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# Influence of Biological Sounds on Long-Term Measurements of Wind Turbine Noise

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***Abstract*— Measuring wind turbine noise poses significant challenges due to dynamic wind conditions, low-frequency components, and the presence of residual noise sources, including insect vocalizations. Long-term measurements are crucial for capturing the complex interplay of variables influencing sound propagation and for informing effective mitigation strategies. Our study leverages extensive insect sound recordings to develop classification methods for automatic exclusion of insect noise during wind turbine noise measurements with feature extraction and unsupervised learning. We highlight the challenges posed by dynamic environmental conditions and advocate for innovative approaches to filter out residual noise sources and enhance the accuracy of wind turbine noise assessment. Insect calls significantly affect sound pressure levels (SPL) at lower wind speeds. Moving forward, interdisciplinary research efforts and technological advancements are essential to address the complexity of wind farm noise and its impacts comprehensively, ensuring sustainable development and minimizing adverse effects on human health and biodiversity.**

**Keywords: Wind turbine noise, Long-term measurements, insect noise, Unsupervised learning**

## I. Introduction

Wind turbines (WT) have become emblematic of the global push toward renewable energy, harnessing the power of wind to generate electricity with minimal environmental impact. However, amidst the whirring blades and rotating turbines, a quieter concern has emerged—noise. The noise generated by WTs has garnered considerable attention for its impact on human well-being, particularly in communities living in close proximity to these structures. Chronic annoyance, sleep disturbance, and potential mental health effects have been associated with exposure to WT noise, prompting concerns and calls for mitigation strategies.

WT noise modelling serves as a valuable research tool [1-3]. Its validity relies on long term measurements of WT sound power. Measurements are crucial for validating and refining modelling predictions, providing empirical data on noise levels over extended periods, [4-7]. However, measuring WT sound power poses significant challenges due to various factors such as the dynamic nature of wind, low-frequency components, infrasound, and pseudosound. WTs operate in constantly changing wind conditions, resulting in fluctuations in noise levels that are difficult to accurately capture. Several papers stress the significance of conducting long-term measurements to gain insights into WT noise. For instance, a study describes a six-year deployment of a three-microphone acoustic array, enabling continuous recording and analysis of acoustic data, [8]. This extensive duration provided a comprehensive dataset for studying various acoustic events, including those associated with WTs. Another paper discusses five extensive measurement campaigns conducted over 13 months at diverse locations, facilitating the assessment of WT sound emissions and their propagation characteristics over prolonged periods, [9]. Furthermore, the importance of long-term measurements is highlighted in studies investigating wind farm noise amplitude modulation, [10,11]. These investigations, spanning extended durations and encompassing variations in day-night cycles and diverse wind conditions, offer valuable insights into the temporal and spatial dynamics of WT noise. Overall, these findings underscore the necessity of sustained monitoring efforts to comprehensively understand WT noise dynamics and their potential impacts on surrounding communities. Necessary long-term measurements of WT noise are prone to residual noise sources, constant changing wind speeds and its gashes, low frequency components of both wind and WT together with amplitude modulation characteristics. When measurement location is placed outside of urban areas, occurrence of biological sound (e.g., bird and insect calling) events is higher. Several studies have encountered this problem and tried to implement different techniques for better filtration of the residual noise sources for the purpose of correct assessment of WT noise, [12-14].

Several studies have noted an abundance of insects in the vicinity of wind farms, with research primarily focusing on flying insects in relation to bat feeding activity, [15-18]. However, the assessment of WT noise has recently highlighted the significance of terrestrial insects, particularly concerning their calling noises. This presents a challenge in accurately evaluating WT noise impacts. To address this issue, researchers have employed frequency filtering techniques to exclude insect communication noise from WT noise measurements. By mathematically removing these frequencies and measuring ambient noise during winter when insect presence is minimal, researchers aim to isolate and quantify the true impact of WT noise, [19-22].

This paper presents an approach for automatic exclusion of insect sounds during WT noise measurements using unsupervised and supervised learning and it also explores the possible influence of WT noise on insects' acoustics communication.

## II. Methodology

As part of the determination of the sound power of the WT, measurements were carried out following the example of the Danish regulation, [23]. The primary purpose of the presented research described in this article was not to calculate the sound power, but to demonstrate the methodology and approach to the filtration of a large number of data/recordings with the aim of isolating those where only the noise of the WT is present. Since the measurement location was in a rural area, different residual noise sources with varying temporal characteristics were present. Most of them were sufficiently far away from the measurement microphone and did not affect signal-to-noise ratio during the WT operation. However, insect noise, especially in the evenings and during the nights, exceeded WT noise levels, because of the proximity to the measurement microphone of individual creatures. To exclude their calling noises, temporal filtration was applied based on features extracted from the recordings. Measurements were taken 6 continuous days. This represented a large dataset that needed automated exclusion of residual noise sources.

### A. *Wind turbine and measurement location*

Subject of measurements was a WT type E-70 with installed power of 2.3 megawatts from the German manufacturer Enercon. The WT has a 97-meter tall tower on which a rotor with a three-bladed blade with a diameter of 71 meters is mounted. The WT was constructed in 2011 and began operating in 2013. The whole measurement procedure was carried out based on Danish regulations for WT noise assessment. The placement of the measurement point is shown in Fig. 1. The distance between the measuring point and the WT is estimated at 134 m ± 5 m. The position of the measuring point with respect to the directions of the sky was chosen according to the average annual values of wind speed and direction for the area where the measurements were taken, [24].


Fig. 1. Measurement location.

### B. *Sound level meter and wind sensor*

The measurements were conducted using the sound level meter Norsonic Nor140. Calibration to verify the instrument during measurements was conducted at the beginning and end of the measurements and at each battery change. The instrument operated stably during the measurements, always within 0.1 dBA, and there was no need to adjust calibration constants.

For wind speed and wind direction measurements, sensor KVT 60A was used, which meets the requirements of the National Meteorological Service and is suitable for wind speed measurements between 0 m/s and 50 m/s and wind direction between 0° and 360°. Its measurement accuracy is +/- 0,5 m/s and resolution of 0,1 m/s for wind speed and +/- 2,75 ° and resolution of 5,5° for wind direction. We have not received the wind speed and direction at the rotor height of the WT from the operator. Wind speed and direction measurements were therefore carried out at a height of 5.5 m above the ground. Wind speed and direction measurements were performed with a time resolution of 1 minute, the measurement time was coordinated with the time on the sound meter. The meter was placed between the microphone and the wind farm. The primary wind screen was a commercially available open-cell foam in the form of a sphere, mounted on the microphone. Secondary protection from rain was used. It was made of polyurethane foam (PU), which has also been used and tested by other studies, [25-28].

### C. *Audio Database Description*

Our study leverages an extensive collection of insect species sounds from the Xeno canto: Sharing bird sounds from around the world, [29], a globally recognized resource for bird and insect recordings. As a result, these original audio recordings were used to evaluate the class proposed by unsupervised classification that represent the audio segments of the insect activity. To ensure a representative database, we selected files based on specific metadata conditions; a high-quality rate, to ensure the clarity and usability of the recordings, and a duration between 20 and 90 seconds for capturing complete insect vocalizations without excessive background noise.

This selection process allowed us to compile a diverse set of recordings, covering a wide array of insect species. These recordings, feature a sampling frequency of 44,100 Hz and 24-bit resolution. These recordings include a mixture of vocalizations from multiple species and ambient noises such as wind and rain, presenting substantial challenges for sound segmentation and classification.

### D. *Threshold Detection and Segmentation*

Due to the diverse and natural settings of field recordings, the audio inherently contains a mix of vocalizations from multiple species, accompanied by ambient noises such as wind and rain. These elements introduce significant challenges for sound segmentation and classification, [30]. To effectively isolate insect vocalizations, endpoint detection is crucial, enabling the extraction of clear, uninterrupted audio segments from the original recordings, as shown in Fig. 2.

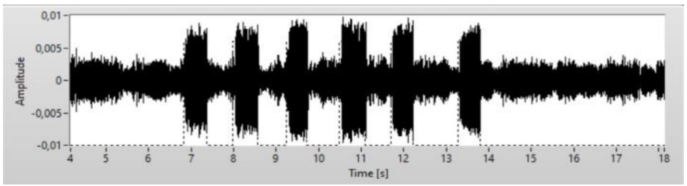


Fig. 2. Endpoint detection diagram.

### E. *Feature Extraction through STFT Spectrogram*

After segmentation, we employ the LabVIEW STFT Spectrogram function to analyze these 1-second clips. The Short Time Fourier Transform (STFT) algorithm, using a Hanning window of 128 points, calculates the signal energy distribution across the time-frequency domain. This computation yields a 2D array that maps the time waveform energy distribution. From each time bin, we extract the maximum frequency value, simplifying the data into a time-frequency graph of dominant frequencies. For insect calls, we found that combining the 95th percentile threshold with a zero-crossing method is highly effective for endpoint detection. The dominant frequency signal is zero-levelled at the 95th percentile, and a unidirectional zero-crossing is executed. This transforms the signal into a binary sequence of zeros and ones, indicating the presence of signal peaks when crossing the zero value. An envelope is then created over this binary data, and the zero-crossing of the envelope's 0.5

value is designated as the start and endpoint of a insect call. This method allows us to extract only the insect call from the original audio, minimizing other environmental noises and setting the stage for precise species classification.

## *F. Segmentation Process*

Our segmentation process starts with the importation of audio files from our extensive database. To improve the clarity of insect sounds and reduce low-frequency environmental noise like traffic and wind, we apply a 6th order band-pass filter to remove frequencies below 2000 Hz and above 4000 Hz, [31]. Each audio file is then segmented into non-overlapping clips of 1-second duration, facilitating focused analysis of brief sound bursts typical of insect vocalizations and aiding the classification of species-specific songs.

## *G. Initial Timeframe Parametrization*

During the initial phase of our parametrization process, each audio file is dissected into smaller subparts of 200 ms each. This timeframe allows for a high-resolution analysis of the sound's temporal dynamics. For each subpart, a Fast Fourier Transform (FFT) with a Hanning window and no overlap is performed to identify and record the dominant frequency, laying the groundwork for extracting detailed frequency characteristics representative of specific insect vocalizations.

## *H. Secondary Timeframe Parametrization -feature extraction*

Following the initial analysis, the data undergo further parametrization within a larger timeframe of 5000 ms. During this phase, two key parameters are derived from the pool of dominant frequencies obtained earlier:

- Mean of Dominant Frequencies: This represents the average dominant frequency observed over the 5000 ms period, providing a central tendency measure of the frequency distribution.
- Coefficient of Variation: It serves as a measure of the variability relative to the mean, offering insights into the stability or fluctuation of insect vocalizations within the given timeframe.

A critical step in our parametrization process involves the normalization of the frequency band used.

## *I. Implementation of K-Means Clustering*

The classification of insect sounds within our dataset was conducted using the k-means clustering algorithm that works by partitioning the dataset into a predefined number of clusters (k), which is determined iteratively. The algorithm assigns each data point to the nearest cluster center (centroid), and then recalculates the centroids based on the assigned points. This process repeats until the centroids stabilize, effectively grouping similar data points together based on the features described.

## *J. Integrating External Audio Data*

To enhance the accuracy of our k-means clustering analysis shown in Fig. 3, we strategically augmented our dataset with selected recordings from the Xeno-canto archive. These recordings cover a diverse range of insect species and provide a rich base of vocalization patterns. By incorporating these additional files, we significantly improve our ability to discern and validate the clusters generated by the k-means algorithm that represent authentic insect activity. The added recordings serve as crucial reference points within our dataset. These are shown as distinct dots among the clusters in the analysis graph. Their inclusion enables us to confidently associate specific clusters with insect vocalizations, ensuring that our classification aligns with known patterns of insect sounds. This visualization aids in distinguishing between clusters that are consistent across different levels of data magnification and those that are not, ensuring a robust identification process.

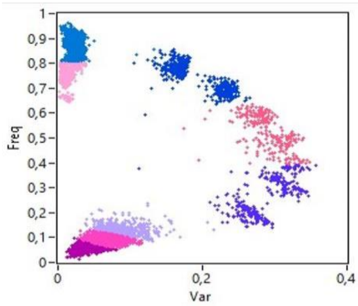


Fig. 3. K-means clustering result.

## *K. Advantages of Unsupervised Learning*

Unsupervised learning, particularly through methods like k-means clustering, is advantageous in ecological studies like ours where labeled data can be scarce or unreliable. This approach can uncover hidden patterns and structures in the data without the need for labeled examples. By analyzing the dataset in this manner, the algorithm can autonomously identify clusters that likely correspond to different insect species, based on similarities in their sound patterns. For instance, as illustrated in Fig. 4, the clusters identified as 1, 5, 6, and 7 represent insect activity.

In our analysis, a critical step involves the separation of timestamps where insect activity is present from those where it is not. This process effectively splits our original, longer-term measurements into two distinct sets of data: those segments where insect vocalizations are detected and those devoid of such activity. This segmentation lays the foundation for more targeted analyses, allowing us to focus specifically on the audio characteristics and patterns that signify insect presence.

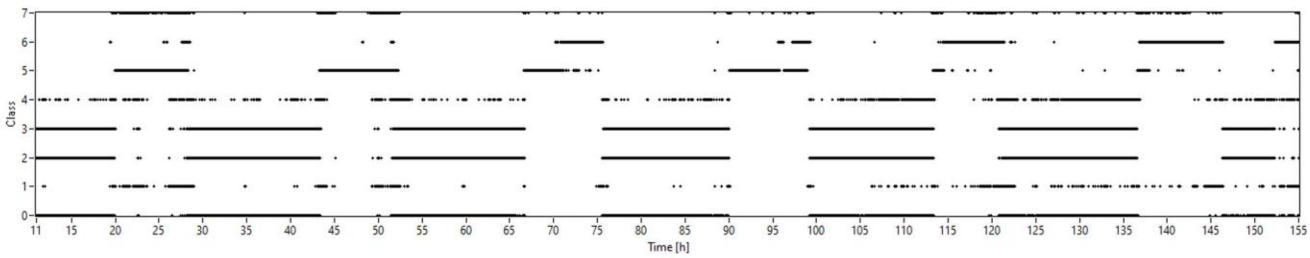


Fig. 4. K-means clustering result where classes 1, 5, 6, 7 represent insect activity.

## III. Results

Data is divided into three groups: a) All measurement data, b) Measurement data without insect noise and c) Measurement data with insect noise. Fig. 5 provides a detailed temporal analysis of recorded parameters essential to the study, with blue dots representing datapoints without insect noise and red dots indicating those with insect noise present. The temporal distribution of insect calling reveals a predominant occurrence during nighttime. Despite the presence of WT and wind noise alongside insect noise in certain datapoints, it's discerned that insect calling predominantly contributes to the noise profile during the observation period. It's noteworthy that datapoints labeled as "without insect noise" may still contain minimal insect noise; however, the signal-to-noise ratio remains sufficiently high.

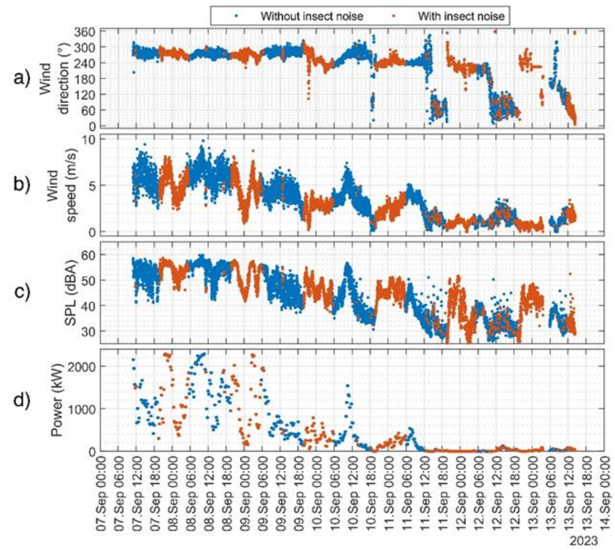


Fig. 5. Measurement data plotted against time: a) Wind direction, b) Wind speed, c) SPL and d) WT power

Furthermore, Fig. 5.d illustrates the wind power output during the measurement period, sourced directly from the turbine owner/operator with a time constant of 15 minutes. The difference in time constants was mended with applying the same value of power output for 15 consecutive wind and SPL measurements. A correlation between wind speeds and power outputs is observed, as expected. However, it's notable that SPL exhibits less correlation with wind speed, particularly during nighttime observations. This nuanced analysis sheds light on the complex relationship between environmental variables and their impact on recorded parameters, contributing significantly to the broader understanding of the research objectives.

Fig. 6 depicts a scatter plot illustrating the correlation between recorded Sound Pressure Level (SPL) and wind speed. The data reveals a notable disparity in the relationship between these variables. Observations within the dataset demonstrate instances where a wide range of SPL values, such as 55 dBA, are recorded across wind speeds spanning from less than 3 m/s to nearly 10 m/s. This variance underscores the complexity of factors influencing SPL beyond wind speed alone. Particularly noteworthy is the observation of higher SPL values in recordings featuring insect noise, especially notable at lower wind speeds. This suggests a significant influence of insect noise on SPL levels, independent of wind speed variations.

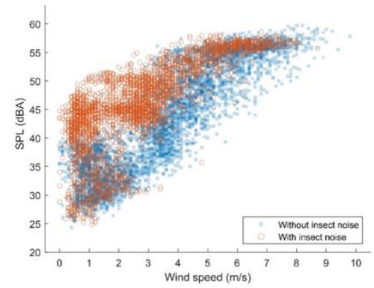


Fig. 6. Scatter plot of SPL and wind speed data for recordings with and without insect noise present.

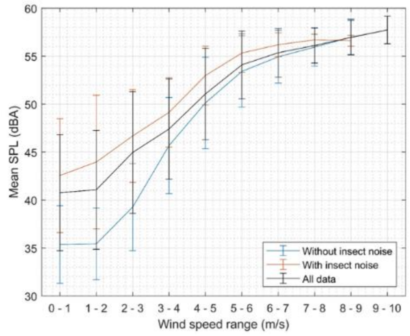


Fig. 7. Mean SPL values for different wind speed ranges.

Fig. 7 presents a comparative analysis of SPL values averaged within 1 m/s wind speed ranges, aiming to delineate differences between data with and without insect noise interference. This segmentation of data into discrete wind speed ranges provides a clearer insight into the influence of wind dynamics on SPL variations, particularly in the presence of insect noise. Notably, the analysis highlights that as wind speed decreases, the mean SPL difference between recordings with and without insect noise intensifies, underscoring the significant impact of low wind speeds on acoustic environments. It must be stated that recordings featuring insect noise also encompass contributions from other concurrent noise sources, predominantly WT and wind noise.

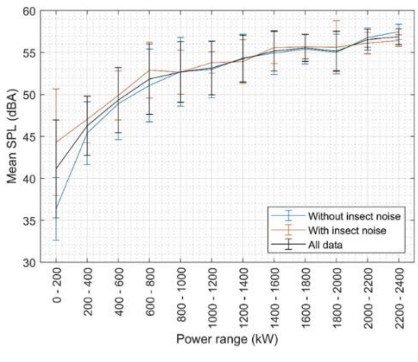


Fig. 8. Mean SPL values for different WT output power ranges.

Fig. 8 illustrates the relationship between power production and SPL variances. Lower power production (corresponding to lower wind speeds) magnifies SPL differences. Conversely, at higher wind speeds and power outputs, WT and wind noise increase, masking insect noise. The standard deviation generally decreases at higher wind speeds. However, differing time resolutions between power data (15 minutes) and wind/SPL data (1 minute) introduced additional data noise.

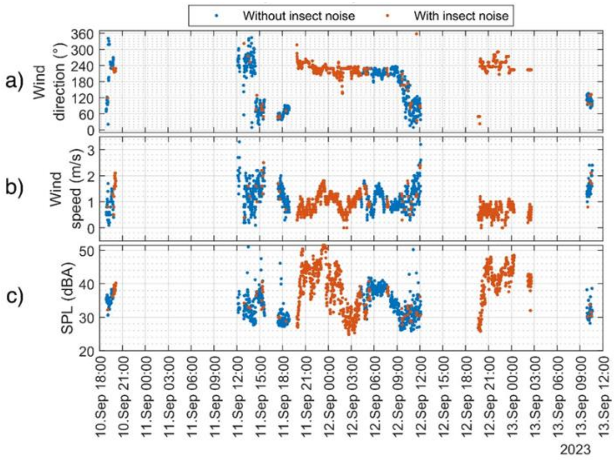


Fig. 9. Measurement data plotted against time: a) Wind direction, b) Wind speed and c) SPL.

Fig. 9 provides an in-depth examination of residual noise sources. Specifically, measurement data during periods when the WT was non-operational was analyzed. This investigation primarily encompassed data from approximately the last three days of the measurement period. During this time frame, prevailing winds predominantly blew from the southeast to the northwest, corresponding to a direction of approximately 225°. An examination of the data reveals some correlation between SPL and wind direction. A notable instance occurs between 6:00 and 12:00 on September 12th, where despite an increase in wind speed, the SPL remains relatively constant, while the wind direction undergoes change. Fig. 10 shows the scattering of the SPL data, whereby a greater scattering is particularly noticeable in recordings with insect noise. It is noteworthy that the WTs are only put into operation at wind speeds of over 2.5 m/s.

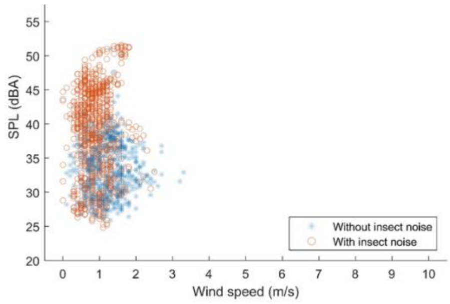


Fig. 10. Scatter plot of SPL and wind speed data for recordings with and without insect noise present filtered by non-operation of WT.

Fig. 11 provides a detailed examination of the relationship between SPL and wind speed and direction. To facilitate analysis, the data was grouped into bins of 15° and 0.5 m/s width. SPL exhibits a notable dependence on wind speed, particularly in relation to WT operation. In Fig. 11.a, this relationship is clear. Unfortunately, winds faster than 4.0 m/s only blew in directions between 240° and 315°, preventing any analysis of WT noise directionality. Nevertheless, analysis of recordings with insect noise present unveils intriguing dependencies of SPL on wind direction. Notably, when the WT was inactive (wind speed below 2.5 m/s), SPL exhibited variations based on wind direction. Specifically, higher SPL values were observed when the wind blew from east directions compared to west directions, with mean SPL differences exceeding 10 dBA.

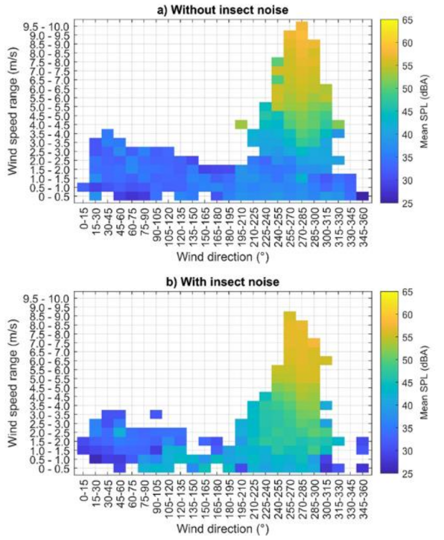


Fig. 11. Mean SPL plotted against wind speed and wind direction for data: a) Without insect noise and b) With insect noise.

Fig. 12 presents data filtered by the non-operation of the WT. Despite the reduced dataset, distinct differences between wind directions are clearly discernible. Notably, higher SPL values from northeast directions (225° to 255°) raise suspicion of potential highway noise influence. This conjecture is supported by Fig. 13, which illustrates the proximity of the highway, located 1.6 km away from the WT.

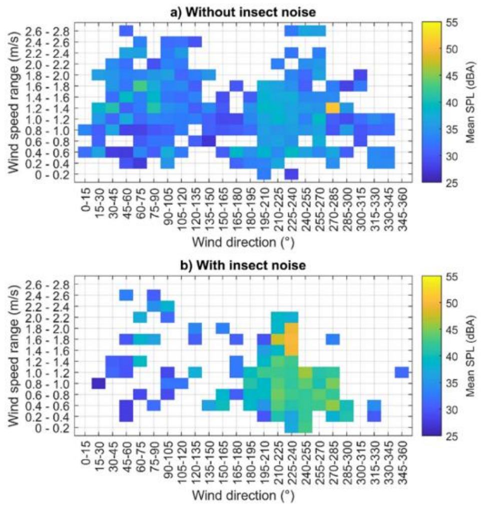


Fig. 12. Mean SPL plotted against wind speed and wind direction when WT was not operating for data: a) Without insect noise and b) With insect noise.

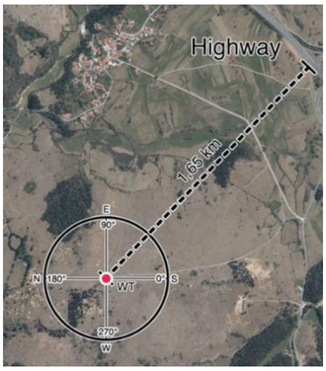


Fig. 13. Location of highway and WT.

## IV. CONCLUSIONS

Long-term measurements are crucial for accurately assessing WT noise, particularly in the presence of significant residual noise sources such as insect sounds. Our study highlights that insect noise, especially during nocturnal hours, poses a major challenge in characterizing WT sound power. Insect calls, dominant in our measurements, notably influence SPLat lower wind speeds. Prolonged observations are necessary to discern patterns, especially concerning wind direction's impact on SPL. Residual noise sources, including highway traffic, further complicate WT noise assessments. Manual data selection for WT noise assessment is time-consuming. Therefore, innovative methods are essential to filter out residual noise sources, both anthropogenic and biological. Future research should focus on developing customized measurement equipment and advanced signal processing techniques. These innovations will enhance the accuracy and efficiency of WT noise assessments and provide a clearer understanding of their impacts on biodiversity and human health.

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