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Influence of wind speed on canopy Normalized Difference Vegetation Index (NDVI) measurements for forest ecosystem

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Abstract: Wind speed can affect the observation of canopy vegetation index. When the wind blows, plants will swing, and the spatial structure of the canopy will change. This change may affect the vegetation index measurements. Normalized Difference Vegetation Index (NDVI) from satellite remote sensing was chosen as the index to explore the influence of wind on canopy measurements for forest ecosystems. Our results show that wind speed has a positive influence on the measurements of NDVI on the whole. While for four main forest types: Deciduous Broadleaf Forests (DBF), Evergreen Broadleaf Forests (EBF), Evergreen Needleleaf Forests (ENF), Mixed Forests (MF), the performances are different, the corresponding value is 0.002, -0.004, 0.003, 0.001 when the wind speed increases by 1m. This effect has a negative to positive trend with the increase of latitude. This study provides a reference for the effect of wind speed on vegetation canopy structure measurements.

Keywords: Wind Speed, NDVI, Forest Ecosystem, Forest Types, MODIS

1. Introduction

The forest ecosystem is a huge carbon pool. As a key indicator that reflects the structure and function of the ecosystem (Litton, Raich, and Ryan 2007), the estimation of productivity got lots of attention (Shao et al. 2018; Soukhovolsky and Ivanova 2013; Skovsgaard and Vanclay 2013). Like the simplicity of canopy spectral reflectance, the vegetation index as a convenient quantitative representation is suitable for quantifying canopy structure and estimating productivity. On the other hand, the remote sensing model method is one of the most effective and accurate ways to estimate productivity, which is more suitable for large-scale investigation (Hilker et al. 2008). Light use efficiency (LUE) model (Lin et al. 2017), Carnegie-Ames-Stanford Approach (CASA) model (Yan, Wu, and Wen 2021), and vegetation index (Dedeoglu et al. 2020) are several main remote sensing methods. For these models, the vegetation index is pivotal input data, which can reflect eco-physiological processes of plants, estimate canopy structure and primary productivity. The Normalized Difference Vegetation Index (NDVI) is the most popular vegetation index, since the era of multispectral remote sensing (Huang et al. 2021). (Noda, Muraoka, and Nasahara 2021). These show that NDVI is becoming more and more important, and it is necessary for its accurate measurement.

Measuring NDVI accurately is a challenge. The measurements of NDVI are impressed by many external factors, like cloud cover(Leblon, Guerif, and La Rocque 2001; de Souza, Scharf, and Sudduth 2010), sun angle (de Souza, Scharf, and Sudduth 2010; Guan and Nutter 2001), sensor angle (Glick et al. 1982), canopy structure induced by wind (Leblon, Guerif, and La Rocque 2001; Rao, Brach, and Mack 1979). Those studies found that cloud cover and sun angle increased the coefficient of variation of the statistical results by about 30% to 50% (de Souza, Scharf, and Sudduth 2010); and the influence of cloud cover is hard to quantify (Leblon, Guerif, and La Rocque 2001). As the increase of sun angle, the incident radiation increase, while the percentage reflectance values decreased between 0.20 and 0.32% for each 100 watts m^{-2} (Guan and Nutter 2001). For vertical and oblique measurement angles of the sensor, the vertical angle is better (Glick et al. 1982). Most vegetation canopies are non-Lambertian reflectors, so view angle can influence spectral response (Wright 1986; Lunagaria and Patel 2017). The change of view angle can be the changes of sun angle, sensor angle, and canopy structure induced by wind.

Wind speed is an important factor in canopy NDVI measurement. The research of the influence of wind on vegetation spectrum measurements is mainly concentrated at the end of the last century. The earliest studies that can be retrieved are experiments for crops on the ground (Rao, Brach, and Mack 1979). It was found that radiance was more sensitive in the 450 to 650 nm to wind speed than in the 650 to 750 nm range. Due to the influence of the instrument at that time, the wavelength region of the field spectroradiometer was in the visible light region (350nm-750nm). As a result, the research on the near-infrared region is almost blank. In the later related research with the wavelength region of red light and near-infrared band, the near-infrared band is more sensitive (Lord, Desjardins, and Dube 1985). Both types of research found that wind had a negligible effect on the reflectance of the low crop (clipped). Later, more in-depth research found that wind was positively correlated to the variability of rice crop's reflectance ($r= 0.245$, $p>0.001$) in near-infrared, but not in red wavelengths (Leblon, Guerif, and La Rocque 2001). In the past related research, there are some characteristics: previous studies focused on crops, whose canopy reflectance is convenient to measure; these studies mainly small-scale in-situ measurement, lack of large-scale verification; the single band was used for correlation analysis with wind speed in data analysis, rather than vegetation index.

Therefore, we have several scientific problems want to explore: different from the previous research on the influence of wind speed on canopy reflectance from the ground measurement angle, what will happen from the angle of satellite? Compared with crops, how might tall forests behave? And as one of the most common vegetation indexes, how much Influence of wind speed on canopy NDVI measurements? Four main forest types all over the world were selected for this study. The major objective of this study was to discuss whether the change of wind will affect the estimation of NDVI from the angle of satellite, and if so, how much influence it will have and whether the impact on different forest types is different.

2. Materials and methods

2.1 Materials

2.1.1 Data sources

To ensure that the selected points have a stable underlying surface, the flux stations were selected in this study. Wind speed data over the canopy were extracted from flux data. FLUXNET2015 Dataset (fluxnet.org/, including more than 900 sites worldwide) and ChinaFLUX (chinaflux.org/, including more than 70 sites countrywide) are two observation flux networks. The min temporal resolution of flux data is 30 minutes. Among the sites covering different vegetation types, 62 forest sites were selected, including 4 forest types, Deciduous Broadleaf Forests, Evergreen Broadleaf Forests, Evergreen Needleleaf Forests, Mixed Forests. These 62 sites have different spatial scopes and time spans of flux data (Table 1).

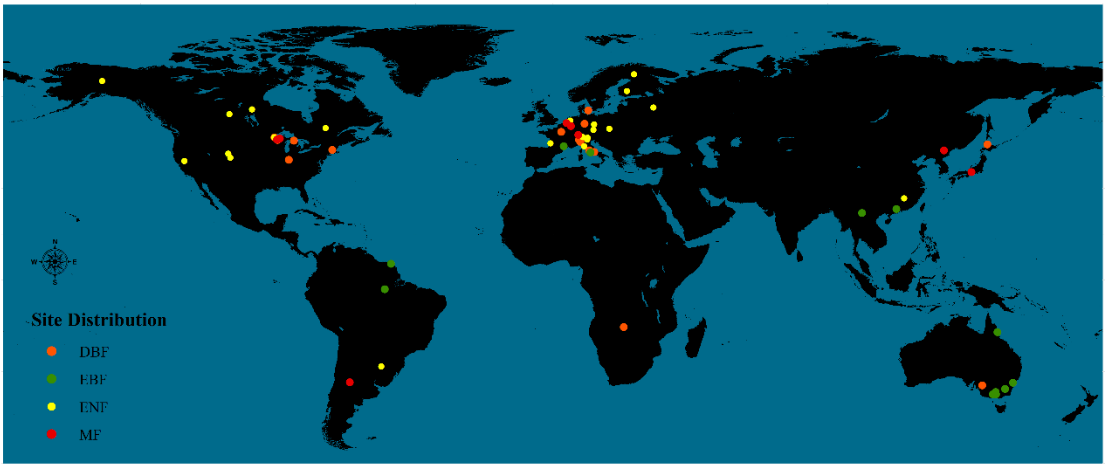

Figure 1. Sites distribution of our study. Including 19 Deciduous Broadleaf Forests (DBF), 13 Evergreen Broadleaf Forests (EBF), 22 Evergreen Needleleaf Forests (ENF), 8 Mixed Forests (MF).

NDVI data were obtained from Terra Moderate Resolution Imaging Spectroradiometer (MODIS). The MOD09GQ Version 6 (lpdaac.usgs.gov/products/mod09gqv006/) is one of the dozens of remote sensing data sets of MODIS, including 8 layers, Surface Reflectance Band 1, Surface Reflectance Band 2, etc. The temporal resolution is daily, and the pixel size is 250 m. Site data were extracted through Google Earth Engine (code.earthengine.google.com). Taking the pixel where the site is located as the center, the mean value of the central pixel and the surrounding 8 pixels is considered as the value of the site.

2.1.2 Data preprocessing

The transit time of the satellite is instantaneous, and the time must be included a certain half an hour. The average wind speed of this half an hour was found from the flux data without other processing. And there is a hypothesis that the wind speed with the temporal resolution of 30 minutes can match remote sensing data, whose acquisition is instantaneous. The corresponding NDVI data of these sites were gained by MOD09GQ and calculated by:

$$\mathrm{NDVI} = \frac{NIR - R}{NIR + R} \tag{1}$$

where NIR is the reflectivity in the near-infrared band, R is the reflectivity in the red band.

The choice of NDVI is based on three principles: the maximum time scope is two weeks to weaken the effects of natural growth; the fluctuation of NDVI is less than 0.1 to reduce the impact of cloud; the part with NDVI lower than 0.25 was discarded with the reason that few leaves in the canopy. Finally, 558 sets of data were screened out from 62 sites, including 192 Deciduous Broadleaf Forests (DBF), 98 Evergreen Broadleaf Forests (EBF), 177 Evergreen Needleleaf Forests (ENF), 91 Mixed Forests (MF). Each set of data contains a different amount of data.

One thing to note is that the time zone convention between flux data (local standard time) and remote sensing data (universal time) need to be converted according to the station location and satellite transit time.

2.2 Methods

NDVI and wind speed were used to establish a univariate linear regression model with intercept terms. The coefficient of determination (R^2), P-value, and slope of linear regression was got and counted. By assessing R^2 and P-value, comparing the slope, study the influence of wind on NDVI. When R^2 is larger, it indicates that NDVI measurements are more likely to be affected by wind. When the absolute value of S is larger, it indicates that NDVI measurements are more affected by wind.

3 Results

3.1 Distribution range of wind speed and NDVI of four forest types

The distribution range of wind speed and NDVI of four forest types was shown in Fig 2. The wind speed is mainly concentrated at 0-7.5 m/s. The wind speed distribution of each forest type is close to the pyramid. While for EBF, the difference is that when the wind speed is 0 m/s, the frequency is not close to 0. Compared with wind speed, the distribution of NDVI is more complex. There are many peaks in the frequency curve of NDVI. For DBF, EBF, MF, there is only one highest peak. And the corresponding NDVI of EBF's peak is smaller than the other two. The curve of ENF is M-shaped. The sites we chose are all over the world, even for the same forest type, the NDVI of the growing season is different.

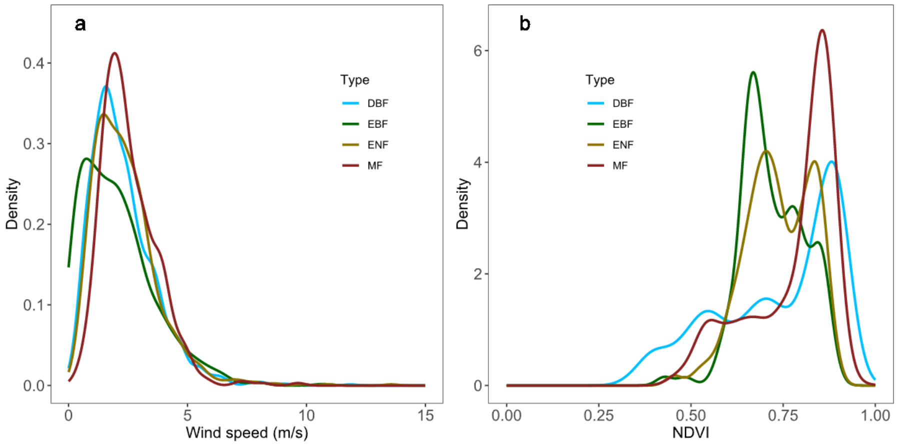

Figure 2. The probability density curve of wind speed (a) and NDVI (b) of four forest types, can represent their distribution.

3.2 The correlation between wind speed and NDVI

Scatter diagrams of three sets of data were shown in Figure 3. The performance of each group of data is different. The results of each group are counted and considered to be the response of NDVI corresponding to forest type to wind speed.

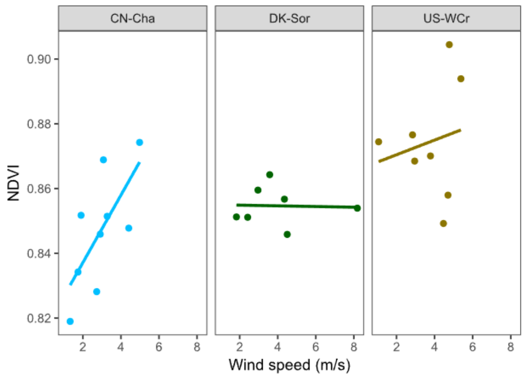

Figure 3. Three of the 558 sets of data were selected as examples to show the relationship between wind speed and NDVI. CN-Cha, DK-Sor, US-WCr represent the site ID of the three sites. The corresponding slopes are 0.0023, -0.0001, 0.0100, respectively.

558 sets of data were fitted to estimate the correlation between wind speed and NDVI, $R^{2,}$ and P-value. 10.0% of the data is in the condition (R^2>0.5, P value<0.05).

The slope of regression shows a single peak distribution (Figure 4), and the slope corresponding to the highest frequency is slightly larger than 0. 92.4% of the slope is in the range of -0.05 to 0.05. There are 306 positive values in all 558 slope values. And the mean value is 0.001. For the data with a large R^2 (Figure 4, Part A) or significant correlation (Figure 4, Part B), the mean value of the slope is larger.

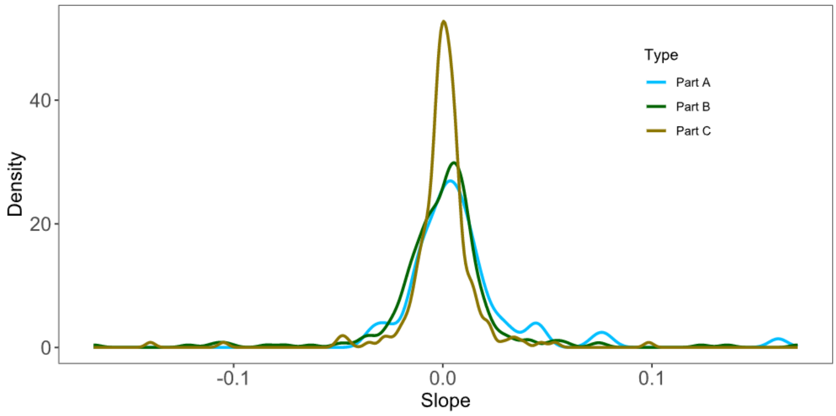

Figure 4. The probability density curve of the slope of the linear regression between winds speed and NDVI. Part A, B, and C represent the data under specific conditions (R^2>0.25; R^2>0.25 and P value<0.05; all data), respectively.

3.3 The correlation between wind speed and NDVI for different forest types

The slope of linear regression of different forest types shows a slightly different (Figure 5). The difference mainly lies in the peak position of the density curve. For EBF and MF, the peaks are on the negative half axis of Slope; and it is opposite for DBF and MF. The mean values are 0.002, -0.004, 0.003 and 0.001, respectively.

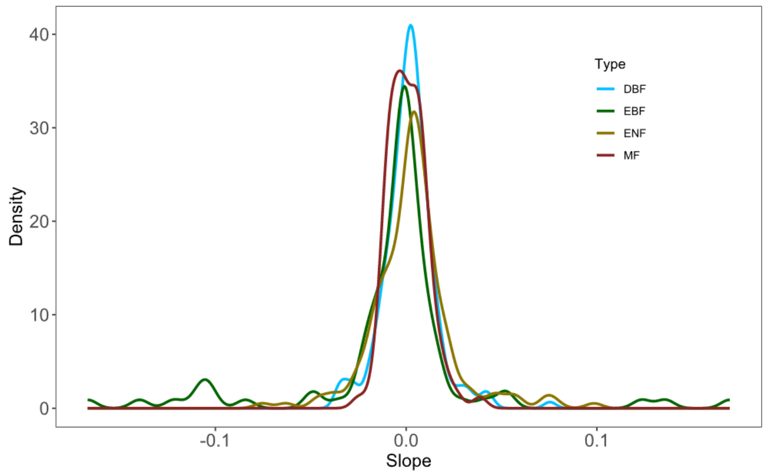

Figure 5. The distribution slope of the linear regression between winds speed and NDVI of different forest types.

4 Discussion

We used satellite data to study the impact of wind speed on forest canopy NDVI measurements. Due to the influence of the atmosphere and solar angle, especially the spatial resolution of the image, the results of satellite remote sensing are usually worse than near-earth remote sensing. This means that it is difficult for us to get a better result than Guan, J. et al (Guan and Nutter 2001), who carry out their research on the ground. But this study is still an interesting attempt with more and more remote sensing products being used widely.

The results show that wind speed has a certain influence on the measurements of NDVI from the perspective of satellites. About 10% of the data have a statistically significant correlation. Even for different forest types, the results are similar. In the early ground study of Leblon et al. (Leblon, Guerif, and La Rocque 2001), the wind speed was positively correlated to the crop's reflectance in near-infrared, which is consistent with our findings.

We try to quantify the impact of wind speed on NDVI estimation, and the results of linear regression analysis show that it can be referred to for future research. This may have some meaningful reference value. For all four forest types, the result shows that the influence of wind on the measurements of NDVI tends to increase. The mean value of regression slope is 0.001, this shows that the influence of wind speed is mainly concentrated near 0.001. in other words, usually the increase in NDVI is 0.001, for every 1m/s increase in wind speed. For different forest types, the performance showed obvious differences. Mainly for EBF, the increase of wind speed reduces the NDVI measurements, whose corresponding value is -0.004, not positive. Considering only the three forest types (ENF, DBF, EBF) whose distribution varies with latitude gradient, it can be found the positive effect of wind on forest canopy NDVI measurements decreases with the increase of latitude. We speculate that there may be two reasons for this difference, one is a difference in solar angles: low latitude has a higher solar angle. The other is the difference of Index reflecting canopy physiological and biochemical parameters: for example, leaf area index is greater than other forest types (Liu and Jin 2016; Munier et al. 2018).

There are some limits to the research. One of the limits is that the time of wind and NDVI is not a perfect match. Satellite transit is often instantaneous; while for global multi-sites meteorological data, the highest time resolution is 30 minutes. Tree height is another limitation. For the same tree species in different regions, the tree height may also be different. At different tree heights, the response of NDVI to wind speed may also be different.

5 Conclusions

To study the influence of wind speed on NDVI measurements, 558 sets of data were extracted from flux data and MODIS. Our results show that wind has a positive influence on the measurements of NDVI on the whole. When the wind speed increases by 1m/s, the corresponding NDVI increases by 0.001 for all forest types. While for four main forest type: DBF, EBF, ENF, MF, the performances are different, the corresponding value is 0.002, -0.004, 0.003, 0.001. This effect has a negative to positive trend with the increase of latitude. This may be the influence of the solar altitude angle and canopy physiological and biochemical parameters. Those results suggest there is a possibility that the large area outliers of NDVI in forest areas are caused by wind speed, which is worth considering in related studies of NDVI. In general, this is an interesting and meaningful study. This research direction is worthy of further follow-up.

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