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Mid-Atlantic Nocturnal Low-Level Jet Characteristics: A machine learning analysis of radar wind profiles

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Abstract. This paper introduces a machine-learning-driven approach for automated Nocturnal Low-Level Jet (NLLJ) identification using observations of wind profiles from a Radar Wind Profiler (RWP). The work discussed here is an effort to lay the groundwork for a systematic study of the Mid-Atlantic NLLJ's formation mechanisms and their influence on nocturnal and diurnal air quality in major urban regions by establishing a general framework of NLLJ features and characteristics with an identification algorithm. Leveraging a comprehensive wind profile dataset maintained by the Maryland Department of Environment's RWP network, our methodology employs supervised machine learning techniques to isolate the features of the south-westerly NLLJ. This methodology was developed to illuminate spatiotemporal patterns and nuanced characteristics of NLLJ events, unveiling their significant role in shaping the planetary boundary layer. This paper discusses the construction of this methodology, its performance against known NLLJs in the current literature, intended usage, and a preliminary statistical analysis. First light results from this analysis have identified a total of 90 south-westerly NLLJs from May - September of 2017 - 2021 as captured by the RWP stationed in Beltsville, MD (39.05°, -76.87°, 135 m ASL). A composite of these 90 jets is presented to better illustrate many of the bulk parameters, such as core height, duration, and maximum wind speed, associated with the onset and decay of the Mid-Atlantic NLLJ. We hope our study equips researchers and policymakers with further means to monitor, predict, and address these nocturnal dynamics phenomena that frequently influence boundary layer composition and air quality in the U.S. Mid-Atlantic and Northeastern regions.

1 Introduction

Nocturnal Low-Level Jets (NLLJs) represent a distinct atmospheric wind pattern, predominantly by a shallow air stream flowing at low altitudes during nocturnal hours. The NLLJ, often observed in the Southern Great Plains (SGP) and the Mid-Atlantic regions, is a nocturnal event associated with the cooling of the low-level air mass more than the air above it, leading to a very stable stratified nocturnal boundary layer (Holton 1967; Whiteman et al., 1997; Van de Wiel et al., 2010). The conditions lead to the decoupling of the nocturnal boundary layer and allow for a low friction residual layer where a wind-maximum emerges close to the surface layer that is super geostrophic due to inertial oscillation, as explained by Blackadar (1957) and subsequent modification of the theory by Holton (1967). A confluence of geographic-specific atmospheric

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dynamics governs the genesis of NLLJs. A prevalent mechanism is the formation of a pronounced temperature cooling and subsequent inversion in the stratified nocturnal boundary layer. Complementing this vertical temperature gradient are essential factors such as diurnal shifts in pressure systems and the influence of terrain (Blackadar, 1957; Shapiro et al., 2010; Weldegaber 2013). The unique synoptic and diurnal combination of physical conditions that define NLLJs makes their occurrence prevalent during spring and summer when conditions for formation are more favorable. NLLJs typically demonstrate a peak in wind speed at an altitude that varies between 200 to 800 m above ground level (AGL), beyond which the speed diminishes towards the free troposphere (Zhang et al., 2006). The directional aspect of these jets is subject to geographical variance and prevailing meteorological conditions, but Blackadar's inertial oscillation theory generally dictates that they move northward.

The implications of NLLJs extend significantly into weather, climate, and air quality. They are instrumental in transporting and mixing atmospheric constituents such as pollutants, moisture, and heat, thereby influencing air quality and facilitating cloud formation (Mahrt, 1998; Banta et al., 2003; Baas et al., 2009). In the Great Plains of the United States, NLLJs have been extensively studied and documented since the 1950s. They are instrumental in moisture transport and regional weather phenomena, including convective storm genesis (Whiteman et al., 1997; Banta et al., 2003; Lundquist, 2003, Wallace 1975, Stensrud 1996; Tollerud et al., 2008; and more recently, Carroll et al. 2019, 2021). It is believed that the mid-Atlantic NLLJ is akin to the SGP NLLJ in that its underlying mechanism is the inertial oscillation theory; however, with lower wind-speed maximums and vastly different topographic influences, with the Appalachian Mountains to the East and North, the Chesapeake Bay and Atlantic Ocean to the West, and the Coastal Plains and Piedmont region in between. In the mid-Atlantic region, the impact of NLLJs on air pollution is of keen interest for its prevalence during the warm seasons and association with the transport of pollutants across the East Coast, attributed to elevated surface ozone and particulate matter concentrations. (Ryan, 2004; Weldegaber, 2009; Delgado et al., 2013; Sullivan et al., 2017; Roots et al., 2023).

Despite the Mid-Atlantic NLLJs' high association with summertime pollution episodes and the importance of LLJs in moisture transport, convection initiation, and wind energy generation, a systematic and well-coordinated long-term study of its physics and implications is lacking. The NLLJ's influence extends beyond a phenomenon of interest as a transport mechanism. It is becoming more relevant for its impact on socioeconomic life and our changing climate, requiring more analysis than currently provided. Understanding NLLJs and their general characteristics is essential for accurate meteorological predictions and effective environmental management strategies. Thus, this study focuses on methods for identifying and isolating the general structure and statistics of the evolving NLLJ to form a dataset on which to perform the needed systematic long-term study.

This work presents the culmination of an investigation into the Nocturnal Low-Level Jet (NLLJ) phenomena within the Mid-Atlantic region, leveraging a supervised machine-learning model tested against a comprehensive dataset including previously reported NLLJ events. The model, designed with a focus on advancing our capability to detect and analyze NLLJs, was subjected to a critical evaluation using cases from notable studies by Delgado et al. (2013), Weldegauber (2009), and Sullivan

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et al. (2017), based on data from the Beltsville, MD Radar Wind Profiler (RWP). Without established benchmarks for NLLJ detection accuracy, our analysis adopts a qualitative approach, emphasizing visual inspection to assess the model's performance in accurately capturing NLLJ characteristics, particularly wind speed and direction. The primary objective of this research is to transition from episodic, qualitative analyses to a systematic, quantitative understanding of NLLJ physics and its impacts, utilizing observational data to explore the temporal distribution, morphology, and statistical properties of Mid-Atlantic NLLJs. Furthermore, developing a generalized representation of Mid-Atlantic NLLJs based on observational data marks a significant step forward in our ability to identify and analyze these phenomena.

The rest of the paper is structured as follows. Section 2 outlines the data and methods, focusing on the selection and analysis of the dataset from the Maryland Department of Environment's 915 MHz Doppler Wind Radar Profiler Network, alongside the development and application of machine learning algorithms for detecting NLLJ features. Section 3 evaluates the performance of these algorithms in isolating NLLJ characteristics within the wind profile data, addressing the efficacy and limitations encountered. Section 4 also presents a detailed statistical analysis of the NLLJs identified by the RWP from May to September 2017 to 2021, revealing insights into their temporal distribution and morphological characteristics. Finally, Section 5 synthesizes the study's key findings and discusses their implications for the understanding of the Mid-Atlantic NLLJ and similar atmospheric phenomena, proposing directions for future research to enhance model accuracy and expand the scope of study within the field of atmospheric science.

2 Data & Methods

Wind profiles originate from the Maryland Department of Environment's (MDE) 915 MHz Doppler Wind Radar Profiler (RWP) Network. Specifically, this study solely employs the 2017 – 2021 dataset of wind profiles from the Howard University – Beltsville Campus (HUBC) in Beltsville, MD RWP (BELT) (39.05°, -76.87°, 135′); see Figure 1 for location reference. These RWP instruments measure the radial velocity of wind from one zenith and four azimuthal beams. These are used to calculate the horizontal speed and direction with the sub-100-meter vertical resolution (100 m - 3000 m AGL) at a sub-30-minute temporal resolution. Thus, the resolution of the dataset is sufficient to capture the temporal and vertical extent of NLLJ events occurring over the Beltsville site. From this, we trained a supervised machine-learning ensemble model, which was used to isolate NLLJ presence in such wind profiles to build a quality-controlled dataset of NLLJs for the study of statistics and general characteristics.

Figure 1 serves as a site map for the MDE RWP network, the motivation for this study, and subsequent analysis of NLLJs in the region. The case presented in Figure 1 is the 950 mb (~500 m AGL identified by ozone sondes) vector wind plot from NOAA NCEP North American Regional Reanalysis (NARR, 0.3 degrees) for the NLLJ case on May 20, 2024, reported and analyzed by Roots et al. (2023). Note the general south-westerly flow near the HUBC site (Figure 1: black star) but the clear

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disagreement in the wind speeds. We take this as motivation to initiate a long-term systematic study of the NLLJs in the region in hopes of rectifying the disagreement between operational models and observations.

We define the Mid-Atlantic NLLJ following closely with the results found by Zhang et al. (2006) and Ryan (2004) in their Fort Meade, MD RWP (decommissioned in 2006) observations. These studies provided detailed observations and analysis of NLLJ events, mainly focusing on their occurrence, structure, and dynamics within the Mid-Atlantic region of the United States. According to Zhang et al. (2006) and Ryan (2004), the Mid-Atlantic NLLJ is characterized by a robust and low-level wind speed maximum that typically occurs during the nighttime hours. These jets are predominantly observed during the warm season (late spring through early fall). The studies noted that winds from the south and southwest directions dominate most of the Mid-Atlantic NLLJs. Zhang et al. (2006) reported that approximately 60% of the Mid-Atlantic NLLJs observed during their study period (warm seasons in 2001 and 2002) exhibited this southerly and south-westerly wind direction. Ryan (2004) contributed to our definition by providing insights into the frequency and timing of NLLJ occurrences, noting that these events were common during the study period from 1998 to 2002, noting 80 warm season cases in total. Together, the work of Zhang et al. (2006) and Ryan (2004) defines the Mid-Atlantic NLLJ as a nocturnal atmospheric phenomenon characterized by a significant increase in wind speed (~15 m/s) at low altitudes (400 – 600 m AGL), typically showing a preferential direction from the south or southwest.

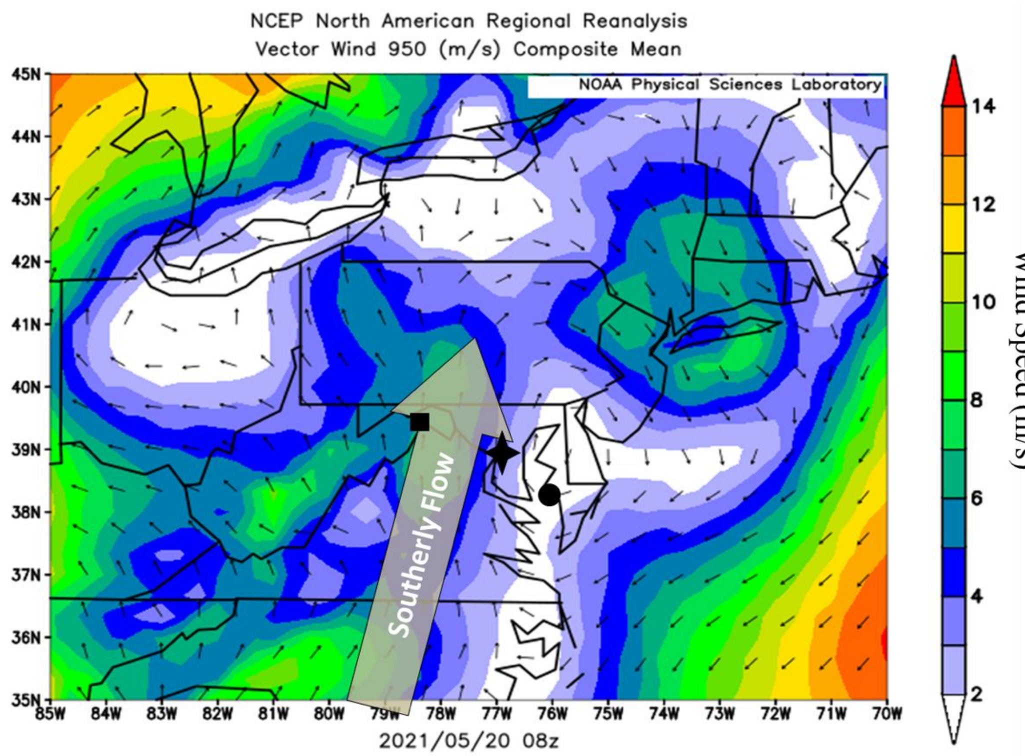

Figure 1: Vector wind plot at 950 mb from NOAA NCEP NARR 3-Hourly temporal with 0.3-degree spatial resolution showing southerly flow following the U.S. Coastal Planes. (square) MDE Cumberland, MD – Piney Run RWP site (star) Beltsville, MD – Beltsville RWP site, (circle) Cambridge, MD – Horn Point RWP site.

We meticulously employed a dataset that is visually depicted in Figure 5, where the dataset's temporal distribution is illustrated through an events plot. The statistical analysis is founded on examining 90 NLLJ events, which were isolated using the algorithm described in section 2.1 of the text. The visual representation of NLLJ occurrence in Figure 5 is shown by the black lines corresponding to the date (in UTC) of the RWP file, which contains the NLLJ features. The grey lines indicate the areas where the RWP data was available from the MDE record, while the red lines indicate unavailable data. That withstanding, only 25 files were unavailable during the study period (May – September 2017 - 2021), making for an optimal observational dataset to analyze. The training dataset was hand-selected from NLLJ events during 2021, while the testing dataset was selected from previously reported and depicted NLLJs by Delgado et al. (2013), Weldegauber (2009), and Sullivan et al. (2017) that were captured by the same instrument (i.e., BELT RWP). In the following subsections, we will describe the development of our training dataset and the schema used in the training and execution of the isolation algorithm.

2.1 Training Dataset

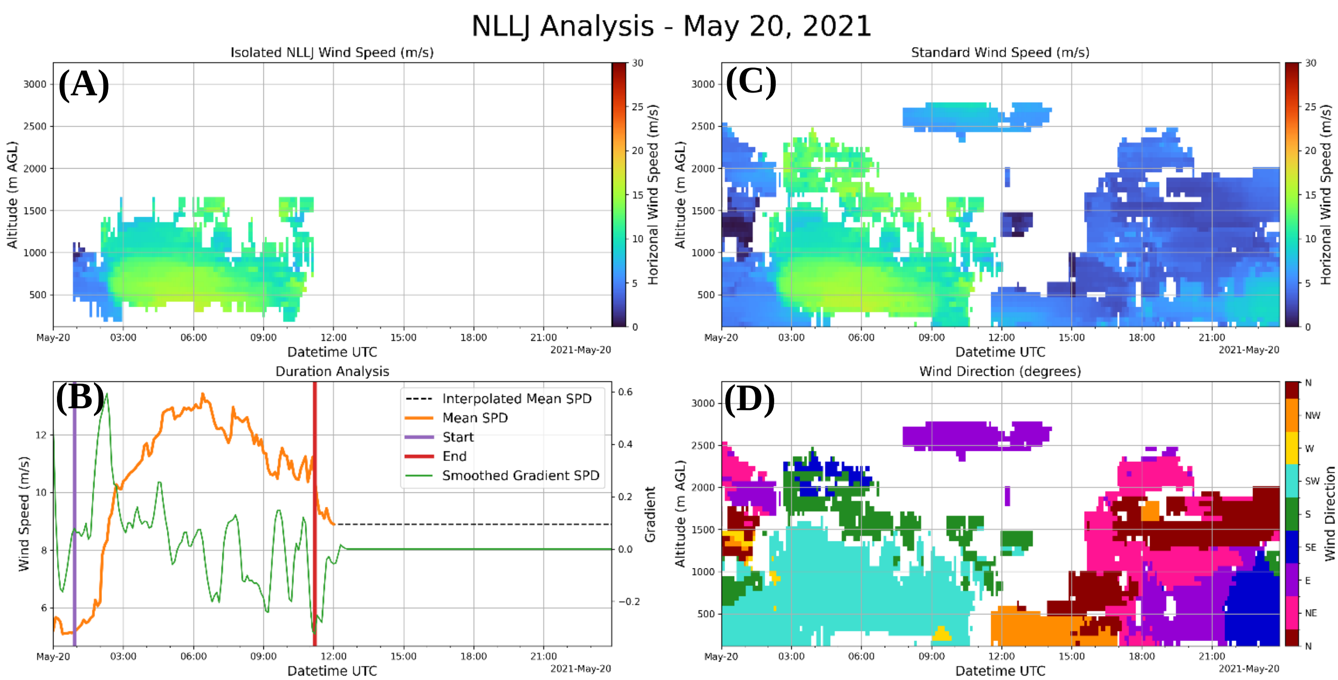

Figure 2: ***Sample of training dataset creation using masking and gradient peak detection in the time and altitude dimensions: (A) Isolated NLLJ; (B) Gradient peak detection in the time axis with only Southerly winds; Full profile of wind speed (C) and direction (D)***

Ensuring a suitable training dataset for the machine learning algorithms requires balanced scenarios expected in the operational dataset from the MDE RWP data archive. A manual and rudimentary identification method was developed using gradient detection of solely southerly winds in both time and altitude to capture the evolution and vertical extent of the NLLJ feature. This manual approach method is demonstrated in Figure 2, where (A) depicts the final isolated NLLJ event from the speed and direction profile data (Figure 2: C and D), and (B) represents the selection of the first positive inflection and the most

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significant negative inflection of the smoothed & interpolated averaged south-westerly (180 – 270 degrees from North) wind speed below 2500 m AGL, an altitude chosen based on the findings of Zhang et al. (2006). The first positive and most significant negative inflections within the local nighttime data range are taken as the start (Figure 2: purple line) and stop (Figure 2: red line) times of the NLLJ, respectively. With the temporal range selected, each profile is analyzed for the top and bottom of the NLLJ, chosen by the positive and negative gradients in the vertical profile. The area bounded by these gradients is considered the region of the NLLJ profile evolution. Note, this process is not suitable for all jets events encountered for all NLLJ events encountered and requires a manually iterative process to fully capture the NLLJ which is part of the motivation for the ML approach. The training dataset is thus composed of 50 NLLJs that were sufficiently isolated, along with 50 cases that contained either no-NLLJ but high wind speed or no-NLLJ with typical diurnal oscillation. The resulting training dataset of 100 files (i.e., a matrix with ten columns and 1.2 M rows) where no less than 10% of the data represent NLLJ data points. Each measurement point (Figure 2: A) is then taken through the same data preprocessing step (see Section 2.2) and fed to the model as truth labels of the training dataset.

3 Algorithm Development & Testing

3.1 Algorithm Development

The algorithm development is comprised of multiple steps, including data pre-processing, model selection, ensemble training, and post-processing, and is laid out in the schematic found in Figure 3. Algorithm usage only encompasses the execution loop (Figure 3: left). The data pre-processing phase, which is critical for the preparation of the wind profile dataset for subsequent analysis, entails refining the data into a format that is amenable to statistical relevance and fitting by the chosen supervised machine-learning models. This phase is orchestrated to include several pivotal steps that ensure the data's integrity and relevance. First, the key features deemed crucial for further analysis are extracted from the data file. Through a covariance analysis, we identified several variables – including wind speed, direction, radial velocities of each beam, averaged signal-to-noise ratio across each beam, altitude bins, and time in minutes of the day – as being particularly pertinent for the chosen analytical approach. Following the extraction of these essential features, we standardize the resolution of each variable. This was accomplished by re-gridding for time and altitude, coupled with the strategic filling of missing data points with 'not-a-number' (NaN) placeholders, thereby ensuring that the dataset maintained uniform dimensions across all the datasets. The culmination of the data pre-processing phase is the transformation of the dataset from two dimensions into one, consolidating each variable into a singular, comprehensive table — a process visually conceptualized in Figure 3. We execute this transform step to enable the models to analyze each measurement point, thereby determining whether a specific instance constitutes part of an NLLJ event or not.

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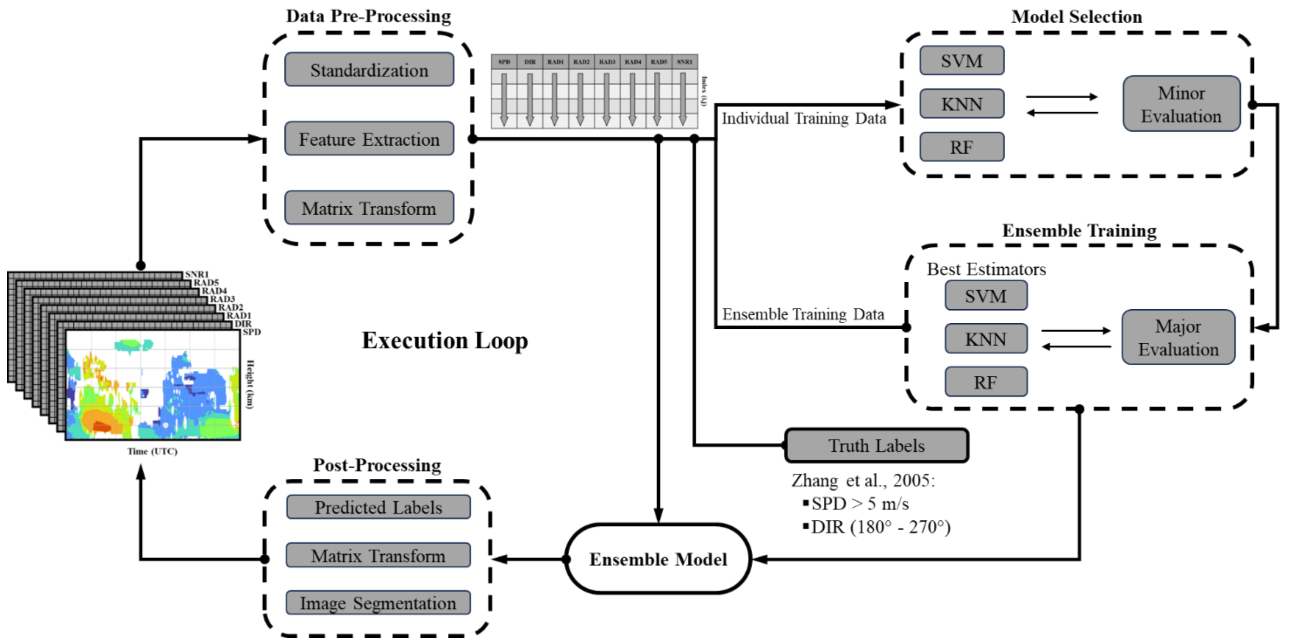

Figure 3: Schematic of the supervised machine learning algorithm execution (Execution Loop, left) and training (right).

The algorithm depicted in Figure 3 represents the process used to isolate NLLJ features in wind profiles from RWP datasets. Its use and implementation are the culmination of an intricate process that harnesses the strengths of three distinct supervised machine learning models available in Python from Sci-kit Learn: Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and the Random Forest (RF). The classification algorithms are combined to harness the unique approaches of each technique. SVMs excel at defining decision boundaries and identifying complex relationships between various atmospheric parameters, enabling the model to discriminate NLLJ events with precision. This supervised algorithm is adept at classification and regression challenges, primarily working by determining the best hyperplane that segregates a dataset into distinct classes, in this case determining whether each measurement point is part of an NLLJ or not. KNN, on the other hand, introduces a neighbor-based learning approach. Examining the proximity of data points leverages the principle that the NLLJ has as a geophysical boundary. Thus, indices containing NLLJ attributes should be close to temporal and spatial proximity. This method enhances the ensemble's capabilities to detect NLLJs through proximity-based patterns, which is particularly beneficial when these jets manifest subtle variations. The third component, RF, operates as a versatile ensemble learning technique that leverages the collective intelligence of multiple decision trees. RF models handle complex datasets with numerous features, which aligns well with the dataset's multi-dimensional nature. The integration of the RF model aids in capturing non-linear relationships and interactions among various parameters, providing robustness to the ensemble. By integrating the insights gained from each model's approach into a two-thirds majority voting system we have found that this approach yields a suitable method of isolating NLLJ features in wind profiles. When training the model, we take note of the spareness of NLLJ features in the training dataset by employing rigorous cross-validation and tuning of hyperparameters in a two-stage process (see Figure 3: Model Selection and Ensemble Training). As a result of this meticulousness were able to achieve F1-macro test scores of 86% for the SVM, 93% for the KNN, and 89% for the RF when trained and tested on 20% of the total training datasets of 100 files. Note that these scores are based on the truth labels supplied, which themselves are imperfect isolations of NLLJ features (see Figure 2). With this in mind, we rely solely on visual inspection of performance on depicted NLLJ in previous literature for validation of testing results, this is discussed further in section 3.

3.2 Algorithm Testing

The fully trained model was tested on previously reported NLLJ events captured by the Beltsville, MD RWP (the same instrument used in this study) by Delgado et al. (2013), Weldegauber (2009), and Sullivan et al. (2017). Given the absence of a standardized metric for assessing NLLJ detection accuracy, our reliance on a qualitative visual inspection is both a necessary and insightful approach to evaluate the model's capabilities. From our visual inspection of the wind speed and direction, we note that the model's isolation of low-level jet features is more than satisfactory for a long-term statistical analysis. However, the model's limitations in capturing the full structure of the NLLJs, as evidenced by missed lower-level structures (see Figures 4: A & B), highlight areas for improvement despite satisfying basic criteria for wind speed and direction. This consistent issue across our testing results suggests that modifying the training set could significantly enhance the model's performance. The presence of outlier points in the visualized data, as seen in Figures 4, underscores the necessity for additional steps in post-processing, such as clustering, to refine the model output further. The examination of the algorithm's performance in isolating NLLJ features, as evidenced in the testing data for June 14, 2008 (Figure 4: A) and June 12, 2015 (Figure 4: B), reveals its capacity to capture the spatial and temporal continuity of these atmospheric events. The figures for these dates illustrate the algorithm's precision in isolating the wind features associated with NLLJs. For instance, on June 12, 2015 (Figure 4: B), the wind speed shows a well-defined NLLJ structure, with wind speeds peaking in the early morning. The corresponding wind direction data for the same date transitions from southerly in the early hours to westerly later in the day, a directional shift that the model effectively captures. Similarly, the June 14, 2008 (Figure 4: A) data presents another clear instance of the NLLJ with the algorithm detecting the jet's peak intensity and subsequent decline. The capability of the model to detect these patterns is crucial. It suggests that the model can identify the presence of an NLLJ and its evolution over time. The initial wind speed data might suggest that the NLLJ event concluded by 15 UTC on June 14, 2008 (Figure 4: A). However, the detailed examination of the wind direction gradients reveals the transition to a westerly-dominated regime, thus indicating the end of the NLLJ event at 12 UTC. The wind direction data from this date indicate a significant shift, with winds starting from a southerly direction and transitioning to a westerly direction as the day progresses. This shift to westerly-dominated high wind speeds indicates the kind of directional change the model can discern, echoing the findings of Rabenhorst et al. (2014) regarding the transitional phases of Appalachian Downslope Winds. These capabilities affirm the algorithm's applicability to isolating NLLJ features in RWP profiles, thus offering a robust tool for advancing the study of the Mid-Atlantic NLLJ.

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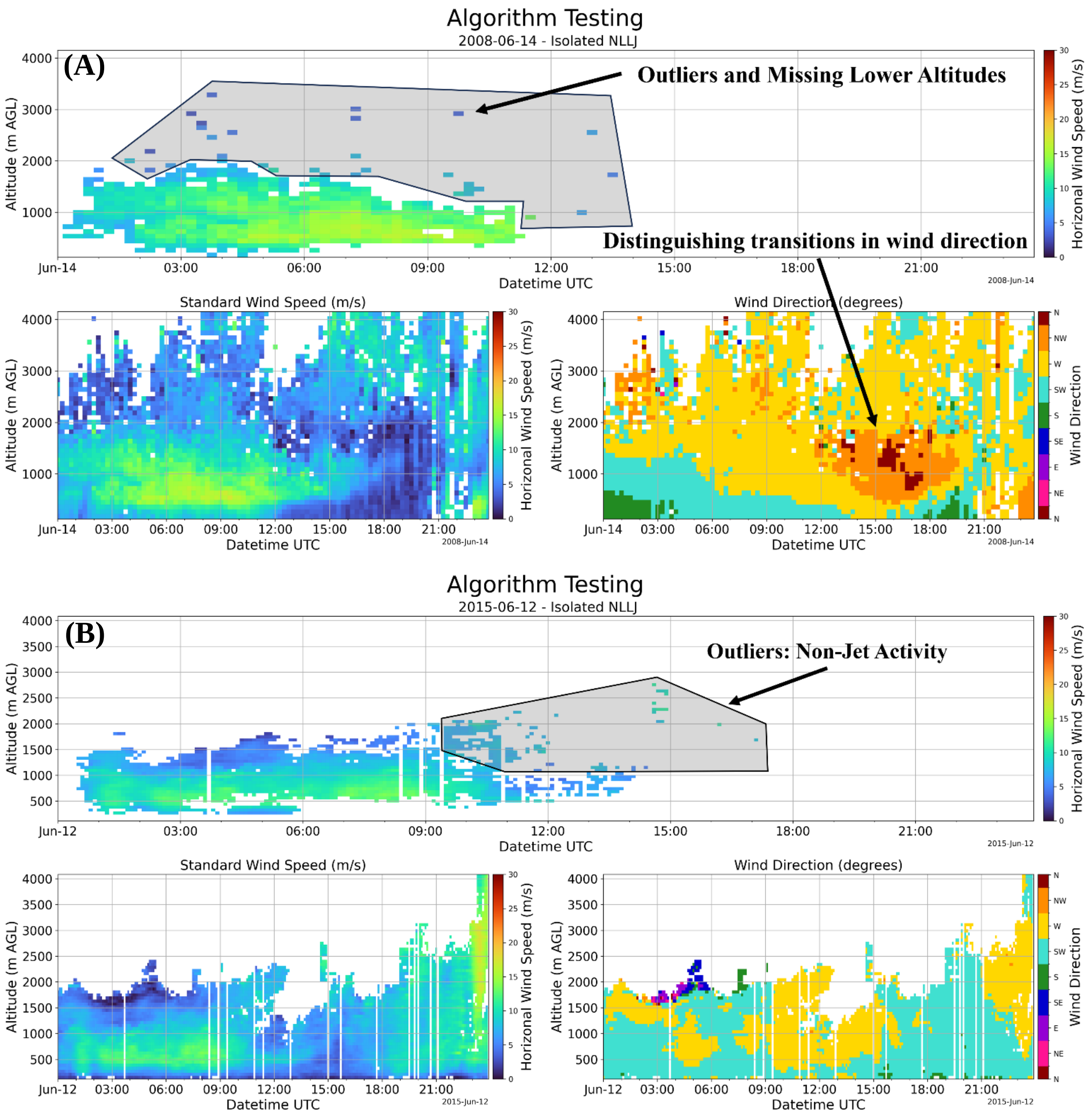

Figure 4: ***Algorithm testing for graphically reported NLLJs from Delgado et al. (2013) and Sullivan et al. (2017). Each shows the NLLJ cases of (A) June 14, 2008, and (B) June 12, 2015, where the top panels show the algorithm's isolation, and both two plots show the original data from each case as measured by the Beltsville, MD, RWP.***

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4 Results & Discussion

The results and subsequent discussion detail the algorithm's efficacy and limitations, illustrating its proficient detection of south-westerly NLLJ events while also acknowledging deficiencies in capturing the complete structural nuances of these atmospheric features. The findings underscore the necessity for ongoing model refinement, with a specific focus on training set optimization and the application of image segmentation techniques to improve the processing and representation of model outputs. Furthermore, we present a preliminary analysis of the temporal distribution, morphology, and statistical attributes of Mid-Atlantic NLLJs. We utilize the Beltsville, MD RWP data to introduce a general representation of the Mid-Atlantic NLLJ, derived from a composite analysis of wind profiles, to serve as a foundational tool for future research.

4.1 Temporal Distribution

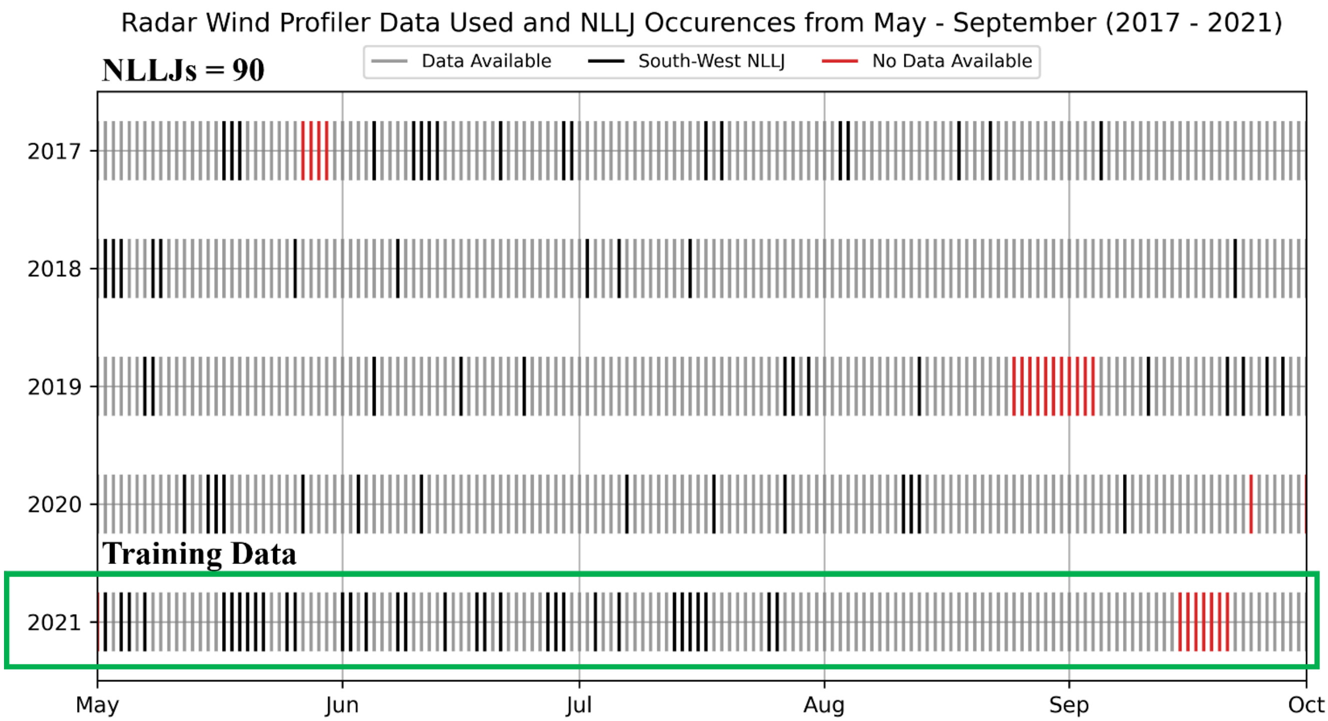

Figure 5: Occurrences of NLLJs (black lines) captured by algorithm from the Beltsville, MD RWP. (red lines) Data that were not available in this study while (grey lines) were available. The green box denotes the year where the training dataset originates.

Analyzing Figure 5, which depicts the occurrences of south-westerly Mid-Atlantic NLLJs from May through September over five years, from 2017 to 2021, we observe that the vertical bars representing NLLJ events are concentrated in the summer months, affirming the seasonal nature of these phenomena. This seasonal pattern, with a higher frequency of events during the core summer months of June, July, and August, corroborates the findings of Ryan (2004) and Zhang et al. (2006), who identified the Mid-Atlantic NLLJ as a predominantly summertime nocturnal boundary layer phenomenon. These studies as The factors traditionally conducive to the formation of NLLJs—such as inertial oscillation, nocturnal cooling of the land surface, and the establishment of a well-stratified nocturnal boundary layer—are indeed most active during these warmer months.

The interannual variability in the number of NLLJ occurrences is noteworthy, with years like 2019 and 2021 exhibiting a higher frequency of events compared to 2017 and 2018 (see Figure 5). This observation suggests a linkage between the NLLJ formation and broader synoptic patterns influencing regional dynamics. Such variability necessitates a deeper investigation across a longer period utilizing a broader network of observational data points. Hence, the extended study of the Mid-Atlantic NLLJ utilizing the RWP dataset from 2006 to the present across the MDE network locations is crucial for understanding the driving forces behind this interannual variability.

This strategic selection of the training period ensures that the model is exposed to a wide array of conditions typical of the NLLJ season, thereby improving its ability to generalize and detect NLLJs accurately. However, the presence of data gaps, as indicated by the red vertical bars, may present challenges to the comprehensive characterization of NLLJs, as such gaps could potentially coincide with periods of NLLJ events. While unfortunate, the marked seasons and days without data serve as an important reminder of the limitations inherent in observational datasets. Future work should also consider incorporating additional datasets, potentially using data synergy techniques to fill the gaps and provide a more continuous and comprehensive picture of the NLLJ occurrences. Moreover, based on the surrounding temporal and environmental context, the algorithm could be trained to predict the likelihood of NLLJ events on days when data are missing. This predictive ability would be invaluable for atmospheric research and could significantly enhance our capacity to anticipate and respond to the implications of NLLJ events on weather patterns and climate dynamics in the Mid-Atlantic region.

4.2 Statistical Analysis

To investigating the critical characteristics of the Mid-Atlantic South-Westerly NLLJ, we performed a preliminary statistical analysis of the 90 NLLJ events we have identified. The histograms, shown in Figure 6, provide a statistical representation of maximum wind speeds, core heights, and core time for each NLLJ event, as derived from the dataset of 90 NLLJ events shown in Figure 5. Figure 6 (top) shows the distribution of maximum wind speed of each jet event, spanning 5 m/s to nearly 30 m/s. The wind speed maximum probability density curve (orange) suggests that the most probable core speeds are between 10 m/s and 15 m/s, with decreasing probability between 15 and 20 m/s and the least probable being between 20 and 30 m/s. This would suggest that in the most probable range exists a prevalent generation mechanism across the observed occurrences.

The core height (Figure 6: middle) illustrates the height at which the maximum wind speed was measured for each NLLJ event capture. We notice that most of the maximum wind speeds occur around 500 m AGL, showing a sharp peak at this altitude range, which can be interpreted as the typical altitude for the core. The narrowness of this peak in the probability density curve implies a strong consensus for this characteristic height, aligning with the notion that the jets are confined to the edge of the

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stable nocturnal boundary layer. Note the low probability and frequency of core height being above 1000 m AGL; we attribute the presence of these altitudes as removable noise from the isolation due to the imperfect nature of our training dataset (see section 3.1).

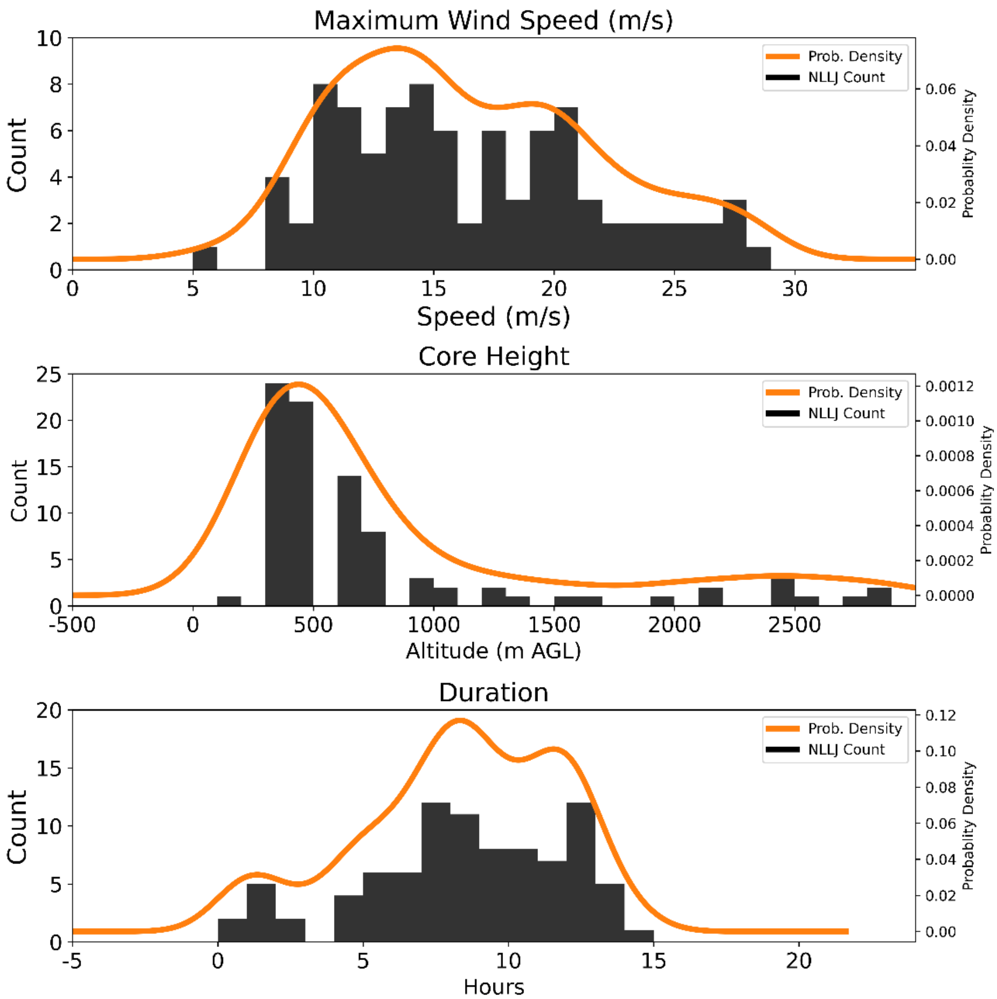

Figure 6: Histogram NLLJ characteristics from the 90 events noted in Figure 2, where: (top) is the distribution of maximum wind speeds, (middle) is the height of the wind speed maximum and (bottom) is the duration of the event at the core height.

When considering the histogram for the duration of the NLLJ (Figure 6: bottom), we encounter a more complex distribution. The duration of the NLLJ event is calculated by finding the elapsed time from each jets core height. The histogram and probability distribution suggest a multi-modal distribution, with two apparent peaks around 8 and 12 hours. This multi-modal nature may hint at the additional influencing factors, such as the baroclinicity of the region, which could induce variations in the timing of the jet's maximum wind speeds.

4.3 Mid-Atlantic NLLJ Morphology

As a result of this isolation of NLLJ occurrence in wind profiles, we have created a general representation of the Mid-Atlantic NLLJ using observations. Figure 7 shows a composite plot of the NLLJ structure using the median of the 90 NLLJ datasets to visualize the temporal evolution as seen from the observations at Beltsville, MD. This offers a basis for future identification and analysis of the general south-westerly NLLJ. The region enclosed by the black line indicates the region in which more than 50% of the cases were present (see Figure 7: bottom), thus serving as the general structure of the Mid-Atlantic NLLJ. Outside the enclosed region is the variability of NLLJs found in our 90 events datasets. Figure 7 (top) describes the horizontal wind speed, which exhibits a shallow layer of high wind speed (~ 15 m/s) concentrated around 500 m AGL; this is noted as the NLLJ's core. This general NLLJ structure lasts from 1 UTC (9 PM EDT of the previous day) to 11 UTC (7 am EDT). The vertical extent is shown to be persistent around 1500 m AGL until the arrival of the horizontal wind speed maximum (NLLJ core) around 5 UTC, at which point the vertical structure of the NLLJ begins to decay.

The middle panel of Figure 7, which illustrates wind direction, shows a clear transition between the dominance of the meridional (South to North; Southerly) and zonal (West to East; Westerly) winds and is indicative of the dynamic atmospheric processes that govern the behavior of the Mid-Atlantic NLLJ. The progression to more westerly winds across the night reflects the diurnal wind shift and underscores the influence of large-scale atmospheric circulation patterns on the NLLJ. This shift in wind direction is often related to the Coriolis force acting on the regional air mass over the night. As the land cools after sunset, the pressure gradients adjust, and the NLLJ develops, initially following the temperature gradient. As the night progresses, the Coriolis force begins to turn the flow toward the right in the northern hemisphere, resulting in the NLLJ acquiring a more westerly component.

The vertical dependence of the oscillation between wind vectors, as observed in the middle panel of Figure 7, indeed underscores the manifestation of inertial oscillation theory in the behavior of the Mid-Atlantic NLLJ. This oscillation between wind vectors at different altitudes signifies the vertical shear, which is characteristic of the NLLJ structure. The presence of wind shear is significant for various atmospheric processes, such as the development of turbulence, the dispersion of aerosols, and the vertical transport of momentum and heat within the atmosphere; notably, strong wind shear associated with NLLJs can induce turbulent downbursts, thereby affecting aviation safety, efficiency of wind energy generation, and surface level air quality. The works of Sullivan et al. (2017) and Roots et al. (2023) both noted the increase of surface-level ozone from a polluted ozone reservoir in the residual layer during the arrival of the NLLJ core, which, as shown in Figure 7, is the maximum point of the horizontal speed and balance between the zonal and meridional wind vectors.

Collectively, these panels deliver a cohesive understanding of the NLLJ's vertical and temporal structure. They demonstrate a pronounced nocturnal intensification in wind speed at low-level altitudes, accompanied by a veering wind direction, which indicates the inertial oscillation's influence on the jet's formation. Furthermore, the event count substantiates the observed morphology, confirming that the algorithm effectively captures the climatological presence of the NLLJ in the dataset. The variability outside the core zone may be attributed to synoptic-scale influences that modulate NLLJ behavior. Understanding this variability is essential for improving weather prediction models, particularly for events sensitive to low-level jet dynamics.

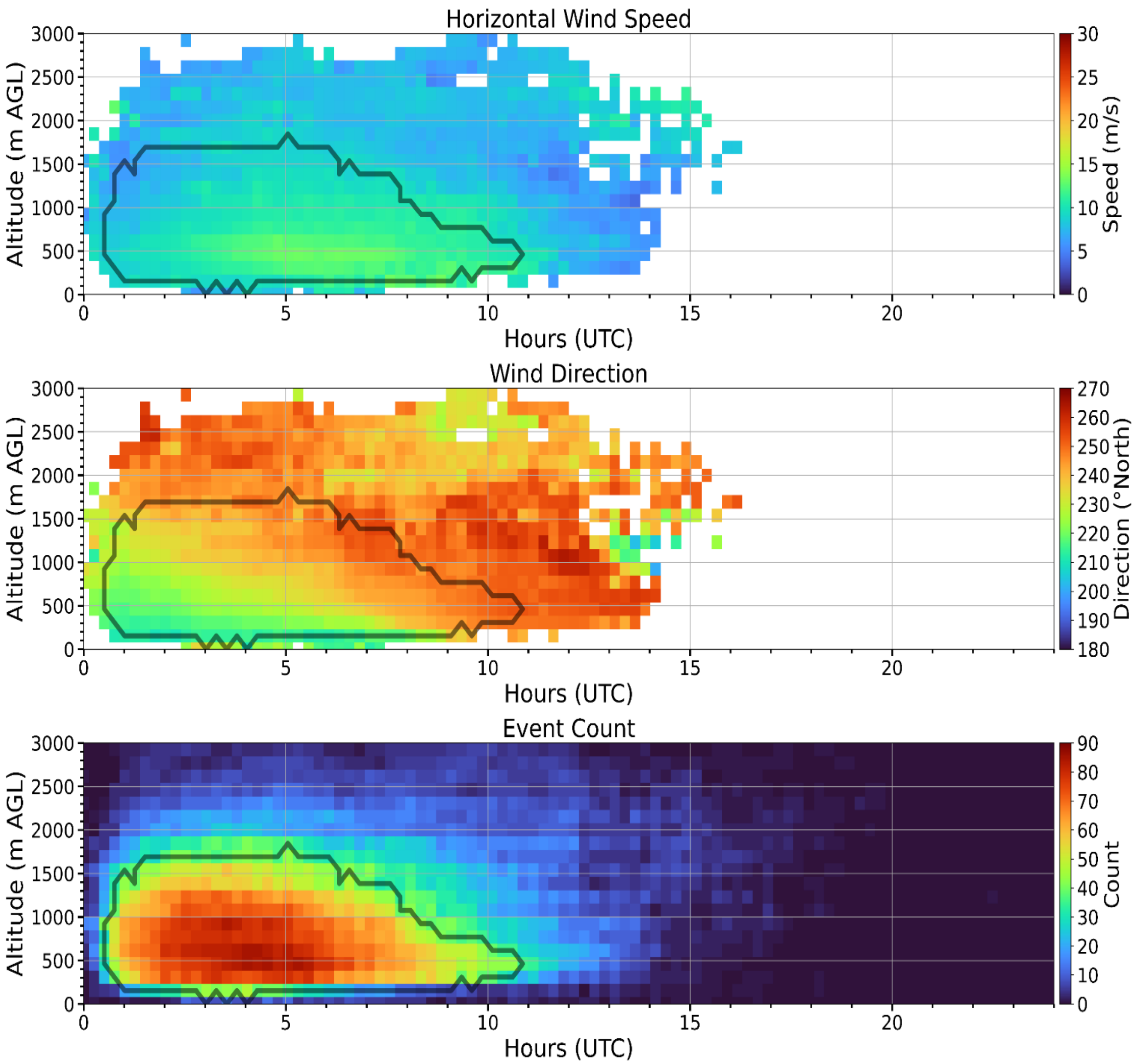

Figure 7: Composite Vertical Profiles of Nocturnal Low-Level Jet (NLLJ) Characteristics: Average Wind Speed (Top), Average Wind Direction (Middle), and Event Count (Bottom).

4.4 Summary

The study successfully implemented machine learning (ML) algorithms to detect and characterize Nocturnal Low-Level Jets (NLLJs) using Radar Wind Profiler (RWP) data.

- The reliability and efficacy of this approach were validated with previously reported and depicted NLLJs.
- The algorithm's ability to detect wind directional changes, especially during key transitional phases, like the Appalachian Downslope Winds, showcases its potential for useful atmospheric analysis.
- Opportunities for improvement include enhancing the dataset by filling in gaps and expanding the temporal range, incorporating a broader set of atmospheric features, and exploring alternative ML architectures for finer detection capabilities.

5 Conclusions

Our analysis of the temporal distribution of NLLJ events has reinforced the understanding of these jets as a seasonal phenomenon, predominantly occurring during the warmer summer months. The interannual variability observed, with specific years displaying a heightened frequency of events, underscores the connection between NLLJ occurrences and broader synoptic patterns that drive regional dynamics. Identifying these patterns has profound implications for the future study of NLLJs, necessitating an extended analysis over a more extended period and across a wider observational network. This approach is critical for comprehensively understanding the atmospheric forces at play and enhancing predictive models' accuracy. The presence of data gaps within the observational period presents a challenge yet serves as a crucial reminder of the inherent limitations of empirical datasets. Addressing these gaps by incorporating additional datasets and employing data synergy techniques will be imperative in future studies to create a more continuous and complete picture of NLLJ occurrences. As presented in Figure 6, the statistical analysis has yielded a quantitative representation of the critical characteristics defining the Mid-Atlantic NLLJ. The distribution of maximum wind speeds and core heights clearly indicates a prevalent atmospheric mechanism driving these jets, with most NLLJ cores residing around 500 m AGL. The bi-modal nature of the core timing distribution suggests additional factors, such as regional baroclinicity, may influence the timing of NLLJ maxima, indicating deviations from classical inertial oscillation predictions. These findings are pivotal for enhancing our understanding of NLLJ behaviors and refining their representation in atmospheric models. The morphological analysis of the NLLJ, informed by the composite plots in Figure 7, has established a general representation of the Mid-Atlantic NLLJ's structure. This representation, highlighting a pronounced nocturnal intensification of wind speed and a distinct oscillation pattern in wind direction, is instrumental in defining the typical NLLJ profile. The observed variability outside the core zone highlights the influence of large-scale atmospheric processes on NLLJ behavior, emphasizing the need for further investigation into these external factors.

The continued study of these low-level wind phenomena is crucial for weather prediction and the strategic management of air quality, particularly in understanding the transport and dispersion of pollutants along the I-95 corridor. This research serves as

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a stepping stone for future investigations into the complex dynamics of low-level mesoscale phenomena and their broader climatic and environmental implications. Accurately identifying and characterizing NLLJs is vital for validating and refining regional climate models, thus enhancing our predictive capabilities regarding future climate scenarios. This work contributes significantly to boundary layer studies, offering a detailed examination of NLLJ phenomena and providing valuable insights for future research. This study's integration of machine learning within the field of atmospheric science marks a promising step toward more advanced meteorological analyses and the future of climate prediction. Future studies should integrate similar techniques to understand the genesis mechanisms of low-level wind phenomena from large observational datasets to enhance our understanding of regional pollutant distribution and mesoscale transport of moisture, momentum, and mass. Furthermore, there is a clear opportunity to expand this research to encompass other geographic regions and atmospheric phenomena, thereby testing the adaptability and versatility of the methodology.

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Code & Data Availability

Radar wind profiler datasets are available from the Maryland Department of the Environment upon request. The algorithm development, data processing, and analysis codes are currently available upon request, as they are in their beginning stages. However, version 1.0 will be easily usable, installable, and open-source through the corresponding authors' Git Hub.

Author Contribution

Maurice Roots: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data curation, Writing – original draft. **John T. Sullivan:** Writing – review & editing, Supervision. **Belay Demoz:** Project Administration, Funding Acquisition.

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Competing Interests

Some authors are members of the editorial board of Atmospheric Measurement Techniques – Gases.

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