v is fixed at half the vertical radius of influence, $11.9/2 = 5.95$, while σ_h maintains a height dependence at half the radius of the lidar's conical probe volume at any particular analysis height. The weighting scheme is implemented to give emphasis to those VR values closest

to the exact coordinates for which the lidar measurements are valid. At least 5 valid VR bins are required to generate an average VR for a particular analysis height.

In addition to spatial considerations, temporal averaging must take place to account for differences in TTU-X and FIL's reporting frequencies. Since the radar volumes have an irregular revisit time around two minutes, less than the 10 min reporting interval of the FIL, all radar data whose volume timestamps fit within a particular 10-min segment are allowed to contribute to the reported mean VR for that 10-min segment; for example, lidar data valid for 00:00–00:10 UTC on any particular date would be compared against an average of the, e.g., [00:01, 00:03, 00:05, 00:07, 00:09] UTC radar volumes on the same date. This compilation allows the radar data to best match the reporting interval for the lidar. Only those 10-min segments with four or more contributing radar volumes are considered, as those with fewer than four tend to be at the edges of cases where radar data starts or ends several minutes off an even 10-min timestamp. To ensure segments with only partial radar coverage are not compared to segments with full lidar coverage, the minimum of four radar volumes is instituted. Radar 10-min averages are computed as an average of individual contributing volume averages.

After this process, the full comparison dataset consists of 11 discrete, continuous measurement periods maintaining >70% raw data availability for all three instruments. For TTU-X, this means at least 70% of polar data bins within a particular volume contain data before editing; for the FIL, this means that, of the 600 1-Hz measurements collected within a 10-min window, at least 70% were valid when computing the 10-min average. These 11 periods span 6 June to 11 September 2023, varying in length from just over one hour to more than 20 h and cumulatively representing around 75 h in time (a total of 450 10-min segments). Of the 11 cases, five contain periods of appreciable precipitation: 10 June, 9 July, 7 August, 14 August, and 11 September.

For most research and industry applications, the main metric or variable of interest when comparing wind sensing instruments is the full scalar WS and, again, the DD WS would typically be used for this purpose, as it represents the reconstructed full wind vector. However, two considerations motivated a different approach in this work: (1), the aforementioned averaging and artifacts the necessary OA process can introduce to DD WS fields, and (2), the FIL's position relative to TTU-X. The FIL sits at the orthogonal intersection of the TTU-X scanning paths, and thus a full vector WS can be computed using the radar azimuths as an axis basis (Figure 3). Essentially, the full WS can be computed trigonometrically at, and only at, Site D without having to conduct any OA to obtain gridded VR fields, yielding a purer point of comparison.

In summary, the (a) TTU-X VR and (b) FIL LOS1 and LOS2 velocity values FIL_1 and FIL_2 each exist at 12 analysis heights between 40 and 200 m AGL, and at 10-min intervals. They can be described in words as (a) an average of all VR data points falling within the lidar's probe volume for a particular analysis height and a particular 10-min time period (Figure 5); and (b) the component of the 10-min lidar wind vector along a line of sight identical to that of the VR values. Additionally, there is the geometrically derived WS from the two orthogonal components of (a), which can be compared to the lidar's reported WS via the equation below:

$$DD\ WS = \sqrt{VR_1^2 + VR_2^2}. \quad (9)$$

3. Results

3.1. Initial WS Comparisons

A preliminary analysis of data obtained from TTU-X and the FIL using the historically applied QAQC and filtering algorithm showed that TTU-X did, on average,

overestimate VR and WS when compared to the FIL. Mean differences in VR magnitude, as shown in Table 3, ranged from +5% to +10%, or from around +0.2 to +0.5 m s⁻¹. In a wind energy context, these differences are not insignificant; at an industry-standard 7 m s⁻¹ hub height WS, an overestimation of 0.5 m s⁻¹ results in a 23% overestimation in power. For this reason, determining the exact cause of the TTU-X overestimation was essential.

Analysis to determine the source of the difference primarily highlighted imperfections in the default QAQC process used to edit the raw radar data. More specifically, while some high-magnitude artifacts and values associated with low-quality data were being correctly discarded, others were not. This preservation of low-quality data was particularly pronounced in clear-air (non-precipitating) cases. Examples can be seen in Figures 6a,b,d,e and 7d,e, where raw VR data in the leftmost column become the filtered data in the center column after undergoing the former QAQC process. While some noticeably “hot” or “cold” spots representing non-atmospheric data are removed from the left panel to the center, the peripheries of many of these spots are left behind. This initial editing process creates a field mottled with partially expunged data, leaving convoluted erroneous data signatures and artifacts to remain. This issue is especially evident in Figure 7d,e from the 28 August 2023 case, which featured some of the lowest-reflectivity (clearest-air) environments in the entire dataset.

Conversely, instances were also identified wherein valid VR data were erroneously discarded; as an example, Figure 7a,b shows a high-quality VR field from a precipitating case seemingly “eroded” by the implemented QAQC algorithm. Such an observation is noteworthy because, especially for analysis heights nearer to the ground—where the lidar probe volume is smaller and fewer radar VR values contribute to the reported average (Figure 5)—even isolated non-atmospheric values can skew averages substantially, especially when the influence of valid data is weakened by the removal of valid values. Moreover, since these unrealistic values tend to be larger in magnitude than the mean flow (rather than smaller), they can contribute to an overall positive bias in the radar data.

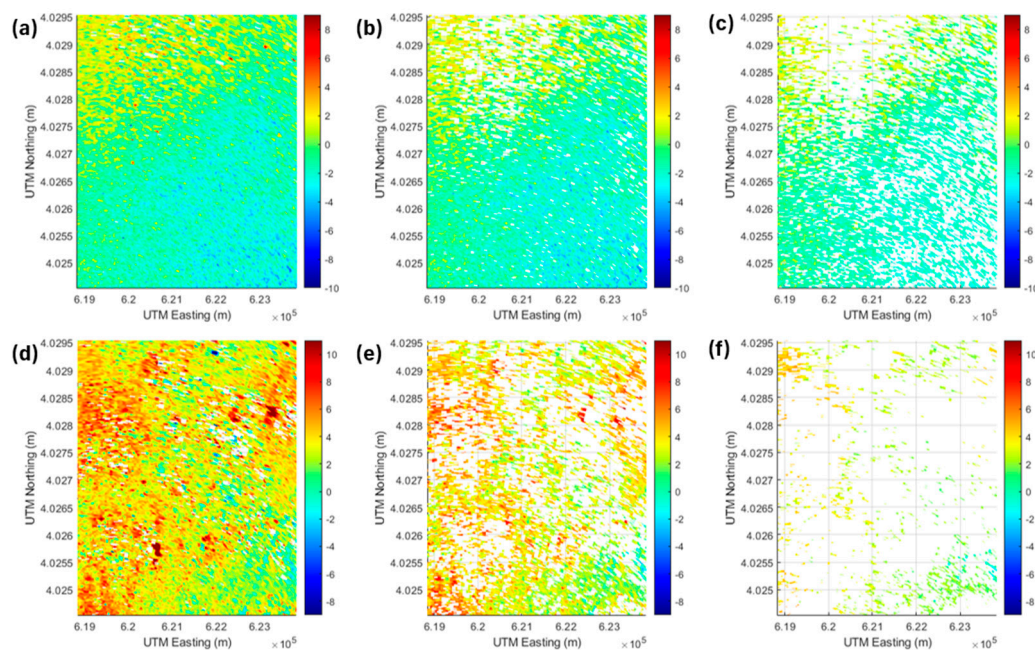


Figure 6. TTU-X1 VR (color-filled, m s⁻¹), 0.6° tilt, for (a–c) clear-air case 6 June 2023, 08:19:42 UTC, and (d–f) clear-air case 11 July 2023, 20:21:22 UTC. Left to right in each row are the raw VR data (a,c), the VR data edited by the initial algorithm (b,e), and the VR data edited by the new algorithm (c,f). Note, in the top row, the removal of extreme orange/red and dark blue values, and in the bottom row, the removal of extreme orange/red values.

Table 3. Bulk statistics for comparisons between TTU-X1 VR, TTU-X2 VR, and TTU-X DD WS compared with respective lidar WS/components (former QAQC/editing method). Bias is defined as radar VR magnitude (R) minus lidar LOS magnitude (L) for the top two rows, and as radar WS (R) minus lidar WS (L) for the bottom row. Bias percentage is defined relative to the respective means of each perspective under the new filtering algorithm, so as to create a common reference with later statistics; for example, for TTU-X1 VR R_1 and FIL component L_1 , $100 \times (|\bar{R}_1| - |\bar{L}_1|)/(|\bar{L}_1|)$. Columns labeled ‘Subset’ contain statistics calculated over only those pairs of matched points that remain valid after the new filtering algorithm detailed in Section 3.3, also to create a common reference.

Comparison	(R–L) Bias (m s ^{−1})	(R–L) Bias (%)	<i>n</i>	Subset (R–L) Bias (m s ^{−1})	Subset (R–L) Bias (%)	Subset <i>n</i>
TTU-X1 vs. FIL ₁	0.488	10.311	5214	0.421	8.895	5111
TTU-X2 vs. FIL ₂	0.214	5.561	5097	0.202	5.249	4806
TTU-X WS vs. Lidar WS	0.534	7.903	5056	0.511	7.563	4775

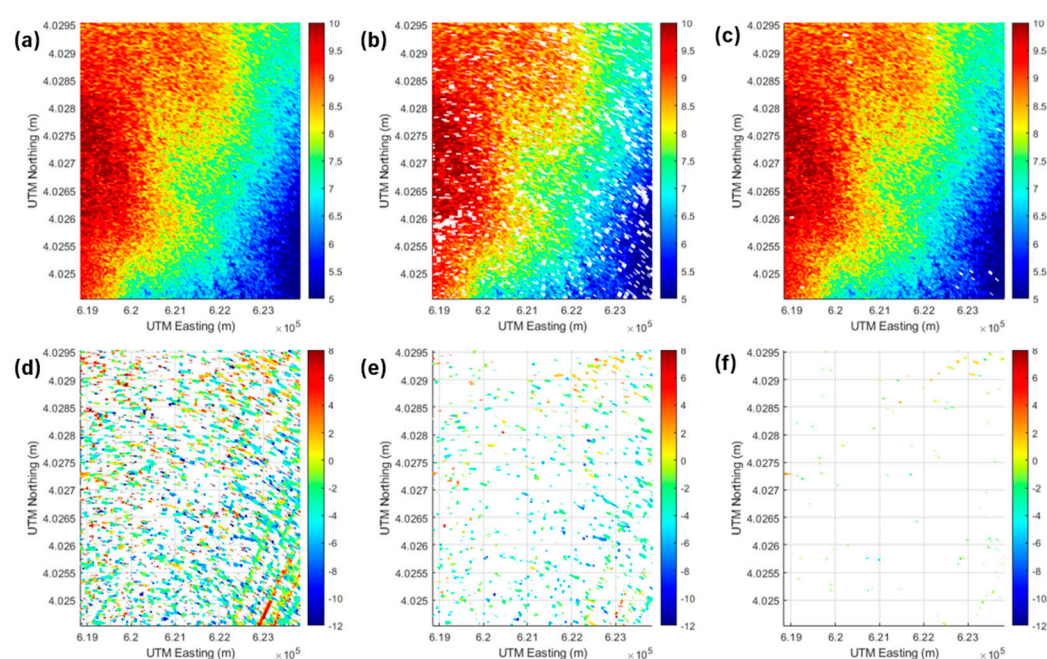


Figure 7. TTU-X1 VR (color-filled, m s^{−1}), 0.6° tilt, for (a–c) 9 July 2023, 10:19:09 UTC, and (d–f) 28 August 2023, 12:20:00 UTC. Left to right in each row are the raw VR data (a,c), the VR data edited by the initial algorithm (b,e), and the VR data edited by the new algorithm (c,f). Note, in the top row, the restoration of initially removed high-quality VR values, and in the bottom row, the removal of almost all (noisy) values. The presence or absence of hydrometeors mainly drives the difference in appearance between (c,f).

3.2. Presence of Biological Tracers & Activity

What further emerged after the initial instrument comparison was that biological tracers were a possible source of non-meteorological return embedded in the AWAKEN radar data. As biological scatterers fly, their group and individual size is sufficiently large to be detected by radar [22–24]. However, the flight paths of biological targets are not restricted to the ambient WS or WD; animals can and do move at speeds and directions different than the air through which they fly, often faster [22–25].

There are several signatures that can indicate the presence of biological tracers. First, it is expected that flying creatures would not be present during periods of heavy or prolonged precipitation; rather, they would be active during clear-air periods. Thus, in a field of low clear-air ZT, a creature or creatures in flight would appear as a “hot spot”, a zone of greater return featuring a highly visible tracer. This would be reflected similarly in the

SQ field, as a local “hot spot” with reliable return signal amid a field with an otherwise weaker return signal. An example of these signatures can be seen in Figure 8a,c. Incongruities caused by flight behavior also appear in the VR field as localized areas with a noticeably different VR magnitude or sign than their surroundings, caused by a given biological tracer flying at a speed and direction differing from the background flow. This signature can be seen in Figure 8b, as well as in Figure 9a–c.

Importantly, not every artifact or visual outlier in radar fields can or should be attributed to the presence of biological tracers. One distinguishing characteristic of biological activity is its persistence in space, but not in time: as biological scatterers fly, especially in groups, they can be detected on multiple radar tilts, as these are only a few seconds apart in time and 10–15 m apart in altitude for the ranges in this study. However, while this “hot spot” appears on consecutive tilts within the same volume, it will not appear in consecutive volumes at the same tilt, because these are two or more minutes apart for the implemented AWAKEN scanning strategy. In that elapsed time, movement will have taken place, sometimes more than a kilometer’s worth; as a result, the “hot spot” will have shifted an appreciable distance in the radar fields.

The above phenomenon is exemplified in Figure 9, where measurements from TTU-X1 show that a reddish zone of anomalously high VR (several 15–20 m s^{−1} bins in a background field of around 4–7 m s^{−1}) is present around the same x-y location over consecutive intra-volume tilts (Figure 9a,c). However, the feature translates around 1.5 km to the northeast in just over two minutes between inter-volume scans at identical elevation angles (Figure 9a,b). Given the moderate positive (outbound) VR values along the north-northeasterly LOS for TTU-X1, these VR snapshots suggest a group of scatterers moving with, though faster than, the ambient wind.

It should also be noted that this study focuses on a three-month period during the summer season (June through September), where biological activity is greatest. In winter months, as biological activity subsides, irregularities would theoretically become much more minimal; thus, it is hypothesized that there may be a strong annual signature to these effects depending on regional weather patterns and biota behavior.

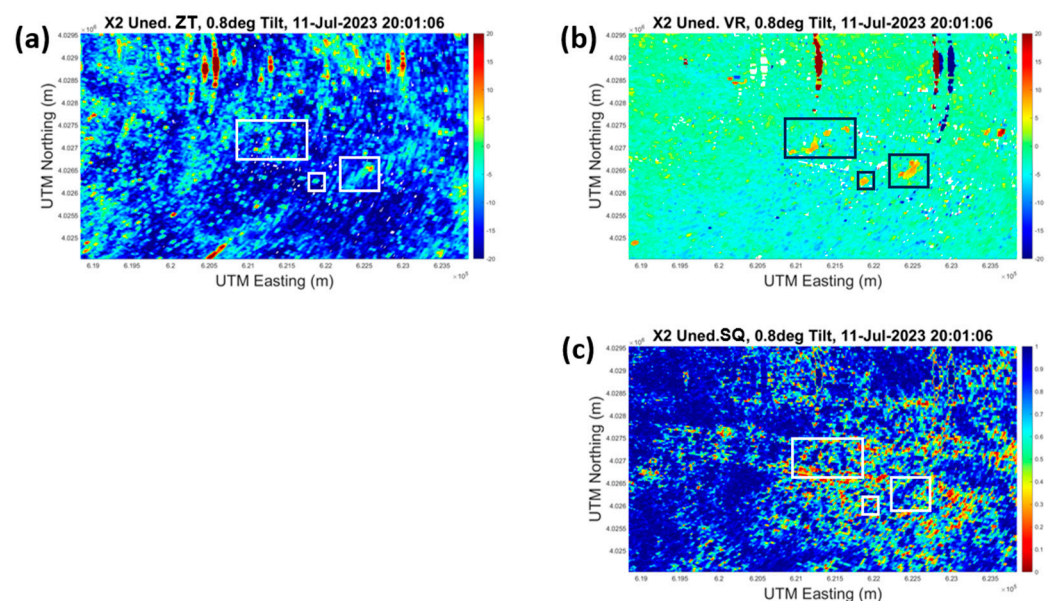


Figure 8. Raw TTU-X2 (a) ZT, (b) VR, and (c) SQ for 11 July 2023, 20:01:06 UTC. The three boxes are colligated on each image. Note the localized warm (yellow-green) spots in the ZT field, coincident with the anomalous warm values in the VR field as well as the higher-quality return (darker blues) in the SQ field, in a region of relatively low-quality (red-orange) return.

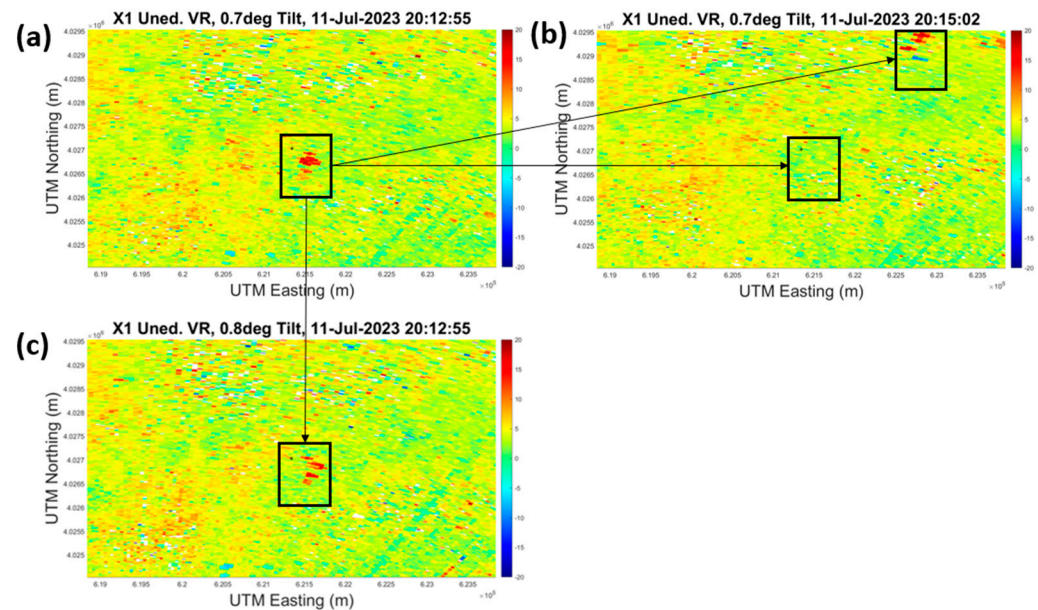


Figure 9. Raw TTU-X1 VR on 11 July 2023 for (a), the 0.7° tilt in the 20:12:55 UTC volume; (b) the 0.7° tilt in the 20:15:02 UTC volume (one volume later than (a), on the same tilt); and (c), the 0.8° tilt in the 20:12:55 UTC volume (the same volume as (a), but one tilt higher). Note the “hot spot” located near the FIL in (a): it is still visible having only slightly shifted in (c), valid a few seconds later, but has shifted substantially in (b), just over two minutes later. TTU-X1 VRs are positive in this volume, indicating flow away from the radar along its north north-easterly LOS to the FIL. Here, the tracers appear to be flying with, but faster than, the wind.

3.3. Development of a New QAQC Algorithm

As a result of the above findings, a new QAQC algorithm was devised to attempt a more targeted removal of low-quality and non-meteorological data. This new algorithm focuses on the treatment of outlier values in the ZT and VR distributions, implements a methodical search for biological or non-atmospheric tracers, forgoes the data mask used in the original filtering algorithm, and more stringently removes data that are noisy or associated with radar artifacts, particularly in clear-air environments (Figure 10). It employs a localized moving window through the raw polar data to statistically identify, and remove, individual bins within the window that are deemed outliers using various combinations of all radar moments.

Some steps of the algorithm defined below—mainly step 1 (fixed ZT and VR thresholding) and 3f (environment-relative anomalously high ZT removal) are focused on removing the influence of fixed non-meteorological targets, while others such as step 2 (dynamic ZT and VR thresholding) and 3b–d (the ‘window’ outlier search) are designed to detect and remove values that are anomalous relative to their individual environments (e.g., the presence of biological or other non-atmospheric targets). Step 3a, which generates vertical profiles of ZT to detect sharp gradients therein, focuses on near-surface high-return ground clutter from fixed targets, but is versatile in that it can also flag discontinuities higher above the surface where creatures may be in flight.

It should be noted, as is mentioned in Section 2.2.1, that the new filtering algorithm was initially developed for use in an unrelated overseas measurement campaign [20], which leveraged similar radar technology to measure WS over a smaller domain than in AWAKEN. When high biases in these radar measurements were observed with respect to other instruments as they were in AWAKEN [3–6], the new algorithm was developed first for the overseas deployment, then upon successful mitigation of the bias was retroactively applied to the raw AWAKEN radar datasets. The procedures defined below are thus not

inherently tied to the AWAKEN domain or to the associated VR datasets collected by TTU-X; thresholds and parameters were fixed prior to the new method's application.

Since six of the cases analyzed saw no precipitation, these periods were subject to significantly more data removal, as seen in Figure 11. These cases are also evidenced in Figures 6d–f and 7d–f, where the raw VR field is filtered to near-emptiness by the new algorithm. Figure 12 similarly shows example distributions of contributing VR values from a single volume, at a single analysis height, during the low-return clear-air 28 August case seen in Figure 7d–f before and after the editing process, to demonstrate the scale and relative magnitude of points removed. Tables 4 and 5 collectively quantify the new algorithm's data removal rate, from a clear-air versus precipitating perspective (Table 4) and from an analysis height perspective (Table 5).

It is worth noting, since often precipitating cases in this region of the United States in the summer months feature convection, that the algorithm allows for multiple velocity “bands” in the histograms created in step 2 and accordingly adjusts the envelopes created in step 3d. In other words, if a window exists at the boundary of a convective feature, the often higher-magnitude VR values characteristic of that convective feature are still included in the calculated admissible VR range, and are not filtered out. This is done so that the wind associated with the convection—a true atmospheric phenomenon which the instrument(s) are indeed experiencing—is not erroneously removed.

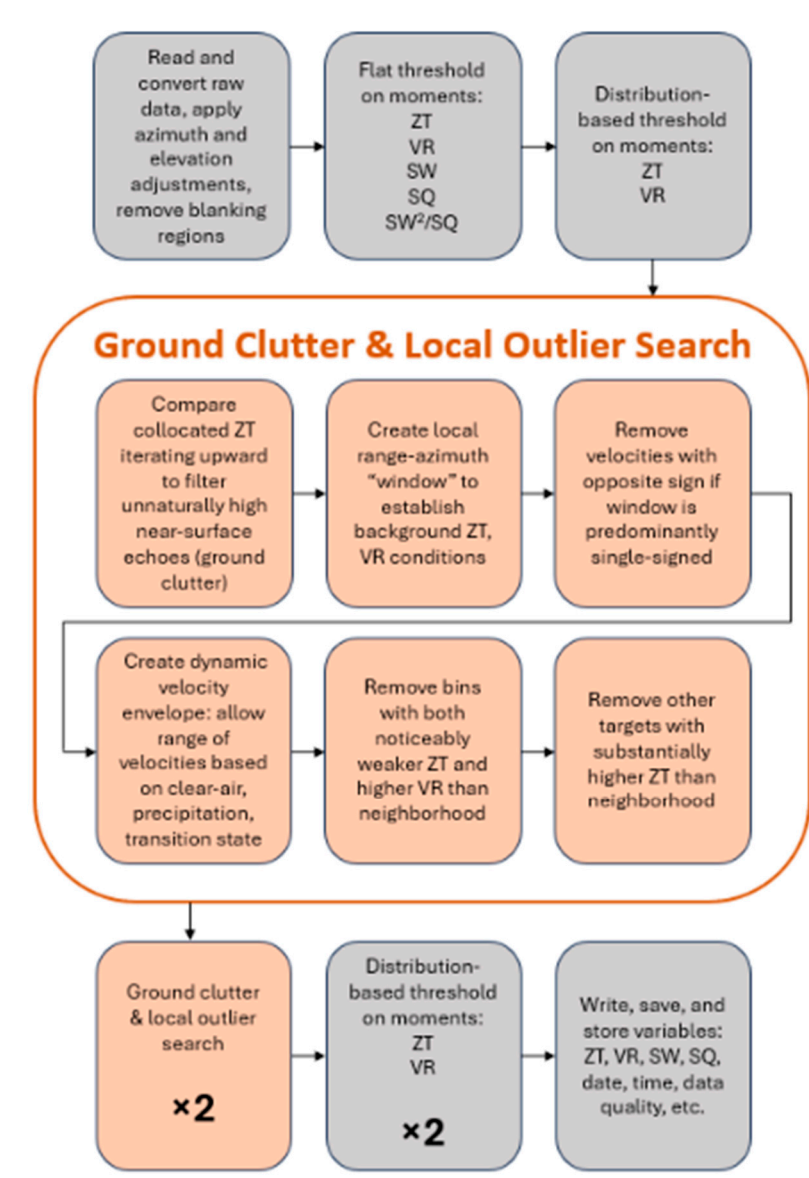


Figure 10. Flow chart showing the steps implemented in the revised filtering algorithm. Orange boxes indicate where the ground clutter and local outlier search methodology is applied, and the six steps enclosed by the orange curve represent a zoomed-in version of the orange box in the bottom-left.

The revised strategy operates as follows, after raw radar data are read in:

1. A first-pass, flat threshold is applied to each radar moment, and data points for which any of the following are true are removed: $ZT > 50$ dBZ (to exclude situations affected by very heavy precipitation and possible attenuation, as well as large ground targets); VR magnitude > 30 m s⁻¹ (to exclude velocities outside those climatologically expected); $SW > 2.75$ m s⁻¹ (to exclude bins with highly variable or inconsistent VR measurements); $SQ < 0.3$ (to exclude noisy, low-quality data); or $SW^2/SQ > 15$ (a composite to exclude data with high SW and low SQ not filtered by the individual SW and SQ thresholds) [11,19,26,27].
2. A distribution-based threshold is applied to the ZT and VR moments. On a per-volume basis, 1000-bin ZT and VR histograms representing all raw data are constructed, and all bins with zero count are discarded. The first bin count working inward from the tails to exceed 1% of the total population is recorded; looking from these 1% bins tailward, the first bin count to fall below 0.1% of the total population is recorded, and all values tailward of those bins are removed.
 - a. This order-of-magnitude, population-based filtering removes only the most extreme values, and allows for relatively uncommon, but possibly still physical, ZT and VR values to be kept for further quality assessment. Bin population percentages are held at low magnitudes in this stage because the population-based filtering does not yet take into account the unique atmospheric state of each scan; this follows in step 3.
 - b. The 1%/0.1% bin method allows for multiple “modes” within a given volume’s ZT or VR distribution, specifically for cases where small portions of a volume may experience precipitation and/or comparatively high winds (due to, e.g., convection) while other portions do not. Both portions of the volume—those with precipitation and/or high winds and those without—are represented in the distributions, and thus no valid data is erroneously discarded due only to averaged numerical thresholding.
3. A first-pass ground clutter and local outlier search (orange boxes in Figure 10) is conducted, consisting of the following:
 - a. Comparisons of ZT at multiple vertical levels, to isolate any bins with anomalously high return that is not consistent through the atmosphere (as is expected with ground targets); bins with a more than 15 dBZ difference not sustained in height are removed.
 - b. The creation of a local “window” with a 10-gate azimuthal dimension and a 100-gate range dimension; the mean ZT and median VR are computed for this window and used for comparison in (d). Windows are overlapped by one-half in each dimension to avoid boundary discontinuities, and expand in size with range to accommodate radar beam spread.
 - c. The removal of oppositely signed velocities when the VR values within the window are more than 90% positive or 90% negative; this order-of-magnitude test removes spikes due to noise or range aliasing artifacts.
 - d. The creation of a dynamic velocity envelope. The width of this envelope is dependent on the characterization of the window as low-velocity (median VR magnitude ≤ 2 m s⁻¹), mid-velocity (2 m s⁻¹ $<$ median VR magnitude < 12 m s⁻¹),

or high-velocity (median VR magnitude $\geq 12 \text{ m s}^{-1}$), as well as the characterization of the atmosphere as clear-air (mean ZT $< 0 \text{ dBZ}$), precipitating (mean ZT $> 3 \text{ dBZ}$), or transitional ($0 \leq \text{mean ZT} \leq 3 \text{ dBZ}$). Threshold values for ZT and VR regimes were determined based on prior radar deployments [26,27].

- e. The envelope is centered on the window median VR and calculated with the use of gust factors (GF) [28–31]. The tightest envelopes are used in clear-air and high-velocity environments, while the widest are used in those featuring precipitation and low velocities. For precipitating regimes, a range of $\text{GF}_{\max(\text{p})}$ (for low VR) of 1.87 to $\text{GF}_{\min(\text{p})}$ (for high VR) of 1.48 is used, while for clear-air cases a range of $\text{GF}_{\max(\text{c})} = 1.40$ and $\text{GF}_{\min(\text{c})} = 1.20$ is used. For all regimes, a low-end GF_{low} of 0.3 is used to filter low-quality VR data near zero. Calculation of the envelopes with these GS ranges is described below:
 - i. For low-speed, precipitating cases: VR magnitudes greater than double $\text{GF}_{\max(\text{p})}$ are removed.
 - ii. For mid-speed, precipitating cases: GF is calculated as a linear interpolation between $\text{GF}_{\max(\text{p})}$ and $\text{GF}_{\min(\text{p})}$, scaled by the window median VR's position between 2 m s^{-1} and 12 m s^{-1} (the edges of the velocity determination ranges). VR magnitudes greater than the window median VR times the window GF, or less than the window median VR times GF_{low} , are removed.
 - iii. For high-speed, precipitating cases: VR magnitudes greater than the window median VR times $\text{GF}_{\min(\text{p})}$, or less than the window median VR times GF_{low} , are removed.
 - iv. For transition cases: GF is calculated as a bilinear interpolation between $\text{GF}_{\max(\text{p})}$, $\text{GF}_{\min(\text{p})}$, $\text{GF}_{\max(\text{c})}$, and $\text{GF}_{\min(\text{c})}$, based on the window mean ZT and median VR. VR magnitudes greater than the window median VR times the window GF, or less than the window median VR times GF_{low} , are removed.
 - v. For clear-air cases: identical computation and logic to precipitating cases, but $\text{GF}_{\max(\text{p})}$ and $\text{GF}_{\min(\text{p})}$ become $\text{GF}_{\max(\text{c})}$ and $\text{GF}_{\min(\text{c})}$.
 - f. In clear-air environments only: the removal of bins with a ZT more than 5 dBZ lower than the window mean ZT and more than 120% of the window median VR; accounts for low-quality, high-velocity data not filtered in steps (a) through (d).
 - g. The removal of bins whose ZT is more than 10 dBZ greater than window mean ZT; accounts for other miscellaneous non-atmospheric clutter or ground targets not filtered in steps (a) through (e).
4. The ground clutter and local outlier search is conducted a second time.
 5. The distribution-based thresholding is conducted a second time.
 6. The edited data are written, saved, and stored.

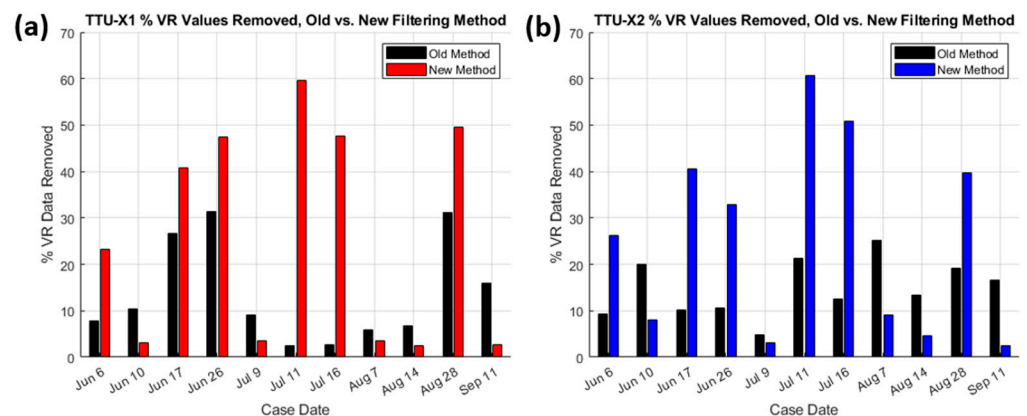


Figure 11. Percentage of raw VR values removed by the old (black) versus new (red/blue) QAQC algorithm, for (a) TTU-X1 and (b) TTU-X2 and for each of the 11 cases within the comparison dataset. Note the difference in precipitating cases (10 June, 9 July, 7 August, 14 August, 11 September) vs. clear-air (6 June, 17 June, 26 June, 11 July, 16 July, 28 August): in precipitating cases, the old algorithm invariably removed more than the new, while the opposite is invariably true for clear-air cases.

Table 4. TTU-X pre- and post-QAQC total valid bin count and data availability (as percentage of original) by case type. Again, note the difference between precipitating and clear-air cases for VR bin removal rate: nearly half of all recorded VR bins from clear-air cases are removed by the filtering algorithm, while only about 5% are removed in precipitating cases.

Case Type	TTU-X1 Pre-QAQC Bin Count	TTU-X1 Post-QAQC Bin Count	TTU-X1 Post-QAQC Availability	TTU-X2 Pre-QAQC Bin Count	TTU-X2 Post-QAQC Bin Count	TTU-X2 Post-QAQC Availability
Clear-Air	628,486	329,105	52.4%	1,001,111	579,991	57.9%
Precipitating	247,506	239,864	96.9%	405,807	384,914	94.9%
Total	875,992	568,969	65.0%	1,406,918	964,905	68.6%

Table 5. TTU-X pre- and post-QAQC total valid bin count and data availability (as percentage of original) by analysis height. Here the marked influence of ground clutter can be seen for TTU-X2, where VR bins are removed at nearly twice the rate at the lowest analysis height as compared to upper levels.

m AGL	TTU-X1 Pre-QAQC Bin Count	TTU-X1 Post-QAQC Bin Count	TTU-X1 Post-QAQC Availability	TTU-X2 Pre-QAQC Bin Count	TTU-X2 Post-QAQC Bin Count	TTU-X2 Post-QAQC Availability
40	9423	5786	61.4%	13,231	5236	39.6%
50	23,107	14,117	61.1%	17,100	8108	47.4%
60	28,093	17,396	61.9%	26,690	12,890	48.3%
70	17,631	11,273	63.9%	26,514	14,347	54.1%
80	35,788	23,121	64.6%	28,690	18,256	63.6%
90	49,675	32,845	66.1%	69,126	44,390	64.2%
100	46,435	31,855	68.6%	94,101	63,391	67.4%
120	73,083	48,378	66.2%	113,921	82,078	72.0%
140	140,481	91,371	65.0%	177,568	125,935	70.9%
160	150,363	99,705	66.3%	197,686	137,994	69.8%
180	112,516	73,551	65.4%	271,099	190,849	70.4%
200	189,397	119,571	63.1%	371,192	261,431	70.4%

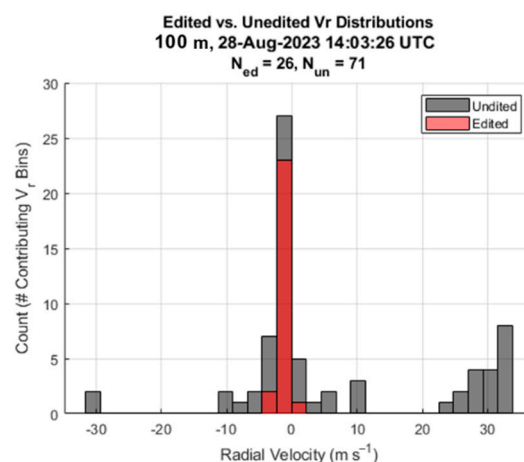


Figure 12. Distributions of VR values falling within the $q_z = 100$ m AGL analysis height frustum and contributing to the 100-m VR average before (gray), and after (red), the revised editing methodology; valid for the 14:03:26 UTC, 28 August 2023 volume. Note the removal of the highest-magnitude, non-atmospheric VR values from the average, while more physical values nearer zero are kept, demonstrating effect of low-quality data on reported VR average—a hypothesized source of the observed high bias.

3.4. Results of the New QAQC Algorithm

Once a larger amount of low-quality data are removed (and a small amount of high-quality data are reinstated) by the new editing process, comparisons between the lidar and radar improve. Table 6 shows the same metrics as Table 3—comparison of radar VR/lidar LOS velocities and full radar/lidar WS values—and mean differences between instruments are limited in magnitude to within 3%, around 0.1 m s^{-1} , and are no longer unanimously high. Perhaps most notably, the overall mean difference in full radar WS and full lidar WS is less than 0.01 m s^{-1} , or about 0.02%. Given a study-mean lidar WS of about 6.5 m s^{-1} for measurements below 135 m AGL (i.e., the lidar’s range of defined measurement uncertainty), these values fall within the quoted 0.6–2.6% bands (approximately 0.039 to 0.169 m s^{-1}), making bulk bias indistinguishable from zero given the reference uncertainty. Scatter plots showing comparison for the TTU-X1, TTU-X2, and DD perspectives are shown in Figure 13, and bulk as well as height- and WS- dependent bias statistics follow in Tables 6–10.

Table 6. Bulk statistics for comparisons between TTU-X1 VR, TTU-X2 VR, and DD WS compared with respective lidar WS/components (revised QAQC/editing method). Bias and percentage bias are as defined in Table 3. While the signs of the mean bias for the TTU-X1 and TTU-X2 perspectives are opposite, implying some degree of cancellation between the two radars in the generation of the full WS, it should be noted that the computation of the full WS is nonlinear

Comparison	(R–L) Bias (m s^{-1})	(R–L) Bias (%)	95% Case-Cluster Bootstrap CI (m s^{-1})	r
TTU-X1 vs. FIL ₁	0.042	0.888%	[−0.1387, 0.4352]	0.992
TTU-X2 vs. FIL ₂	−0.102	−2.651%	[−0.3640, 0.1039]	0.972
TTU-X WS vs. Lidar WS	0.001	0.018%	[−0.2334, 0.3857]	0.980

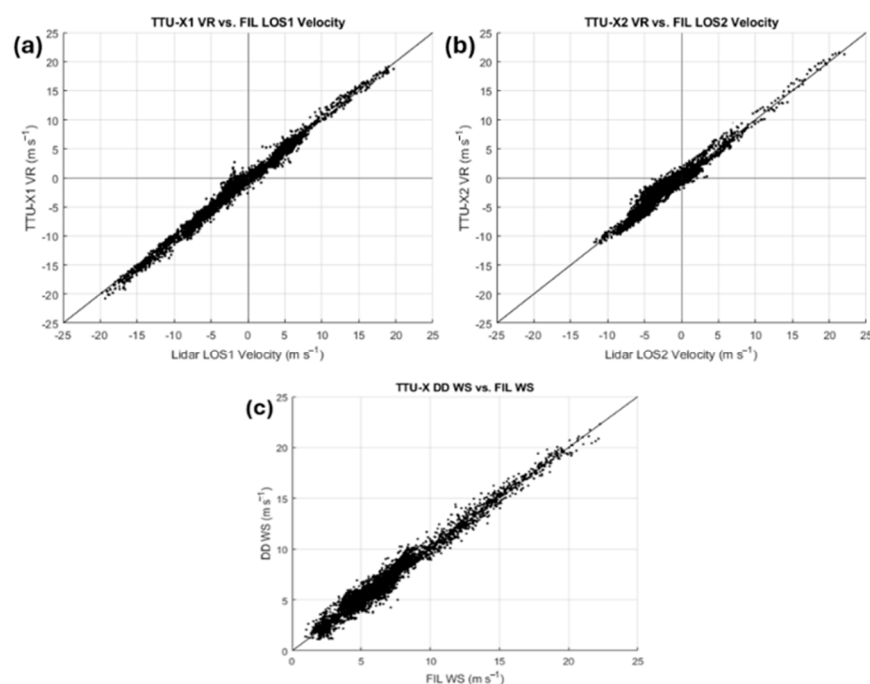


Figure 13. Scatter plots showing comparisons for (a) TTU-X1, (b) TTU-X2, and (c) DD perspectives.**Table 7.** Reduced main axis (RMA) regression statistics for comparisons between TTU-X1 VR, TTU-X2 VR, and DD WS compared with respective lidar WS/components (revised QAQC/editing method), as shown in Figure 13a–c. RMA regression was used to allow for the presence of error in both variables. Overall, TTU-X2 performs the best, with the slope nearest 1 and the intercept nearest 0, while the full WS comparison performs least well, likely due to the compounding of error from both radars in generating reported values.

Comparison	MAE (m s ⁻¹)	<i>n</i>	Regression Slope	Regression Intercept
TTU-X1 vs. FIL ₁	0.586	5111	0.969	0.108
TTU-X2 vs. FIL ₂	0.658	4806	0.999	−0.032
TTU-X WS vs. Lidar WS	0.679	4775	1.067	−0.419

Table 8. TTU-X1 difference statistics by analysis height. Bias is as defined in Table 3.

Analysis Height (m AGL)	TTU-X1–FIL ₁ Bias (m s ⁻¹)	<i>n</i>	95% Case-Cluster Bootstrap CI (m s ⁻¹)
40	0.126	427	[−0.049, 0.301]
50	−0.043	429	[−0.179, 0.093]
60	−0.019	431	[−0.144, 0.106]
70	−0.007	431	[−0.117, 0.103]
80	−0.018	431	[−0.130, 0.094]
90	0.065	430	[−0.053, 0.183]
100	0.066	430	[−0.043, 0.175]
120	0.055	430	[−0.069, 0.179]
140	0.042	430	[−0.082, 0.166]
160	0.050	429	[−0.073, 0.173]
180	0.082	417	[−0.053, 0.217]
200	0.108	396	[−0.004, 0.220]

Table 9. TTU-X2 difference statistics by analysis height. Bias is as defined in Table 3. Note again the strong influence of ground clutter, where *n*₄₀ is substantially lower than other levels.

Analysis Height (m AGL)	TTU-X2–FIL ₂ Bias (m s ⁻¹)	<i>n</i>	95% Case-Cluster Bootstrap CI (m s ⁻¹)
40	−0.105	205	[−0.249, 0.039]
50	−0.253	368	[−0.421, −0.085]
60	−0.289	405	[−0.453, −0.125]
70	−0.239	418	[−0.378, −0.100]
80	−0.098	432	[−0.222, 0.026]
90	−0.125	433	[−0.238, −0.012]
100	−0.083	433	[−0.196, 0.030]
120	−0.021	433	[−0.123, 0.081]
140	−0.040	432	[−0.136, 0.056]
160	−0.021	430	[−0.117, 0.075]
180	−0.033	419	[−0.120, 0.054]
200	0.056	398	[−0.017, 0.129]

Table 10. Instrument difference statistics by wind speed/VR magnitude. Square brackets indicate inclusive bounds on WS/VR magnitude, while parentheses indicate exclusive bounds.

WS/VR Magnitude (m s^{-1})	TTU-X1-FIL ₁ Bias (m s^{-1})	TTU-X2-FIL ₂ Bias (m s^{-1})	TTU-X Bias (m s^{-1})
[0,5)	−0.124	−0.117	−0.161
[5,10)	−0.133	0.034	−0.110
[10,15)	0.160	0.115	0.237
[15,20)	0.094	0.316	0.309
>20	—	0.054	−0.292

4. Discussion

While the amount of data the revised filtering algorithm at times removes may seem concerning, it is nonetheless prudent; as a remote sensor, the radar only reports the measurements it observes, and does not discern the “representativeness” of those measurements (i.e., their physicality, their depiction of the atmospheric state or of a biological tracer, or their overall usability). First-pass information on the quality of measurements in the form of SW and SQ can be useful but is not a one-size-fits-all filter, as phenomena like biological activity can just as well result in “high quality” yet non-atmospheric data.

The implications of this reasoning are twofold: first, the QAQC process is uniquely responsible for identifying which VR data are not just “high-quality” but usable and representative of the atmospheric flows, and which should be discarded. Second, radars as instruments are capable not only of sensing atmospheric variables like wind, but may also serve as a detection or warning system for biological activity; ideally, a method of corroboration (e.g., nacelle- or tower-mounted cameras, drones, tracking systems) would exist to verify the presence of biological tracers and identify them.

The second round of comparison demonstrates that the proper removal of noisy, low-quality as well as non-atmospheric, “high-quality” measurements, is integral to obtaining physical, realistic, and usable data from remote sensing instruments. Takeaways from this investigation include: (1), the value of visually inspecting filtered and edited data fields, to ensure what is left after the QAQC process is only high-quality, and that what has been removed is low-quality; and (2), the importance of considering the movement of biological tracers, which substantially alter instrument measurements by flying in a manner incongruent with the background environment.

While this study utilized the orthogonal situation of TTU-X and the FIL to bypass traditionally employed OA schemes and their possible spatial averaging effects, the ultimate goal of TTU-X is to generate DD fields of complete wind vectors across large areas over the full range of acceptable look angles. Thus, the implications of the new VR coverage (i.e., those in Figures 6 and 7) on those DD fields is important to consider. Clear-air cases are likely to see the largest changes, as the amount of data removed in the noisiest, lowest-return periods could result in DD data gaps. This is because the OA process undertaken to generate DD fields requires a minimum number of contributing VR bins, but also institutes a maximum range from which those VR bins can be drawn. If enough VR data are removed, the OA may not be able to find a sufficiently large number of VR bins within the acceptable ranges to generate a DD value. That said, many clear-air cases—despite their low return—still feature an overabundance of VR bins that the OA can utilize, meaning more stringent filtering will not unequivocally result in DD gaps.

Changes in the DD fields in precipitating cases are likely to be less pronounced, as the amount of data reinstated by the new algorithm is smaller than the amount of data newly removed (Figure 11). However, the reinstatement of this data helps to fill gaps in DD fields, and reduces the distances to which the OA must reach to gather the required

number of VR bins to generate DD data. In a broad sense, while DD availability may decrease in some of the lowest-return clear-air cases as a result of the new filtering algorithm, the DD data that are present are of higher quality and are truer to describing the state of the atmosphere. Work and analysis with these fields continues as of this writing.

5. Conclusions

The present comparison analyzed independent VR measurements from each of two radars—as opposed to the grid-interpolated DD WS values typically used in multi-radar studies—and decomposed full lidar wind vectors into radar-respective along- and across-beam components to match VR measurements' orientations, allowing for an analysis as “true to the data” as possible. Particular attention was also paid to the accurate matching of probe volumes between instruments by way of a novel spatial averaging technique. This averaging leveraged knowledge of each VR data bin's three-dimensional coordinates to create space-time composited measurements that described identical physical volumes, over identical periods of time, in order to eliminate potential sources of confounding and more robustly identify sources of bias.

The first round of such comparisons between TTU-X and the FIL showed a positive radar bias between 5 and 10%, or around 0.5 m s^{-1} . Further investigation into the source of this difference showed that the previous QAQC algorithm allowed high-magnitude non-atmospheric data to pass through, and also filtered some high-quality data out. However, after the implementation of a refined algorithm, one developed in response to parallel findings in a similar but unrelated field campaign, this bias was ameliorated. The new algorithm, more stringent and focused on outliers and non-atmospheric tracers, more effectively removes high-magnitude and low-quality or noisy VR values, bringing radar bias within the bounds of reference uncertainty. In particular, clear-air cases (those without precipitation) saw the removal of many VR data points. In these low atmospheric return environments, it is believed that biological targets constituted a meaningful ZT such that their associated VR values became convoluted within the background VR field (or lack thereof), yielding a high WS bias. Further, the influence of even a single noisy high-magnitude VR bin to the comparisons is adequate to introduce a meaningful bias, especially at lower levels.

It is worth noting, however, that scatter remains roughly an order of magnitude larger than bias and lies outside the bounds of reference uncertainty (Table 7), likely as a result of the probe volume spatial averaging technique implemented. Ancillary analysis in this study did reveal some dependence of VR bin spread on spatial averaging envelope, a relationship reasonably expected as VR bins from a larger volume and at further ranges from the (D_x, D_y, q_z) points are allowed to contribute. This larger-envelope spatial averaging technique was nonetheless applied as it aimed to characterize the entire probe volume of the lidar in accordance with its homogeneity assumption, rather than isolating, e.g., nearest-neighbor VR bins.

The revised process yields better agreement between the instruments, acting as a testament to the adage of “quality over quantity”: a comparison of fewer high-quality periods, rather than more, lower-quality periods, much better characterizes radar's ability to measure WS at long range and over large areas, for wind energy purposes or any other. Moreover, it behooves wind researchers and practitioners to understand the variable definitions of data quality as well as the importance of data verification, as instruments report only what they “see” and do not discern measurement context. Because all the original, unedited data from the AWAKEN campaign have been publicly archived, it is possible to reprocess all VR and DD wind fields using these (or other) updated algorithms for future analysis efforts. Given the choice to in this study analyze radar performance without OA influence, comparisons of full WS were possible only at Site D where WS could be

calculated trigonometrically, meaning the timeframe of the study was limited to one summer period; testing the new filtering method on a larger, more diverse dataset, necessarily with other instruments as points of comparison, would be prudent.

Finally, the observations made in this study serve as a testament to the varied capabilities of radars as remote sensors in the wind energy field: depending on an operator's choice of filtering algorithm, a radar can be used more "traditionally" to sense velocities in the vicinity of a wind plant for the purposes of, e.g., gauging inflow and predicting power output or documenting wake flows and losses; however, it also shows promise in its ability to function as a detector for non-atmospheric phenomena such as animals in flight, an often equally-important consideration in wind farm operation in adherence with wildlife protection guidelines and legislation.

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Data Availability Statement: Raw (unedited) VR data from TTU-X for the duration of the AWAKEN campaign, as well as data from the FIL, are available at <https://wdh.energy.gov/data/wind-energy> (accessed on 5 August 2024). Due to file size limitations, edited VR data and scripts can be made available by the authors on request.

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Abbreviations

The following abbreviations are used in this manuscript:

AWAKEN	American Wake Experiment
WS	Wind speed
TTU-X1	Texas Tech University X-band radar 1
TTU-X2	Texas Tech University X-band radar 2
TTU-X	Texas Tech University X-band radars
IWES	Institute for Wind Energy Systems
OA	Objective analysis
ZT	Return power
VR	Radial velocity
SW	Spectrum width
SQ	Signal quality index
LOS	Line of sight
DD	Dual-Doppler
WD	Wind direction
FIL	Fraunhofer-IWES Lidar
AGL	Above ground level
QAQC	Quality assurance/quality-control

CNR	Carrier-to-noise ratio
CI	Confidence interval
GF	Gust factor
R	Radar LOS/VR magnitude
L	Lidar LOS/VR magnitude
RMA	Reduced major axis

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