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Climate Change-Based Coastal Wind Modeling

Heri Sulistiyono[1*], Eko Pradjoko[1], I Wayan Yasa[1]

Master Program of Civil Engineering, University of Mataram, 83125. Indonesia[1]

Corresponding Author: 1*

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ABSTRACT

Wave data is an essential element in coastal disaster risk studies. The dimensions and structural types of seawalls and breakwaters on the coast depend on these elements. Extreme storm surges can cause significant damage to coastal areas. In wave theory, the wind can produce waves. The bigger the wind, the stronger the waves. According to the Intergovernmental Panel on Climate Change (IPCC), the wind is a part of the climate element that has the potential to change along with climate change. This paper proposes a new approach to predict future waves based on climate change. The technique contains slope correlation and regression analysis. The slope correlation is proposed in this paper to improve the performance of the Pearson Correlation for such a particular purpose. This study uses the Ampenan coastal area to demonstrate the proposed approach. This research implements wind data from the Selaparang Airport Station to represent the coastal winds in Ampenan, Indonesia, and climate change data from the IPCC. The recorded wind is from 1988 to 2020, and the climate change data is from 1988 to 2100. Selaparang Airport Station is the closest wind station to Ampenan beach. The distance between the Selaparang station and the Ampenan beach is less than ten kilometers. The result of the demonstration showed an increase in the average and minimum wind speed values. The average increase is about 3 knots from 1990 to 2100. However, the maximum value of wind speed remains the same until 2100. In addition, the standard deviation of wind speed gradually decreases in the future.

1. INTRODUCTION

Engineers use coastal dikes and seawalls to reduce the risk of coastal disasters [1], [11], [5]. However, coastal dikes and seawalls can collapse [26]. Seawalls can collapse due to coastal abrasion [7], [16], [9]. Wind and waves can cause those coastal abrasions [13].

Engineers use wave and ocean current data to design coastal protection for coastal disaster risk reduction [9]. However, some coastal areas do not have sufficient data on ocean waves and currents [4], [23], [30]. In this case, engineers and researchers must generate information about future waves and ocean currents based on future winds. In wave theory, gust and wind speed determine the height, length, and strength of wave-current [14]. The essential parameters of wind data include wind speed, wind gust duration, fetch, and wind direction [15]. Engineers use the maximum or the average of wind data parameters to calculate wave heights, peak wave periods, and wave growths. After climate change has become a global consensus, engineers must carefully consider emerging trends and the heteroscedasticity of wind data in their designs for coastal reduction.

It is stated in the IPCC Synthesis Report that global warming causes climate change [12]. After the climate change consensus in Kyoto in 1992, the use of historical wind data was no longer sufficient for designing coastal protection. Today, engineers must consider the impacts of climate change in the design of coastal protection. All climate elements, including wind, will gradually change following the development of climate change status. As the average wind speed changes with climate change, the average wave size generated by the wind will also change in the future. Engineers can utilize climate change data from the IPCC to simulate future waves. Based on the above problems, this paper proposes a technique to model coastal wind speeds based on climate change. By knowing the model of coastal wind speed, engineers can predict the magnitude of the waves that may occur in the future. The authors design the proposed technique in this study to ease as possible for engineers and researchers to understand comprehensively.

2. MATERIALS AND METHOD

2.1 Climate Change Studies

Engineers and researchers utilize General Circulation Model (GCM) data for simulating future climatic conditions. However, the resolution of GCM data is still rough because the GCM model covers a large area. Therefore, engineers and researchers should apply the downscaling method to get a better resolution of data for basin-scaled studies. Engineers employ statistical, dynamic, or hybrid methods to determine a better result. The first step of developing the downscaling model is to obtain a significant relationship between GCM data and local historical data [22], [29], [10], [32], [17].

2.2 Climate Elements

One of the elements of climate is wind. The wind will cause disaster when it comes at high speed. High-speed winds can directly cause tremendous physical damage and are able to generate large waves. Physical damage becomes greater when storms and large waves hit areas with poor infrastructures [27]. Furthermore, according to Marchigiani, good preparation can minimize the damages.

2.3 Relationship between winds and waves

Long-distance high-speed winds in the ocean can generate big waves [8]. Five following factors: wind speed, fetch, fetch width, wind duration, and water depth affect the formation, the structure, and the size of waves.

The reduction in beach area due to abrasion and erosion occurs when the backwash wave is stronger than the swash. Under these conditions, engineers can understand the concept proposed by Planck [2], [24] that the increase in frequency will increase the energy.

$$\mathrm{E} = \mathrm{h}f \tag{1}$$

which: E is the Energy in Joules, J; h is 6.626 x 10-34, J Hz^{-1}; f is the frequency, Hz^{-1}.

2.4 Wind Speed-Based Wave Height and Wave Speed Estimation

The equations to relate wind and wave [18] are as follows

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$$\frac{gH}{U^2} = f_1\left[\frac{gH}{U^2}, \frac{gt}{U}\right] \tag{2}$$

$$\frac{C_0}{U} = \frac{gt}{2\pi U} = f_2\left[\frac{gF}{U^2}, \frac{gt}{U}\right] \tag{3}$$

which: g is the acceleration of gravity, 32.2 in feet/second^2; H is the significant wave height in feet; U is the wind speed in feet/second; t is the duration of wind in seconds; C_0 is the wave speed in deep water in feet/second; F is the fetch length in feet.

Engineers can understand Bretschneider's thinking that there is a function of the relationship between the wave speed and the duration of wind.

2.5 Wind Speed-Based Wave Length Estimation

A wavelength is a distance between one another peak of a frequency wave. Cassidy used the wavelength equation below [3]

$$\lambda = \frac{\nu}{f} \tag{4}$$

which: λ is Wavelength in m; ν is Speed of light in m/sec; f is Frequency in Hz.

Furthermore, the wavelength is a function of frequency [3].

2.6 Proposed Technique

The incorrect approach in the analysis can lead to producing wrong results. The authors propose a technique to identify the relationship between climate change variables and historical local coastal wind data. This technique also contains the development of models to predict future wind data based on climate change variables. The diagram in Figure 1 shows three steps of the proposed procedure.

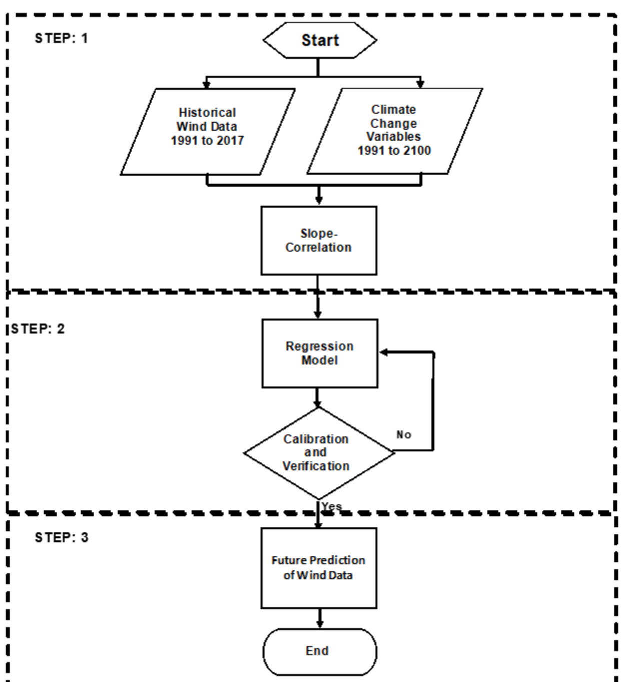

Figure 1. Proposed Procedure

1) Identification of Slope-Correlation: In some cases, a Correlation Coefficient of less than 0.5 can have a strong trend relationship as it turns out to have a Slope-Correlation Coefficient of greater than 0.5. Relying only on the Correlation Coefficient is not the best way to measure the relationship between two groups of variables. In this study, the authors propose a new approach of measuring the relationship between two groups of variables. The new approach is named a Slope Correlation. This new approach still uses the basic Pearson correlation formula, but the variables used in the calculation must be modified first. The modification made is to remove the random effects of the variables to get new variables without the influence of random. The employment of a Slope Correlation Coefficient is better than a Correlation Coefficient Analysis because Correlation Coefficient Analysis considers the relationship between each data set in one data set and another data set. Data contains a random variable; the random variable influences the value of the Correlation Coefficient. Therefore, the authors need to remove the influence of random variables in the data set by regression.

This step identifies a slope correlation between climate change data and wind data. A slope correlation is not a correlation between one data set and another. In this study, the authors define a slope correlation as a correlation between two slopes that are the slope of climate change and the slope of wind data. A slope correlation coefficient expresses the strength level of the relationship between two trends. This study utilizes the method of Pearson's product-moment to obtain the slope-correlation coefficient. The equation below expresses the coefficient of correlation [25], [31], [21], [28], [20].

$$r = \frac{N\sum XY - \sum(X)(Y)}{\sqrt{[N\sum X^2 - \sum(X^2)][N\sum Y^2 - \sum(Y^2)]}} \tag{5}$$

Which: r is the Pearson r correlation coefficient; N is the number of value in each data set; X is the values on the regression line between local coastal wind variables and time; y is the values on the regression line between climate change variables and time.
The degree of correlation is as shown in Table 1.

Table 1. Definition of Correlation Values

Value of r	Definition of relationship
0.80 ~ 1.00	Very strong and in the same direction
0.60 ~ 0.79	Strong and in the same direction
0.40 ~ 0.59	Moderate and in the same direction
0.20 ~ 0.39	Weak and in the same direction
0.01 ~ 0.19	Very weak and in the same direction
0	No correlation
- 0.01 ~ - 0.19	Very weak but in the contrary direction
- 0.20 ~ - 0.39	Weak but in the contrary direction
- 0.40 ~ - 0.59	Moderate but in the contrary direction
- 0.60 ~ - 0.79	Strong but in the contrary direction
- 0.80 ~ - 1.00	Very strong but in the contrary direction

[25], [31], [21], [28]

Table 2 proves that adding random variables to variable X and variable Y, which initially had a perfect correlation coefficient, became smaller than 0.5.

Table 2. Correlation Coefficient of Non-Random Variables and Random Variables

Y	X	r	R1~(100,25)	R2~(100,25)	r	Y+R1	Y+R2	r
(1)	(2)	(3)	(4)	(5)	(6)	(7)=(1)+(4)	(8)=(2)+(5)	(9)
1	5	1	93.23	84.71	0.021	94.23	89.7159	0.243
2	10		103.01	116.65		105.01	126.657	
3	15		123.36	124.65		126.36	139.651	
4	20		33.04	102.16		37.04	122.165	
5	25		141.44	68.1		146.44	93.1057	
6	30		110.44	135.58		116.44	165.588	
7	35		81.84	128.16		88.84	163.162	
8	40		115.08	109.34		123.08	149.343	
9	45		104.82	133.42		113.82	178.421	
10	50		155.38	127.48		165.38	177.481	

In Table 2, columns (1) and (2) are the two groups of variables that have a perfect correlation coefficient, as shown in column (3). Columns (4) and (5) are random variables. Column (6) is the value of the correlation coefficient between the variables in columns (4) and (5). Column (7) is the sum of the variables in columns (1) and (4), while column (8) is the sum of the variables in columns (2) and (5). The correlation coefficient between the variables in columns (7) and (8) expressed in column (9) is 0.243. This calculation shows that the random variable causes the relationship between the two groups of variables to become less significant, even though the two groups initially have a strong correlation.

2) Development of Regression Model: This step is to develop the best regression model to generate the local coastal wind based on climate change variables. The selected climate change variables involve in the regression modeling. Engineers can develop regression models based on the polynomial model involving climate change variables that have a high slope correlation coefficient and as shown below

$$Y = A + \sum_{i=1}^{n} B_i \mathrm{X}_i + \varepsilon \tag{6}$$

Which: Y is the response variables; A is a constant; n is the number of predictor variables, B is the coefficient of predictor variables; X is the predictor variables; ε is the residuals

This study uses the goodness of fit test to select the best model. Acceptance criteria used in this study were a sign, P value, Variance Inflation Factor (VIF) variable, and R^2 regression model. The explanation of the acceptance criteria is as follows

1. The sign of the independent variable must be reasonable. For instance, the global variable wind speed must have a positive sign.
2. The VIF of all independent variables must be less than 5 (five) to indicate no multi-collinearity among the independent variables.
3. P-values of all variables considered in the model must be less than 5%.
4. R^2 of the regression model should be close to one to indicate a high level of acceptance.

3) Generation of Predicted Wind data in The Future: This step produces predictions of future coastal

wind data up to 2100 based on climate change variables.

3. CASE STUDY

A case study of the Ampenan coastal disaster demonstrates the use of the proposed technique. Ampenan Beach is a sand beach in the western part of Lombok Island. Figure 2 shows the coastal facing the Lombok Strait. Floods and abrasions often occur in the Ampenan coastal area due to the tide's influence, ocean currents, and big waves. The elevation of the Ampenan coastal land is less than 5 m above sea level. Ampenan coastal erosion is becoming a big concern in the last decade. The local government has built concrete seawalls along this coast to protect beaches and residencies along the coast. However, an overwhelming wave has destroyed this protection in less than a year.

Figure 2. Case Study Location

3.1 Identification of Slope-Correlation

The first step of this research is to get the Slope-Correlation between climate change data and local coastal wind data. Figure 3 shows the variables used in this study. The variables are Climate Change Data from 1988 to 2100 and Local Coastal Wind Speed Data from 1988 to 2020.

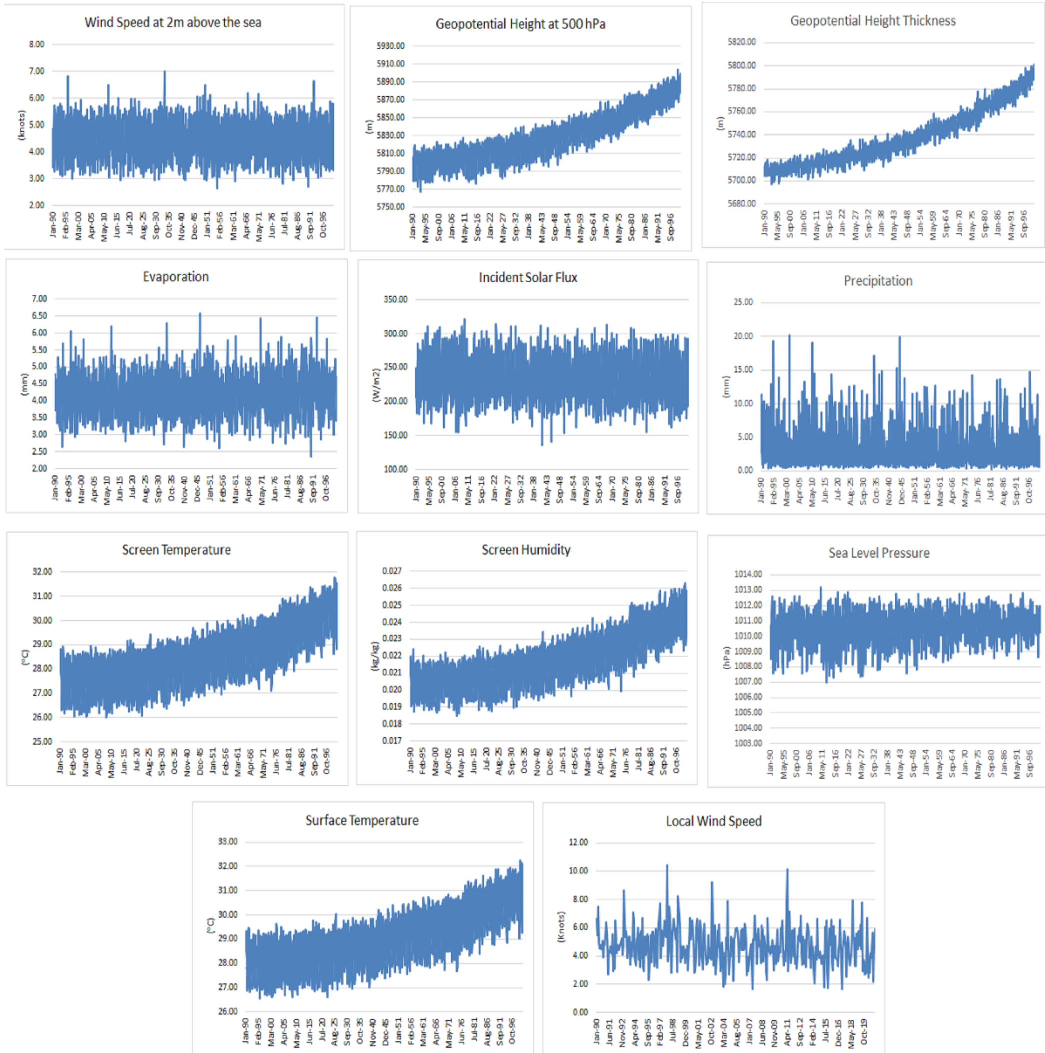

Figure 3. Climate Change Data

Figure 3 shows wind speed at 2 m, evaporation, incoming solar flux, precipitation, and a nearly steady future sea level pressure, whereas geopotential height at 500 hPa, geopotential height thickness, screen temperature, screen humidity, and surface temperature increase in the future. Local coastal wind speed is nearly stable from 1988 to 2020.

This study applies Equation 5 to obtain the values of Slope-Correlation to indicate the strength of the relationship between GCM data and local coastal wind data based on as shown in Table 3.

Table 3. Climate Change Variables with Their Slope-Correlation to the Local Coastal Wind Data

No	Name of climate change variables	Symbol	Unit	r
1	Wind Speed at 2 m	B	knots	-1
2	Geopotential Height at 500 hPa	C	M	0.99
3	Geopotential Height Thickness	D	m	0.98
4	Evaporation	E	mm	1
5	Incident Solar Flux	F	W/m^2	-1
6	Precipitation	G	mm	-1
7	Screen Temperature	H	ºC	0.97
8	Screen Humidity	I	%	0.92

9	Sea Level Pressure	J	hPa	1
10	Surface Temperature	K	°C	0.97

Note: Symbol "A" is to symbolize local coastal wind variable

Table 3 shows the ten Slope-Correlation values associated with local coastal wind data. In Table 3, the Slope-Coefficients of variables B, F, and G are -1 (a negative one). The negative one means that the effect of variables B, F, and G is 100% opposite to the coastal wind. The Slope-Coefficients of the variables C, D, H, I, and K are more than 0.5. This value means that variables C, D, H, I, and K have a strong correlation and are in the same direction as the Coastal Wind. The Slope-Coefficients of the variables E and J are one. The value of one means that the effect of variables E and J is about 100% linear to the Coastal Wind.

3.2 Development of Regression Model

This study applies Equation 6 to develop regression models. The Regression Analysis: A versus B, C, D, E, F, G, H, I, J, K. Table 4 shows the result of the regression analysis.

Table 4. Analysis of Variance

Source	DF	Adj	SS
Regression	2	28.35	14.17
B	1	1.75	1.75
Error	261	0.00	0.00
Total	263	28.35	
R-sq	100.00%		
R-sq(adj)	100.00%		
R-sq(pred)	100.00%		
Constant	4.807		
B	-0.00272		

Table 4 shows the results of the regression modelling. Term B is the only remaining variable accepted in the regression model because it is significant to the local coastal wind variable. The model does not involve variables: C, D, E, F, G, H, I, J, and K because they are not significant to the local coastal wind data. Table 3 also shows the coefficients of B.

The Regression Equation is

$A = 4.807 - 0.002720*(r_B)* B$

As seen in Table 2, the value of (r_B) is (-1). The final regression equation becomes

$A = 4.807 - 0.002720*(-1)* B + \varepsilon_B$

$A = 4.807 + 0.002720* B + \varepsilon_B$

Accordingly, the equation of future local coastal wind data (A) only relies on wind variable (B) of climate change data and its residuals (ε_B)

3.3 Future Prediction of Wind Data

The regression obtained in step 2 is a model for generating future predictions of coastal wind data. The random variable addition to the regression results will accomplish the predictive data. The random variables are the same type of random variable as the random variable in the climate change variables. Figure 4 and Figure 5 show the results of Ampenan coastal wind predictions.

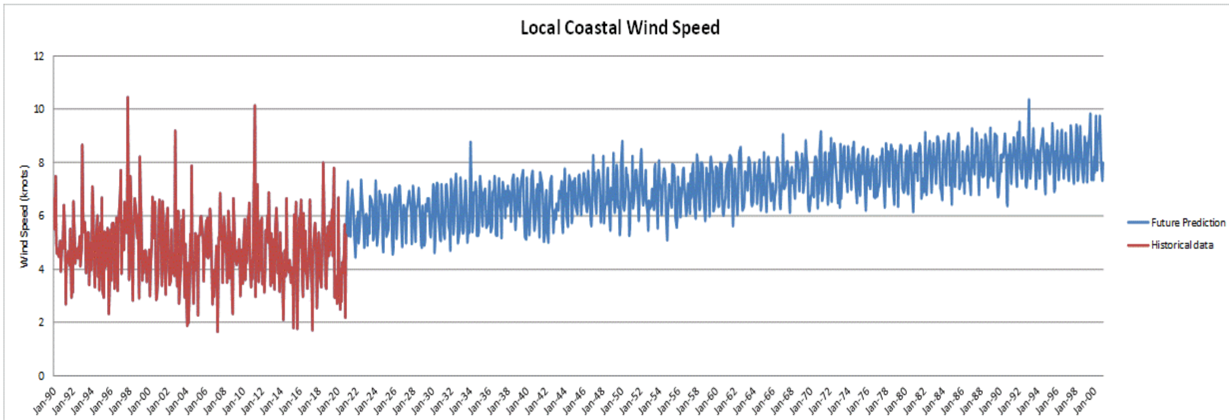

Figure 4. The Ampenan Coastal Wind Prediction

Figure 4 shows the connection graph of historical wind data and future predictions from the simulation. There is a trend of increasing wind speed in the future; however, there is a significant difference in variance. Combining the characteristics and type of random variables of climate change variables might cause variance difference.

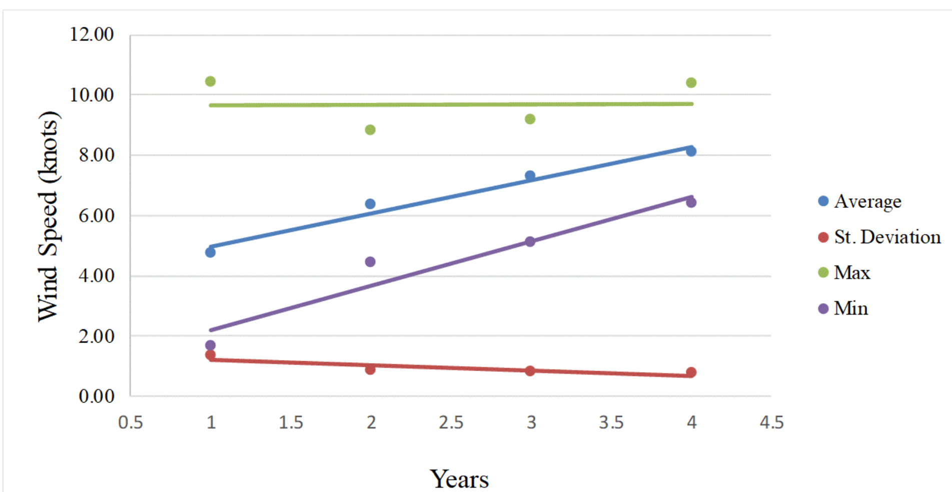

Figure 5. The Statistical Summary of Ampenan Coastal Wind Prediction

Figure 5 shows four statistical descriptions of the simulation results. There is a trend of increase in average and minimum values of wind speed. However, the maximum values of wind speed remain the same until 2100, and the standard deviation even decreasing.

By knowing that the wind speed in the future tends to increase, based on Equation 2, Equation 3, and Equation 1, it is understandable that predicted wave frequency and predicted wave energy increase in the future. Therefore, engineers need the effort of wave energy reductions to reduce coastal disaster risks.

4. CONCLUSION

The causative identification of marine and coastal disasters is essential. This identification is to ensure the success of coastal disaster risk reduction. The wind is a natural variable that can be very influential in marine and coastal disasters. This paper proposes a technique to identify the relationship between climate change variables and local coastal winds and to develop climate change-based wind prediction models useful for marine and coastal disaster reduction studies.

From the case studies, the results show

a. There is an increasing trend in the average and the minimum wind speed,

b. The increase in average is about 3 knots from 1990 to 2100

c. The maximum wind speed remains the same until 2100,

d. There is a decrease in the standard deviation of wind speed.

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