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***Abstract*—The wind is one of the major factors that may cause unmanned aerial vehicles (UAVs) to crash and pose fatality risk to the population and property damage risk to infrastructures. This paper investigates wind patterns on temporal scales to identify high-risk periods in terms of wind conditions for safe UAV operations in urban airspace. The research starts with the historical wind speed data analysis using statistical approaches. As the wind speed data does not follow normal distribution after checking, a nonparametric approach of the Kruskal-Wallis test is applied for hypothesis testing to see if there is a significant difference in the median wind speed in different years. Regression analyses are also performed for monthly wind speed data to check any significant trends that could facilitate the predictions of average wind speed in the long term. This study will contribute to safe air traffic management for UAV operations in low-altitude urban airspace by mitigating adverse wind effects.**

***Index Terms*—UAV, wind speed, operational safety, urban airspace, nonparametric statistics**

I. Introduction

UAVs can be used in a variety of applications in urban airspace [1], such as cargo delivery and photography [2], which bring opportunities to unlock the potential of the sky. However, UAVs may not be able to operate under all types of weather conditions [3]. The weather effects on UAVs may reduce their reliability, causing safety issues and hindering their widespread uses [4].

The weather conditions that may exert an adverse effect on UAV operations can be strong winds (which may cause UAVs loss of control [5,6]), precipitation (damage onboard electronics and affect airworthiness [4,7]), and low temperatures (reduce the battery performance [8]). Thus, weather data is critical for UAV flight planning, forecasting, and overall operations [9]. However, there are few published standards and specifications that cover weather requirements for flight operations of UAVs [4,9]. The American National Standards Institute (ANSI) identified weather conditions related to UAV operations as a gap that needed additional research and gave this gap high priority [9].

Furthermore, as most UAVs are light and have small sizes, they can be susceptible to wind [4,5,6]. Once UAVs are out of control due to strong winds, they may crash to the ground and pose risks to the population such as fatality risk to pedestrians [10,11], property damage risk to ground facilities [12,13], and airborne collision risks [14,15,16]. To avoid such incidents, analysis of wind patterns and enhancing the stability of UAVs are therefore essential. Some researchers focused on wind effects on UAV operations, and they modeled all different kinds of wind including constant wind, turbulent flow, wind shears, and propeller vortex. The models were then implemented in simulation tests to show the effects of all sorts of wind on UAV paths and flight states [6]. Another study modeled the interaction between wind and a UAV from the perspective of the UAV's onboard sensors [17]. To implement UAV operations in such windy urban environments, some studies proposed a novel flight mode for UAVs to offset the trajectory deviation [18] caused by side wind [5]. Novel path-planning techniques were also investigated for UAVs pursuing ground moving targets [19,20]. However, existing models are heavily relied on mathematical models and may not sufficiently consider the real-world wind data. Others examined the impact of wind speed on UAV flyability at a global scale with a given maximum wind speed tolerance of 10 m/s for common UAVs and 14m/s for weather-resistant UAVs respectively [4]. However, wind speed variability has not been investigated and localized wind pattern analysis is still lacking. This paper will investigate the localized real-world wind speed data.

Enhancing UAVs' wind resistance ability is a good way to improve its reliability and safety threshold [21]. To obtain a reliable threshold, we analyze wind patterns in urban airspace by answering three questions:

1) Do the wind patterns have any regularity or irregularity?
2) Do the wind patterns present yearly consistency?
3) Do the wind patterns follow any monthly trend?

By understanding the wind patterns in urban airspace, the influence of wind on UAV operations can be reduced by identifying and avoiding periods with severe wind conditions. This study will contribute to future air way design [22] considering wind-related risk source and improve the UAV operational safety.

II. Methodology

The methodology of this study starts with the analysis of historical wind speed data. Statistical approaches are used to investigate the wind pattern, including the normality test, homogeneity of variance test, Kruskal-Wallis test, and regression test.

Firstly, a proper statistics approach is determined based on the feature of obtained data by testing their normality and homogeneity of variance. If the data follow a normal distribution and have equal variance, a parametric statistic test will be performed; otherwise, a nonparametric statistic test will be conducted.

The next step is to check if the wind patterns from different years present statistical consistency. The null hypothesis in this section is defined as no significant difference between the wind speed in different years. If failed to reject the null hypothesis, it means that the wind speed presents statistical consistency. If the null hypothesis is rejected, we analyze the causation and remove outliers that cause the inconsistency of the sample data.

After analysis, if the wind patterns have yearly consistency, we test their monthly trends. Tests for linearity and quadratic trends will be conducted, respectively. The purpose of this section is to find the monthly regularity and obtain a reliable regression equation for forecasting wind speed.

The research findings are discussed in the last section of this paper, and the possible applications of this study to weather-based air way design for safe UAV operations is also discussed.

The overall workflow of this study is shown in **Figure 1**.

A. *Hypothesis testing for yearly consistency*

The independent variable is each particular year (e.g., the years 2011, 2012, ..., and 2020). They are between factors. The dependent variable is the weekly mean wind speed of the corresponding year.

We define the mean and variance of the ith group as μ_i and σ_i respectively for the parametric test. In nonparametric statistics, we use median as a measure instead of mean. Hypotheses we take for checking yearly consistency are defined as follows.

i) Hypothesis for sampled population means/medians
   H_0: $\mu_1 = \mu_2 = \cdots = \mu_{10}$
   H_1: Not all means/medians are the same

ii) Hypothesis for sampled population variances
   H_0: $\sigma_1 = \sigma_2 = \cdots = \sigma_{10}$
   H_1: Not all variances are the same

B. *Regression analysis of monthly trends*

The independent variable is each month (e.g., January (1), February (2), ..., December (12)) in a year. They are between factors. The dependent variable is the monthly mean wind speed.

We conduct regression analysis on linear and quadratic trends, respectively.

i) The linear trend model and hypothesis are given as

$$y = \beta_0 + \beta_1 x \tag{1}$$

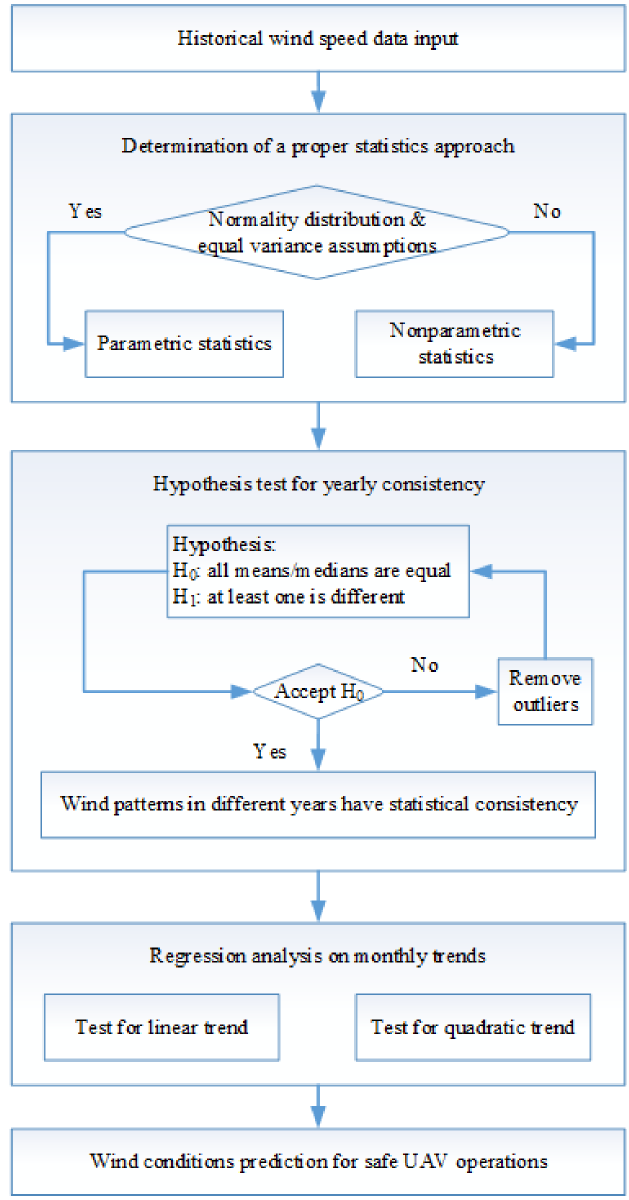

Fig. 1. Workflow of the study

Assuming that the null hypothesis is there is no linear relationship between the independent and dependent variables, presented as H_0: β_1=0. And the alternative hypothesis is as H_1: $\beta_1 \neq 0$.

ii) The quadratic trend model is presented as

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 \tag{2}$$

Departure from linearity is represented by x^2. Thus, to test a significant departure trend from linearity, the null hypothesis is H_0: β_2=0. And the alternative hypothesis is as H_1: $\beta_2 \neq 0$.

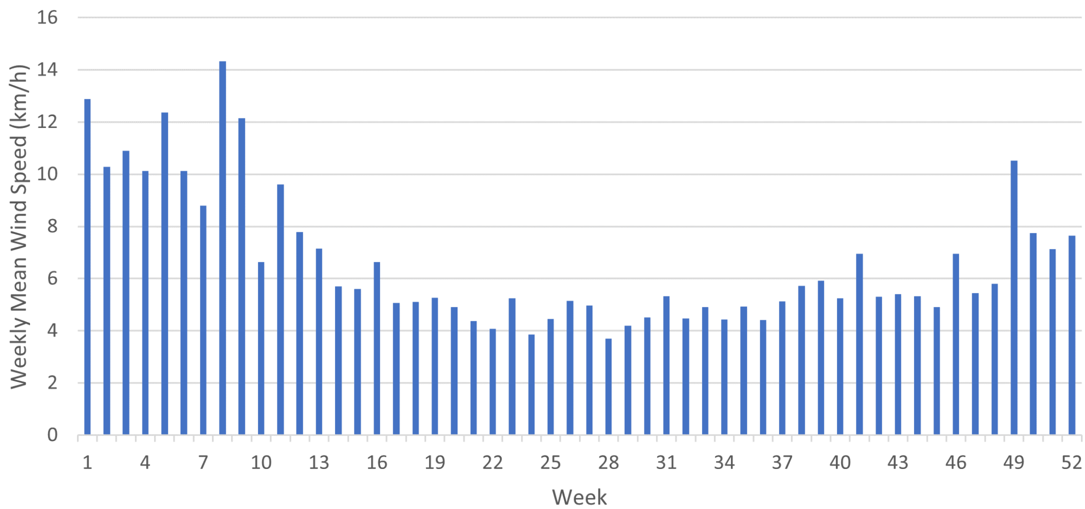

Fig. 2. Example of sample data in a group (Year 2020)

III. Preliminary analysis for hypothesis testing on yearly consistency

A. Data description

To analyze the wind patterns in urban airspace, we collect the amount of wind speed in a station named Marina Barrage in Singapore from the official meteorological website of Singapore [23].

The features of the samples are described below:

- Group: there are ten groups of sample data (i.e., years from 2011 to 2020, ten years in total).
- Sample size: 520 in total, as each group has 52 samples (i.e., each year has 52 full weeks).
- Value: the value of each data is the amount of weekly mean wind speed (km/h).
- Independence: the samples are independent of each other.

An example of one group of sample data (the year 2020) is given in **Figure 2**. The means, medians, and standard deviations of all groups' samples are listed in **Table 1**.

TABLE I
Means, medians, and standard deviations of samples from years 2011-2020

Group (Year)	Count (Weeks)	Mean	Median	Standard Deviation
1	52	6.3489	5.8357	1.5477
2	52	5.8025	5.3429	1.4639
3	52	6.0165	5.3714	1.6962
4	52	6.2896	5.1929	2.3294
5	52	6.2812	5.5179	2.0368
6	52	10.6588	10.5143	3.6208
7	52	9.4958	8.0500	4.4974
8	52	6.4596	5.7586	1.8845
9	52	6.8759	6.0786	2.4198
10	52	6.6429	5.4214	2.6184

B. Determine a proper statistics approach

a) Two categories of statistics approaches: Statistic approaches include parametric statistics and nonparametric statistics. Parametric statistics are robust and can measure sample data accurately, while they have a stringent assumption that the data must follow the normal distribution and are subject to outliers. As there is only one factor and more than two groups of sample data in this study, one-way ANOVA, a typical parametric statistics approach, is expected to conduct if parametric statistics are appropriate for this study. There are three basic conditions for one-way ANOVA: i) the dependent variables are statistically independent of each other; ii) the variances of each sample are assumed equal; iii) the residuals are normally distributed.

Nonparametric statistics do not involve population parameters and can be used for more general distributions by reducing data to an ordinal ranking and testing sample median, which reduces the impact or leverage of outliers. One of the main disadvantages of nonparametric statistics is the important feature of actual data might be lost.

Therefore, parametric statistics is preferred to be used in this study. We check the underlying assumptions of one-way ANOVA first. If these assumptions are violated, we then consider a nonparametric statistics approach.

b) Normality distribution and homogeneity of variance tests: A MATLAB *Lillietest* function is used for the normality test. We first take one group sample (the year 2020) as an example. The obtained histogram and Quantile-Quantile plot for the normal distribution of this group are shown in **Figure 3**. The Quantile-Quantile plot is a graphic technique and is commonly applied in the comparison of distributions [24]. In this section, we use the Quantile-Quantile plot to compare the distribution of obtained sample with the standard normal distribution. If the distribution of obtained sample data is similar to the standard normal distribution, the points in the

Quantile-Quantile plot will approximately lie on the 45°-line $y = x$.

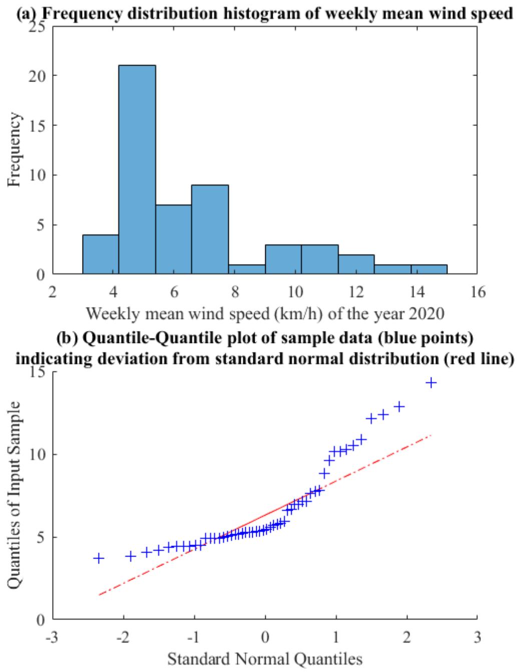

Fig. 3. Example of a normality test (Year 2020)

The “S” shaped Quantile-Quantile plot in **Figure 3** indicates that the sample for the year 2020 is more skewed than the symmetric standard normal distribution. This skewed distribution feature can also be seen in other groups, as shown in **Figure 4**.

We can see from **Figure 4** that the plots on each subplot generally do not follow the 45° line, except for the year 2016. To verify with accuracy the sample distribution is not with normal distribution, we compute the P-value of each group, summarized in **Table 2**. If a P-value is larger than 0.05, its corresponding sample follows a normal distribution at the significance level of 5%.

TABLE II
P-VALUES OF NORMALITY TEST FOR PARAMETRIC STATISTICS

Testing year	2011	2012	2013	2014	2015
P-value	0.001	0.001	0.001	0.001	0.001
Testing year	2016	2017	2018	2019	2020
P-value	0.189	0.001	0.001	0.001	0.001

We can see from **Table 2** that 9 out of 10 groups’ sample data are not with normal distribution at a 5% significance level (P-value$<$0.05).

Moreover, the p-value of the homogeneity test for variance is also smaller than the significance level of 0.05 after checking, which means that the variances of all groups of sample data have a difference at a 5% significance level.

Both normality distribution and equal variance assumptions are violated. As the parametric statistics (e.g., one-way ANOVA) is premised on the two assumptions, we can conclude that the parametric statistics is not suitable for the data used in this study.

Since nonparametric statistics do not rely on any underlying assumptions about the probability distribution of the sampled

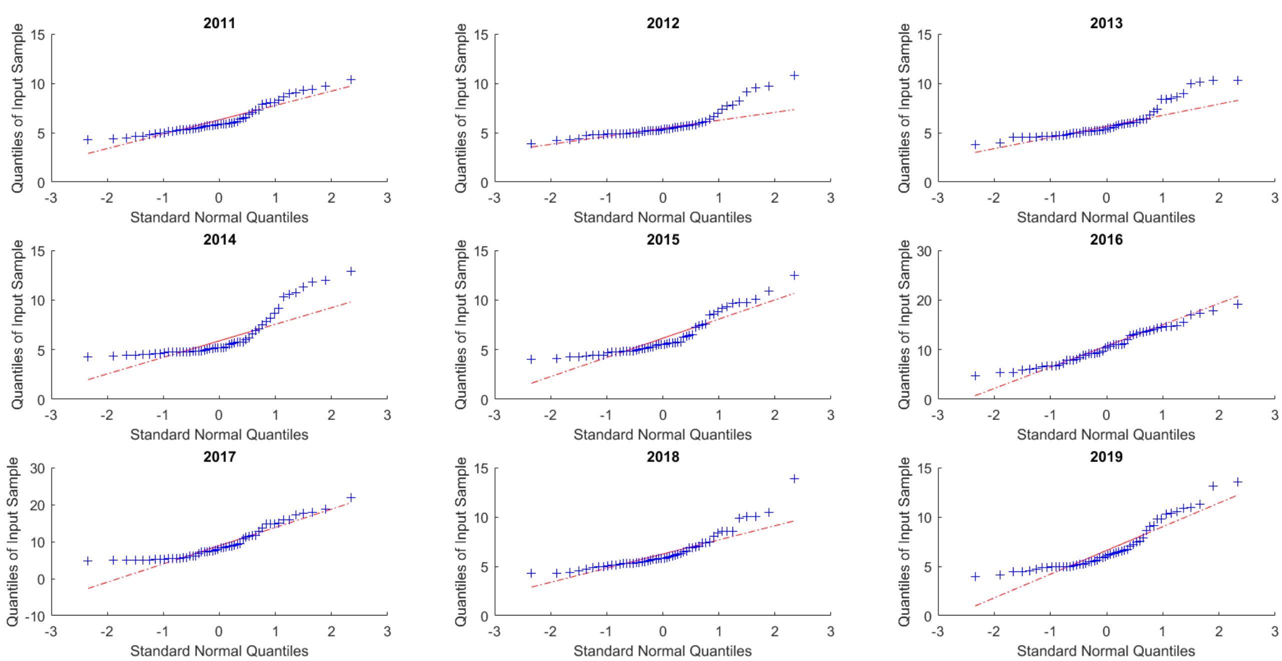

Fig. 4. Quantile-Quantile plot of sample data versus standard normal distribution (Years from 2011-2019)

population, we choose the nonparametric statistics for wind patterns analysis.

IV. Nonparametric Statistics for Identifying the Consistence of Wind Data

A. Skewed distribution feature

According to the outcomes of the Quantile-Quantile plot in **Figure 3** and **Figure 4**, the distribution of wind speed pattern is skewed rather than symmetrical. To better demonstrate their patterns, the box-plots are produced and shown in **Figure 5**. The box-plot is a graphical method reflecting dispersion and skewness of data by displaying the maximum, minimum, median, and quartiles.

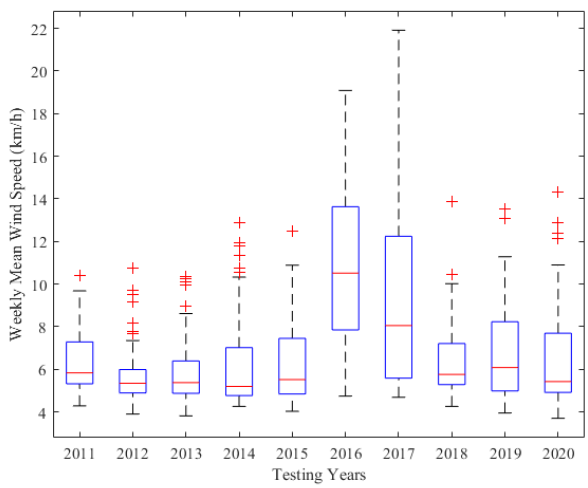

Fig. 5. Data distribution of each testing year

The interquartile ranges in **Figure 5**, presented by blue rectangles, cover the range between the 25^{th} and 75^{th} percentile (i.e., the middle 50%) of corresponding groups of sample data. The red lines are medians, and the upper and lower black lines are maximum and minimum scores, respectively. If a distribution is symmetrical, the interquartile range and median will lie in the middle of each box-plot; conversely, the interquartile range and median of skewed distribution skew towards either side. The interquartile ranges and medians in **Figure 5** are more skewed towards the left side, indicating that wind speed patterns are positively skewed. In skewed distributions, the median is a more appropriate measure. Thus, the null hypothesis made in this section is based on medians.

B. Kruskal-Wallis test and outliers removal

There are various approaches for nonparametric statistics, such as the Sign test, Wilcoxon signed-rank, Wilcoxon rank-sum test, and Kruskal-Wallis test. Among them, the Kruskal-Wallis test is used with three or more groups of sample data. Thus, we conduct the Kruskal-Wallis test in this study and the obtained results are shown in **Table 3**.

As the P-value 2.2300×10^{-18} <0.05, we can reject the null hypothesis that all medians are the same and conclude that

TABLE III
Results of the Kruskal-Wallis test in nonparametric statistics

Source	SS[a]	df[b]	MS[c]	Chi-sq	P-value
Columns	2.35×10^6	9	261357.6	104.19	2.23×10^{-18}
Error	9.36×10^6	510	18362.6		
Total	1.17×10^7	519			

[a]Sum of squares. [b]Degree of freedom. [c]Mean of squares.

there is at least one group have different sampled population distribution. It probably results from outliers, which can be reflected in a line graph, shown in **Figure 6**.

According to **Table 1**, **Figure 5**, and **Figure 6**, we can see the data for the years 2016 and 2017 are different from the other years in aspects of mean, standard deviation, median, and appearance. There are inaccuracies in these two groups of data. The outliers are removed to improve the quality of the data used in the testing. To verify the rationality of outliers removal, we conduct the Kruskal-Wallis test again to test if there is any consistency presented in the other eight years' wind patterns. The results are shown in **Table 4**.

TABLE IV
Kruskal-Wallis table (Remove years 2016 and 2017)

Source	SS	df	MS	Chi-sq	P-value
Columns	171286.7	7	24469.5	11.85	0.1056
Error	5827761.3	408	14283.7		
Total	5999048	415			

The P-value (0.1056) of the hypothesis test is higher than a significance level of 5% after we remove these two groups of outliers. We can conclude that the other eight groups (years 2011-2015 and 2018-2020) follow a similar population distribution at a significance level of 5% and perform yearly consistency. Thus, it makes sense to only use these eight groups of sample data in the following studies.

V. Regression Analysis for Monthly Trends of Wind Speed

So far, a yearly regularity has been proved to exist in the amount of wind speed. We now investigate if there is any regularity in a length of time shorter than a year. Therefore, the next step of our study is monthly trends analysis. The purpose is to identify severe wind condition and low-risk period for safe UAV operations.

The amount of monthly mean wind speed of each group is presented in **Figure 7**.

From **Figure 7**, a temporal trend appears in a monthly pattern. To verify the regularity and obtain a numerical expression, we then conduct regression analysis.

The independent variable for monthly trend analysis is each month within a year and its corresponding monthly mean wind speed of eight groups is the dependent variable. The value of independent and dependent variables is listed in **Table 5**.

Firstly, we test for linearity. According to Eq. (1), a MATLAB *regress* function is used to compute the two parameters

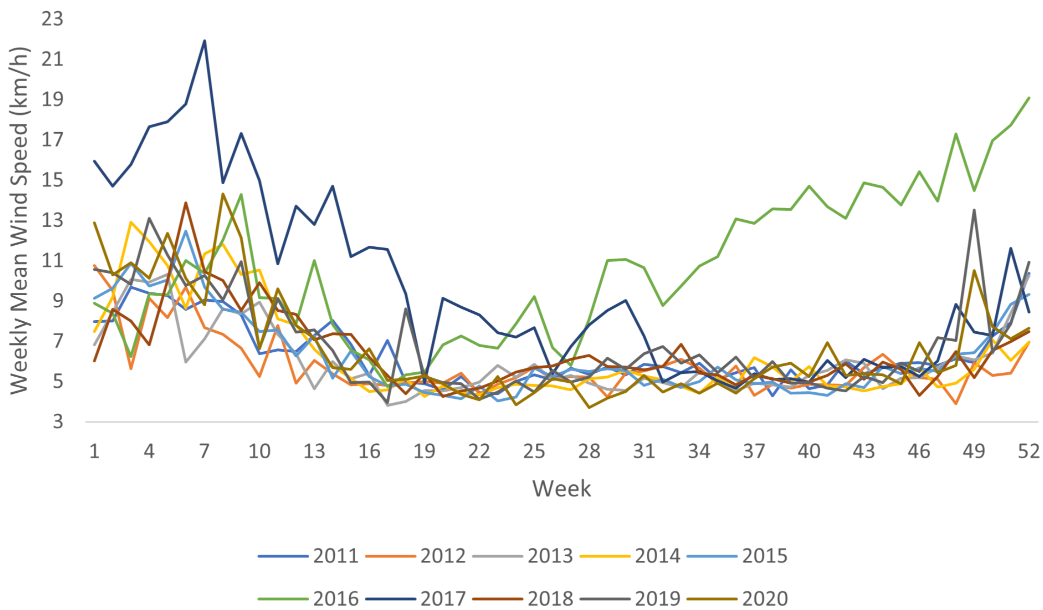

Fig. 6. Weekly mean wind speed (km/h) of the years 2011 to 2020

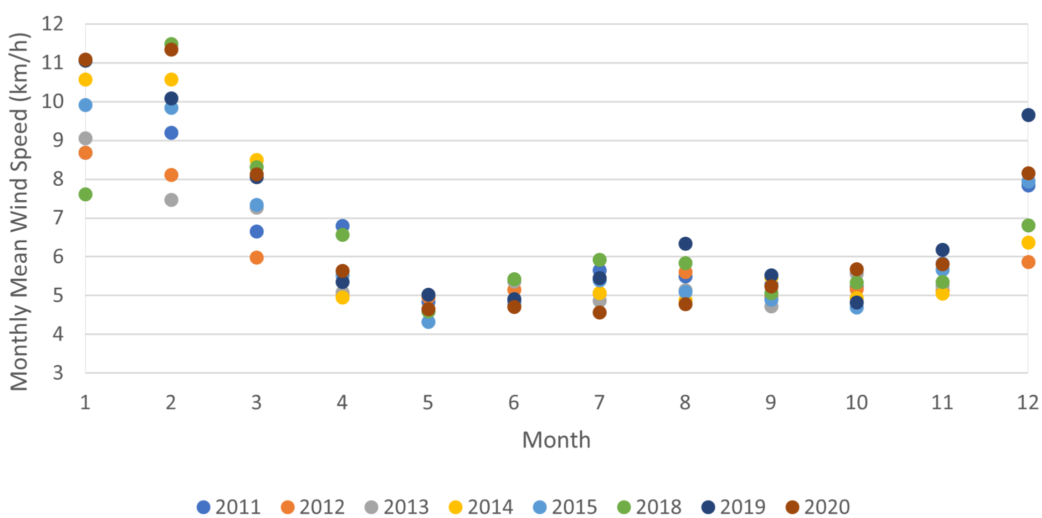

Fig. 7. Monthly mean wind speed (km/h) of each group

(β_0, β_1), we have β_0=8.1011 and β_1=-0.2679. The linear regression equation is therefore presented as

$$y = 8.1011 - 0.2679x \tag{3}$$

To test if the linear trend is significant, we conduct a hypothesis test and the obtained results are R^2= 0.2876, F_{obs}=4.0374<$F_{crit(0.05;1,10)}$=4.96, and P-value = 0.0723>0.05. Thus, we fail to reject the null hypothesis at a 5% significance level and conclude that the linear regression model is not acceptable.

We then test if the sample data follow a quadratic trend. According to Eq. (2), a MATLAB *polyfit* function is used to compute the three parameters (β_0, β_1, β_2), we have β_0=11.9229, β_1=-1.9058, and β_2=0.1260. Thus, the quadratic regression equation is presented as

$$y = 11.9229 - 1.9058x + 0.1260x^2 \tag{4}$$

Also, to test if the quadratic trend is significant, we conduct a hypothesis test. The obtained results are F_{obs}=2048.41>$F_{crit(0.05;1,9)}$=5.12. Hence, we reject the null hypothesis and conclude that the quadratic model is acceptable. The predicted quadratic trend is presented in **Figure 8**.

We can see from **Figure 8** that the wind speed on the monthly scale represents a general concave trend, meaning that

TABLE V
INDEPENDENT AND DEPENDENT VARIABLES OF THE REGRESSION TEST

Independent Variable (Month)	**Dependent Variable** (Mean, km/h)
Jan (1)	9.59
Feb (2)	9.77
Mar (3)	7.53
Apr (4)	5.62
May (5)	4.71
Jun (6)	5.00
Jul (7)	5.25
Aug (8)	5.40
Sep (9)	5.15
Oct (10)	5.18
Nov (11)	5.54
Dec (12)	7.58

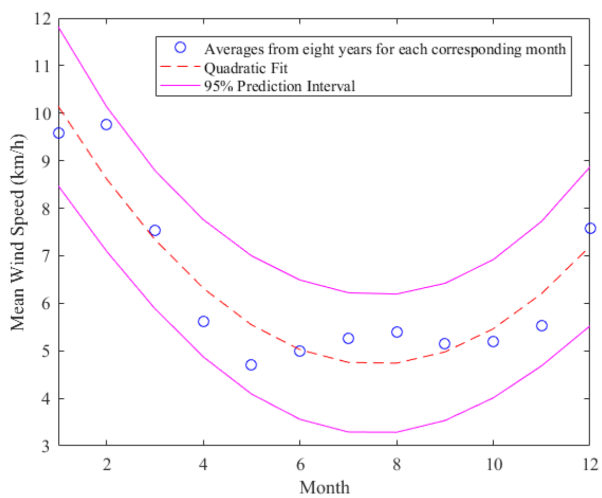

Fig. 8. Quadratic fit of data with 95% prediction interval

the minima wind speeds are most likely to occur in mid-year while the maxima exist in early and late years. The regression result is expected to be used as an environmental safety guide for the flights of UAVs, as we prefer UAV operations in a safer period where wind speed is relatively low rather than in unsafe windy environments. To identify windy weather, we further introduce prediction intervals.

Prediction intervals are a common tool for regression analysis, and they help express the potential value of a new observation. In **Figure 8**, the quadratic fit curve represents the predicted values of regression, and the prediction interval provides the lower and upper boundaries of prediction. For instance, we calculate the expected mean wind speed in January as 10.14 km/h according to the regression Eq. (4). The lower limit of the prediction interval is approximately 8.47 km/h, and the upper limit is approximately 11.82 km/h, thus we can be 95% confident that the mean wind speed in a future January will fall to this range of [8.47, 11.82] km/h. In other words, a UAV should have the ability of wind resistance of at least 11.82 km/h to keep its operational safety if it operates in January.

Compared to the 95% prediction interval, the 90% prediction interval is narrower, and the 99% prediction interval is wider, as shown in **Figure 9**.

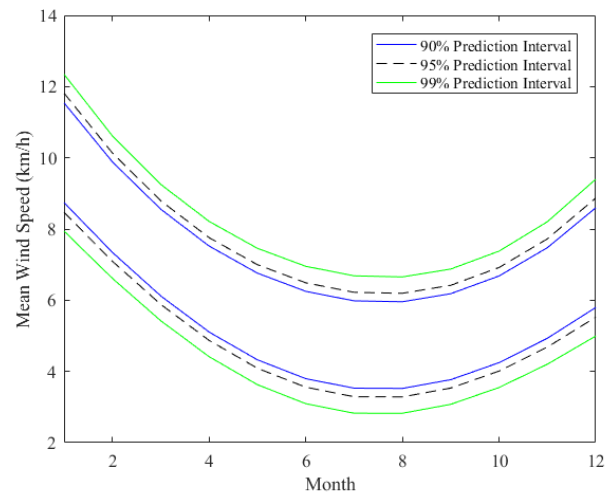

Fig. 9. 90% and 99% Prediction Intervals Comparison to 95% Prediction Interval

We also take the monthly mean wind speed in January as an example. The 90% prediction interval means that we can be 90% confident that the new observation will be between 8.74 km/h and 11.54 km/h, and the 99% prediction interval indicates that there is a 99% probability that the new observation will fall within the interval of 7.94 km/h to 12.35 km/h. The wider the prediction interval, the more potential observations will be covered. Since individual observation is subject to circumstance and is likely to deviate from the predicted regression value, it is liable to omit extremes of wind conditions that might act as risk sources for UAV operations if we use a narrow 90% prediction interval as a guide. If we treat the 99% prediction interval as a guide, it can cover more severe windy conditions and improve UAV operational safety. However, this strict guide will scarify UAV flyability and damage the utility of limited urban airspace, as extreme windy days are not frequent after all. Therefore, it is more reasonable to take a 95% prediction interval into account for predicting wind conditions. Which benefits UAV flyability to a significant degree as well as guarantees UAV operational safety in generality.

VI. CONCLUSIONS

We investigate wind patterns in this study and find their regularity from the aspects of yearly consistency and monthly trends. The key research findings are concluded below:

1) The wind speed feature does not follow symmetric distributions such as normal distribution but rather presents positive-skewed distribution.
2) Wind patterns show yearly consistency, meaning that wind speed patterns in different years statistically follow a similar distribution.

3) A quadratic trend of monthly wind speed is presented within a year. The maximum mean wind speed occurs in the beginning and at the end of a year while the wind speed from May to September is relatively lower, which is a safer period for UAV operations.

By investigating the wind patterns in urban airspace, the adverse effect of wind can be mitigated by avoiding high-risk windy periods and the safety of UAV operations can be improved. This study can also contribute to weather-based air route network design for safe UAV operations in urban airspace.

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