



Approaches for predicting wind turbine hub-height turbulence metrics

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Abstract. Hub-height turbulence is essential for a variety of wind energy applications, ranging from wind plant siting to wind turbine control strategies. Because deploying hub-height meteorological towers can be a challenge, alternative ways to estimate hub-height turbulence are desired. In this paper, we assess to what degree hub-height turbulence can be estimated via other hub-height variables or ground-level atmospheric measurements in complex terrain, using observations from three

- 5 meteorological towers at the Perdigão and WFIP2 field campaigns. We find a large variability across the three considered towers when trying to model hub-height turbulence intensity (TI) and turbulence kinetic energy (TKE) from hub-height or near-surface measurements of either wind speed, TI, or TKE. Moreover, we find that based on the characteristics of the specific site, atmospheric stability and upwind fetch either determine a significant variability in hub-height turbulence or are not a main driver of the variability in hub-height TI and TKE. Our results highlight how hub-height turbulence is simultaneously sensitive
- 10 to numerous different factors, so that no simple and universal relationship can be determined to vertically extrapolate turbulence from near-surface measurements, or model it from other hub-height variables when considering univariate relationships. We suggest that a multivariate approach should instead be considered, possibly leveraging the capabilities of machine learning nonlinear algorithms.
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20 1 Introduction

As wind energy expands and becomes an increasingly large portion of energy portfolios, collecting data on wind speed and atmospheric conditions at turbine hub height is essential for the high performance of wind plants and their successful integration





into the electric system. Hub-height quantities of wind speed and direction, turbulence intensity (TI), turbulence kinetic energy (TKE), and atmospheric stability within the rotor disk and at turbine hub height impact turbine power generation (Wharton

and Lundquist, 2012a,b; Vanderwende and Lundquist, 2012; Murphy et al., 2020; Vahidzadeh and Markfort, 2019). Analysis of hub-height TI and TKE is instrumental in the control strategy for wake steering (Fleming et al., 2019, 2020). Turbine siting and power forecasting also rely on hub-height quantities and are determining factors of whether a wind plant will be financially advantageous (Optis and Perr-Sauer, 2019; Bodini et al., 2021).

Although useful, hub-height turbulence measurements are difficult to obtain because they require the construction and management of a 80-m or taller meteorological tower, or the installation of a lidar or sodar for an extended period of time (Brower, 2012). Ground-level measurements are more readily obtainable—because shorter meteorological towers are easier and less expensive to construct—and more can be deployed around a turbine site. To reduce dependence on hub-height meteorological towers, researchers and wind turbine developers desire a method where ground-level measurements can be used to predict hub-height quantities.

- 35 Various formulations have been proposed for estimating hub-height TI, or TI profiles, as a function of surface quantities. The Mann model (Mann, 1994, 1998) provided an analytic model for turbulence profiles in the presence of uniform linear shear. Cheung et al. (2016) proposed and tested a formulation based on assumptions for turbulent boundary layers in a range of stability conditions. Building from the power-law approach for extrapolating wind speeds from surface-level measurements to hub height, Gualtieri (2017) proposed and tested an empirically based approach for using 30-m measurements to extrapolate
- 40 to 100-m altitudes, finding that considering atmospheric stability is critical.

In this analysis we examine whether hub-height turbulence, measured in terms of either TI or TKE, can be successfully derived from other atmospheric variables measured at ground level or hub height in complex terrain. We use data from two meteorological towers at the Perdigão field campaign (Fernando et al., 2019) and one additional tower at the WFIP2 field campaign (Shaw et al., 2019), both of which provide plentiful near-surface measurements as well as hub-height or near-hub-

- 45 height measurements. In Section 2 we define the atmospheric variables considered in the analysis and summarize the important features of the two field campaigns. We also analyze how hub-height measurements vary between the considered locations, and suggest potential reasons for the observed variability. Section 3 investigates the efficacy of using ground-level measurements to predict hub-height turbulence quantities, with a focus on the variability of the results among the considered locations. We also segregate measurements by atmospheric stability condition and wind direction to assess whether these metrics are influential
- 50 factors in determining the observed variability of hub-height turbulence. Finally, we summarize our results and suggest future work in Section 4.

2 Data and methods

In our analysis, we focus on two observational data sets in complex terrain, which both offer profiles of turbulence measurements from near the surface to hub height. Parameters useful to quantify atmospheric turbulence can be calculated by leveraging





55 the sonic anemometer high-frequency measurements at the sites. We calculate TI as

$$TI = \frac{\sigma_U}{U} \tag{1}$$

where σ_U is the variance of the horizontal wind speed, and U is the mean horizontal wind speed, both calculated over 10-minute intervals to match the current wind energy industry standard (Emeis, 2018).

The TKE quantifies the mean kinetic energy per unit mass of air in turbulent flow and is defined as

60 TKE =
$$\frac{1}{2}(\sigma_u^2 + \sigma_v^2 + \sigma_w^2)$$
 (2)

where we calculate the variances of the wind speed components over 30-minute intervals, a common choice to study atmospheric boundary layer processes (De Franceschi and Zardi, 2003; Babic et al., 2012).

To classify atmospheric stability, we calculate the Obukhov length, defined as

$$\mathbf{L} = -\frac{\overline{T_v} \cdot u_*^3}{k \cdot g \cdot \overline{w'} T_v'} \tag{3}$$

where T_v is the virtual temperature (K), u_{*}=(u'w'² + v'w'²)^{1/4} is the friction velocity (m s⁻¹), k = 0.4 is the von Kármán constant, g = 9.8 is the acceleration due to gravity (m s⁻²), and w'T'_v is the kinematic buoyancy flux (K m s⁻¹). As for TKE, we use a 30-minute average period to apply the Reynolds decomposition. To simplify the atmospheric stability classification, we consider stable conditions for z/L > 0 m, and unstable conditions for z/L < 0 m. Other analyses of the stability conditions at these campaigns find few times with neutral stratification given the strong diurnal forcing (Menke et al., 2018; Bodini et al., 2019).

2.1 The Perdigão field campaign

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The Perdigão field campaign was designed to observe the microscale flow across a valley between two nearly parallel ridges in central Portugal (Fernando et al., 2019). A multinational group of scientists carried out a massive data collection campaign from 1 May–15 June 2017. The site is largely covered in trees, which increases the surface roughness. The areas outside the ridges and valley are largely farmland and eucalyptus groves. Instrumentation at the site includes meteorological towers, scanning

- and profiling lidars, sodars, radiosonde devices, and a host of other instruments. In our analysis, we consider observations from two 100-m meteorological towers: TSE04, located on the southwest ridge, and TSE09, located on the valley floor, as shown in the map in Figure 1. At each tower, we use data collected by sonic anemometers at 10 m above ground level and 80 m above ground level. The third 100-m tower at Perdigão was excluded from this analysis because of a data outage for a
- significant portion of the campaign at the 10-m sonic anemometer. We also discard from the analysis time periods where the sonic anemometer observations are affected by the tower wake, which artificially enhance measured turbulence. To do so, we eliminate observations when the wind direction is $\pm 30^{\circ}$ from the direction opposite to the tower boom (285–345° for TSE04, $305-5^{\circ}$ for TSE09).

Because of the effect of the terrain, different wind regimes characterize the two towers considered here, as seen in the roses in Figure 2. Located on the SW ridge, TSE04 mostly experiences wind from the NE and SW quadrants, with the wind flowing







Figure 1. Map showing the location of the two 100-m meteorological towers at Perdigão that we considered in the analysis.

perpendicular to the ridge. On the other hand, at TSE09, located on the valley floor, wind blows primarily from the NW and SE directions, parallel to the valley axis. Also, TSE09 experiences lower wind speeds than TSE04 because it is sheltered by the ridges. At TSE04, the majority of the wind from the SW is associated with unstable conditions, whereas NE winds bring predominantly stable conditions. At TSE09, stability does not drive wind direction: both up-valley and down-valley flows occur in both stable and unstable conditions. As for atmospheric turbulence, we see that the sheltered valley TSE09 experiences stronger turbulence compared to TSE04, displaying more instances of both high TI and TKE values.

2.2 The WFIP2 field campaign

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The Second Wind Forecast Improvement Project (WFIP2) took place in the United States Pacific Northwest region between October 2015 and March 2017. Shaw et al. (2019) provide a general overview of the project, while Wilczak et al. (2019) describe the measurement campaign and Olson et al. (2019) summarize modeling advancements afforded by this campaign. Like the Perdigão campaign, the aim of the WFIP2 campaign was to better understand wind speed variability through complex ter-

rain to improve numerical weather prediction models. Instrumentation was arranged in a series of nested arrays that range from the mesoscale, so that current numerical weather prediction models could be validated, to the microscale, with meteorological towers and remote sensing instruments deployed amid wind plants along the Columbia River Gorge (Wilczak et al., 2019).
The wind plant shown in Figure 3 is located in very hilly terrain, with turbines arranged on the slope or on top of hills. High

wind speeds are generated through the Columbia River Gorge by multiple influences, notably a pressure differential between the cool damp air at the coast, and the warmer drier air to the east of the Cascade Mountains (Sharp and Mass, 2004).

In our analysis, we consider sonic anemometer measurements collected at the so-called Physics Site, the most densely instrumented location at WFIP2 (Figure 3). The data span from 16 July 2016 to 17 March 2017. We use data from a sonic anemometer at 80 m above ground level on tower P12 to quantify hub-height wind speed and turbulence. We also use measurements collected from 10-m sonic anemometers at towers P04, P05, and P10, just a few kilometers west of P12. The median value of the measurements from the three 10-m sonics was used to characterize near-ground level quantities for this analysis.







Figure 2. Roses of wind speed, atmospheric stability (expressed in terms of z/L), TI, and TKE at Perdigão, using data from the 80-m sonic anemometers. The left column shows values from the TSE04 ridge tower, and the right column shows the TSE09 valley tower. The gray shaded regions show the wind direction sectors excluded because of tower wake effects.







Figure 3. Map of the WFIP2 Physics Site, with the locations of the four meteorological towers considered in our study highlighted.

At P12, we discard all observations when wind direction is between 45° and 210° , to filter out for wake effects caused by either the meteorological tower itself or the nearby wind turbines. No such corrections were needed for the 10-m towers, which are not in close proximity to wind turbines, and whose sonic anemometers were mounted directly on top of the towers, 110 therefore not affected by tower wakes. Roses showing wind speed, stability, TI, and TKE as a function of wind direction at WFIP2 are shown in Figure A1 in Appendix A.

2.3 Analysis of hub-height quantities

Hub-height TI and TKE are directly calculated using wind speed components, so the first relationship we consider is how they 115 vary as a function of hub-height wind speed itself. We first analyze the wind speed distributions at each tower (Figure 4), where Weibull distributions have been fitted to each case. TSE09 has the the lowest average wind speed given its location in the valley, whereas wind speed at the WFIP2 tower has a much wider distribution, with high wind speed occurring more frequently than at Perdigão.

- Hub-height wind speeds influence hub-height TI and TKE. Figures 5 and 6 show how hub-height TI and TKE vary as a 120 function of hub-height wind speed at the three considered towers. Because of the large number of raw data points involved, in this and many of the subsequent plots in this paper we adopt a binning approach. In each plot, we bin individual measurements based on the magnitude of the x-axis quantity, so that there are an equal number of raw data points represented by each point shown in the plots. The x and y coordinates of each point shown in the plots are calculated as the median of all the raw data points in each bin. A total of 100 points is shown for each relationship. Furthermore, we use a polynomial regression to
- determine the line of best fit for each set of points. When looking at such a general relationship between binned data, a defined 125 relationship between hub-height wind speed and TI emerge, but still with a large variability among different sites. In general, hub-height TI displays an inverse relationship with speed—higher wind speed values display lower values of TI—as has been







Figure 4. 80-m wind speed distributions with Weibull best-fit parameters for the Perdigão and WFIP2 towers.

seen at other locations (Emeis, 2018). At TSE04, this relationship levels out at wind speeds higher than about 7 m s⁻¹. On the other hand, the relationship at TSE09 is closer to being linear, likely because high wind speed rarely occurs at this location. On the other hand, the WFIP2 data show a remarkable agreement with the TSE04 tower. Also, the WFIP2 data set contains more measurements at high wind speeds, where the TI values asymptote as wind speed increases.

On the other hand, hub-height TKE and hub-height wind speed have a direct relationship at all towers (Figure 6), again with a large variability among the three locations. TSE09 generally displays higher values of TKE compared to TSE04, which is consistent with the TKE roses in Figure 2. WFIP2 has lower TKE values at all wind speeds, but demonstrates a highly consistent relationship.

Interestingly, hub-height TI and TKE, when compared directly, show a larger divergence in trends between the three towers (Figure 7). Both TSE04 and TSE09 have lines of best fit showing a proportional relationship between TI and TKE, as is expected from the way those parameters are calculated in Section 2. However, the WFIP2 data show a different trend, with the line of best fit trending slightly downward because of several high values of TI at low values of TKE, likely caused by the faster

horizontal winds at this location. If these points were excluded, WFIP2 would also show a proportional relationship between

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TI and TKE.

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Although first-order relationships to predict hub-height turbulence metrics, such as the ones shown in Figures 5 and 6, might seem simple and well-defined (at least when considering binned data), a host of atmospheric and topographic variables have a strong influence on both TI and TKE. In fact, atmospheric turbulence is affected by a variety of conditions, including the

stability condition of the atmosphere, the wind direction, and the interaction between the wind flow and upwind terrain. As all







Figure 5. Hub-height TI as a function of hub-height wind speed at the Perdigão and WFIP2 towers.

these factors can greatly affect TI and TKE, analyzing different conditions separately will lead to a more accurate analysis of the TI and TKE data sets. In the remainder of the analysis, we dive deeper into such multivariate variability to provide more specific results. This analysis emphasizes the challenge of using surface variables to predict hub-height quantities.

- To guide this additional analysis, we first assess the impact of atmospheric stability on the distributions of TI and TKE at hub 150 height. Histograms of TI and TKE at the TSE04, TSE09, and WFIP2 towers (Figure 8) show significant differences in TI and TKE frequency and magnitude when segregated by stability condition. The TI histograms for TSE04 and WFIP2 are skewed left, showing higher instances of lower TI values, with stable measurements tending to have lower TI values than unstable cases, consistent with the stronger turbulent mixing observed in daytime convective periods. At TSE09 in the valley, the TI distribution is more symmetric, especially in unstable conditions, while the stable case still slightly skews left. Despite this
- 155 significant difference in TI distributions between the two Perdigão towers, the TKE histograms for TSE04 and TSE09 look similar, again with stable cases showing lower TKE values than the unstable cases, as would be expected. The WFIP2 data set shows highly skewed distributions in both stability conditions, with smaller TKE values compared to Perdigão for both stable and unstable cases.

Wind direction regimes can also impact atmospheric turbulence, because the flow interacts with different roughness and
vegetation based on the upwind fetch. Figure 9 shows histograms of hub-height TI and TKE for the dominant wind direction regimes (based on the wind roses in Figure 2) at the two Perdigão towers. At TSE04, we consider northeasterly (between 34°







Figure 6. Hub-height TKE as a function of hub-height wind speed at the Perdigão and WFIP2 towers.

and 74°) and southwesterly winds (between 214° and 254°) per Menke et al. (2019). On the other hand, at the TSE09 tower in the valley, we focus on the down-valley (between 90° and 180°) and up-valley (between 270° and 360°) wind regimes. The TI histogram for TSE04 shows similar distributions for both the SW and NE wind directions, with more measurements from the NE having lower TI. At TSE09, there are fewer measurements from the NW up-valley direction, and these measurements have, on average, lower TI values. The TKE histogram for TSE04 displays similar distributions for both wind directions, again with the NE winds usually associated with slightly lower TKE values. At TSE09, the TKE range is wider, with more values between 5 and 10 m² s⁻² compared to the ridge tower. At the WFIP2 Physics Site, winds are dominantly from the west, and a significant portion of the rest of the wind direction range was discarded from the analysis to avoid contamination caused by wake effects, as shown in Figure A1. As a consequence of this reduced variability, we will not investigate the TI and TKE variability as a function of wind direction at WFIP2.

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This preliminary analysis shows how clear differences emerge when TI and TKE are segregated by stability condition and wind direction. In the following sections, we dive deeper into how these conditions affect the ability to estimate hub-height turbulent quantities from ground-level measurements.







Figure 7. Hub-height TI as a function of hub-height TKE at the Perdigão and WFIP2 towers.

175 3 Results

3.1 Predicting hub-height TI from surface-based quantities

As mentioned in the Introduction, hub-height TI is essential for a variety of wind-energy-related tasks, ranging from siting and turbine selection to wake steering and power forecasting. However, hub-height measurements can be difficult to obtain, whereas ground-level measurements are more readily available. Here we test the ability of ground-level atmospheric measurements to predict hub-height TI at the Perdigão and WFIP2 towers.

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The close relationship between hub-height TI and hub-height wind speed at the TSE04 and WFIP2 in Figure 5 points to the potential predictive power of this metric. We test whether this still holds when using ground-level wind speed instead in Figure 10. As noted, we find reduced variability between the Perdigão tower TSE04 and WFIP2, while TSE09 predicts consistently higher values of TI at 80 m due to its location in the valley. Even for TSE04 and WFIP2, which show a wide range of near-

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surface wind speeds, the resulting relationship with hub-height TI is close to a constant horizontal line for the majority of the wind speed range, therefore limiting the practical applicability of these relationships to predict hub-height TI from a specific value of near-surface wind speed.

Because ground-level wind speed cannot be used as a strong predictor of hub-height turbulence, there may be a better extrapolation performance when considering the same variable at both ground level and hub height. Figure 11 shows hub-height TI







Figure 8. TI and TKE histograms at hub height for the Perdigão and WFIP2 towers, with data segregated by atmospheric stability condition.

190 as a function of ground-level TI for the three considered towers. Each site displays a different relationship between hub-height TI and surface-based TI. The WFIP2 data appear in a tightly gathered cluster of near-surface TI data centered around 0.2, while the TSE09 near-surface TI data are more loosely grouped and centered around 0.5, and TSE04 data are spread more evenly across a wider range of near-surface TI. These differences in compactness and locations of data groupings drive differences in the best-fit lines for each case. Although useful for visualizing an overall trend for the relationship between ground-level and hub-height TI, the binning process applied in making these plots might obscure other important trends that could be used to

estimate hub-height TI more accurately, if segregating the data based on atmospheric stability or wind direction.

We start by considering the impact of atmospheric stability, which we already found to have a significant impact on the distribution of hub-height turbulence properties (histograms in Figure 8). When we segregate TI data at both hub height and near the ground by stability condition (Figure 12), new specific trends emerge. At TSE04, there is a clear separation between stable and unstable conditions, with the unstable cases predicting significantly larger values of 80-m TI for a given value of

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Figure 9. TI and TKE histograms for the Perdigão towers, with data segregated by the dominant wind direction regimes.

ground-level TI. This separation is not at all evident in TSE09, where the stable and unstable cases exist as overlapping clouds, indicating that stability is not the governing factor for TI in the Perdigão valley, producing no clear trends. At WFIP2, the unstable condition displays higher values of hub-height TI overall, but the two sets of points overlap at low values of TI, and the trend for the stable condition is downward, unlike the other lines that all trend upward. Therefore, when considering the impact of atmospheric stability, there is no common trend between the three cases, and no general relationship to vertically extrapolate TI emerges.

Next, we consider how the relationship between ground-level and hub-height TI varies when considering different wind direction regimes at Perdigão (Figure 13). In fact, these two 100-m meteorological towers at Perdigão experience different







Figure 10. Hub-height TI as a function of ground-level wind speed at the Perdigão and WFIP2 towers.

- upwind terrain and vegetation conditions, which influence atmospheric turbulence based on the direction the wind is flowing
 from. At the ridge-top TSE04 we find a clear difference when comparing cases when the wind is from the SW or the NE. Wind from the SW, which flows perpendicular to the ridge without interacting with the valley, is consistently associated with higher values of hub-height TI compared to wind measured from the NE direction, which includes the valley in the upwind fetch. On the other hand, at TSE09 there is very little distinction between the relationships associated with up-valley and down-valley flows, thus indicating that wind direction is not a primary driver of the variability of hub-height turbulence at this valley site.
 215 We quantify this variability in terms of the different terrain roughness and vegetation height, which affect the wind flow for the considered wind direction regimes (Table 1). These terrain data sets are obtained from a lidar terrain survey at 20-m resolution described in Santos et al. (2017); Costa et al. (2019). For each tower and each considered wind direction sector, we calculate the mean and standard deviation of each terrain segment within a 5-km radius sector centered on the location of the tower. We find that at TSE04, both upwind terrain roughness and vegetation height show larger values (both in terms of their means and standard deviations) when the wind is coming from the SW compared to the NE. This variability is consistent with the
- large differences seen in Figure 13, so that the wind flow at TSE04 is much more turbulent when the wind has interacted with a highly irregular terrain. On the other hand, up-valley and down-valley flow at TSE09 show similar surface roughness and vegetation height, which is consistent with the little variability seen in Figure 13. As a reminder, WFIP2 was not included in this analysis because the vast majority of the data share the same westerly wind regime.







Figure 11. Hub-height TI as a function of ground-level TI at the Perdigão and WFIP2 towers.

	TSE04—SW ridge		TSE09—Valley	
	SW flow (214–254°)	NE flow $(34-74^{\circ})$	NW flow $(270-360^\circ)$	SE flow (90–180 $^{\circ}$)
Mean roughness	0.21 m	0.16 m	0.22 m	0.21 m
Std roughness	0.11 m	0.07 m	0.10 m	0.09 m
Mean vegetation height	2.54 m	1.98 m	2.44 m	2.33 m
Std vegetation height	2.94 m	2.04m	2.53 m	2.22 m

 Table 1. Mean and standard deviation of terrain roughness and vegetation height for upwind land sectors with 5-km radius centered at the locations of the two Perdigão towers.

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Finally, we consider whether ground-level TKE might be a better predictor of hub-height TI (Figure 14). Once again, each tower displays a different relationship, with the data largely forming loose clouds rather than clear trend lines, even when considering binned data. This loose relationship demonstrates the low potential effectiveness for ground-level TKE to predict TI aloft. As was done for ground-level TI, we segregated the relationships between hub-height TI and surface-based TKE by stability condition and wind direction. We found no novel results, and included the corresponding plots in the appendix

(Figures A2 and A4).







Figure 12. Hub-height TI as a function of ground-level TI at the Perdigão and WFIP2 towers, with data segregated the stability condition (z/L) calculated at ground level.



Figure 13. Hub-height TI as a function of ground-level TI at the two Perdigão towers, when data are segregated by wind direction.







Figure 14. Hub-height TI as a function of ground-level TKE at Perdigão and WFIP2.

3.2 Predicting hub-height TKE from surface-based quantities

TKE is commonly used in atmospheric science, dispersion modeling, drone piloting, and forecasting applications, and therefore estimating hub-height TKE from ground-level measurements would be beneficial to a variety of applications. The relationship
between hub-height TKE and ground-level wind speed (Figure 15) shows a similar positive, near-linear relation as seen when considering hub-height wind speed (Figure 6). However, in Figure 15 the trend lines for each tower diverge even more, with WFIP2 predicting consistently low TKE values, and TSE09 predicting higher TKE values, but with data only available for low wind speeds. Once again, the specific characteristics of each site have a strong impact on the variability of TKE, limiting the predictive capability of ground-level wind speed.

240 We anticipate that using ground-level TKE to estimate hub-height TKE would produce the most straightforward relationship, because they are the same quantity measured at two heights. Figure 16 shows that for each tower studied, hub-height TKE has a strong near-linear relationship with ground-level TKE. However, the slope of the trend lines varies depending on the site. At TSE09 in the valley, surface-based measurements seen in Figure 16 correspond to hub-height measurements of TKE with slopes higher than a 1:1 line. On the other hand, the trends at TSE04 and WFIP2 have slopes lower than a 1:1 line, allowing

245 for little universal predictive power for this metric across the three towers.







Figure 15. Hub-height TKE as a function of ground-level wind speed at the Perdigão and WFIP2 towers.

Finally, the relationship between hub-height TKE and surface-based TI is explored in Figure 17. While the best-fit lines for the two towers at Perdigão have similar slopes, the WFIP2 tower shows a near-horizontal line. Once again, overall, using TI at ground-level to predict hub-height TKE would not produce accurate results that can be generalized across different sites.

4 Conclusion

- 250 The ability to use measurements taken at ground level of wind speed, wind direction, TI, TKE, and atmospheric stability to estimate hub-height quantities would be extremely useful in all applications where hub-height measurements are crucial, ranging from wind turbine control to power forecasting and—in a broader perspective—pollutant dispersion and drone flight forecasting. Meteorological towers that are tall enough to directly measure hub-height turbulence are both expensive and difficult to construct, especially considering the ever-increasing size of commercial wind turbines, while near-surface measurements are measurements are measurements are measurements are much more readily available. Despite this intense motivation to find accurate approaches for using ground-level measurements
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to estimate turbulence conditions at hub height, few models have been proposed to date for such application, each with their inherent uncertainty and limitations. The challenge is even larger for sites in complex terrain.

We analyzed atmospheric data at 10 m and 80 m above ground level from three meteorological towers at two sites in complex terrain: the TSE04 and TSE09 towers from the Perdigão field campaign, and a third tower from the WFIP2 field campaign.







Figure 16. Hub-height TKE as a function of ground-level TKE at Perdigão towers and WFIP2.



Figure 17. Hub-height TKE as a function of ground-level TI at Perdigão and WFIP2.





- First, we investigated the relationships between hub-height TI and TKE as a function of other hub-height quantities. Although 260 satisfactory site-specific relationships emerge when considering bin-averaged data, the raw data actually present a large scatter, which makes such relationships murkier, as seen in Figure A3. In addition, a large variability among the different sites emerges, even when comparing the TSE04 and TSE09 towers at Perdigão, which are only located a few kilometers apart. The limited skill in predicting hub-height turbulence from a single other atmospheric variable is also confirmed when considering ground-level measurements as predictors. We find large across-site variability when trying to predict hub-height TI and TKE from ground-265
- level wind speed, TI, or TKE. Also, when segregating the data by atmospheric stability, a more nuanced picture emerges. Although unstable conditions are connected to stronger turbulence at WFIP2 and the ridge-top TSE04, atmospheric stability is not a main driver of hub-height turbulence regimes when considering the TSE09 valley tower. Finally, we find that the impact of different wind direction regimes on hub-height turbulence is again highly site-specific, arising from the terrain roughness 270 and vegetation upwind.

Clearly, the results of our analysis underscore the sensitivity of hub-height turbulence to numerous different factors that simultaneously contribute to the variability of hub-height turbulence, so that no simple and universal relationships can be derived when considering a univariate approach. Given the complexity of the desired relationship, and the inherent nonlinearity of turbulent processes, machine learning could be leveraged to successfully model hub-height TI and TKE from a set of other

275 atmospheric variables. Recently, machine learning approaches have been successfully developed and applied to vertically extrapolate wind speed (Bodini and Optis, 2020b,a; Optis et al., 2021), both onshore and offshore, and to better parameterize surface fluxes (Kosovic et al., 2020). Future work could expand these recently developed approaches to predict hub-height turbulence instead, such that assessments of wake steering potential would not need to assume constant values of turbulence Bensason et al. (2021). In addition, our analysis could be replicated in more simple terrain (Takle et al., 2019) or offshore, to assess whether relationships to derive hub-height turbulence can more easily be derived in less complex topography.

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Data availability. WFIP2 observations are publicly available at https://a2e.energy.gov. Perdigão data are publicly available at https://data. eol.ucar.edu/master_lists/generated/perdigao/.

Appendix A: Additional analysis for predicting hub-height TI

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In this study, parameters from the WFIP2 field campaign were not separated by wind direction as was done with the Perdigão towers. As seen in Figure A1, the dominant wind direction is from the west. Measurements from $45-210^{\circ}$ were discarded due to wake effects from the tower or nearby wind turbines.

When segregated by stability condition, Figure 14 shows that stable conditions consistently display lower values of TI at each TKE level. Even though TKE at ground level will not likely lead to an accurate prediction of TI at hub height, the differences caused by stability further demonstrate the inability of TKE data at ground level to accurately predict TI aloft (Figure A2).







Figure A1. Roses of wind speed, atmospheric stability (expressed in terms of z/L), TI, and TKE at WFIP2, using data from the 80-m sonic anemometers.

At both TSE04 and TSE09, when segregated by wind direction, there is little distinction between the two dominant wind directions at each tower, as seen in Figure A4. For these two cases, segregating by wind direction does not improve the predictive ability of ground-level TKE.

Appendix B: Additional analysis for predicting hub-height TKE

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Hub-height TKE as a function of ground-level TKE segregated by stability condition is shown in B1. Each tower displays
widely varying trends between stable and unstable cases. At TSE09 there is little distinction, while at TSE04 and WFIP2 the fit lines of the stable and unstable cases depart dramatically. Overall, no universally valid relationship for using ground-level TKE and atmospheric stability to predict hub-height TKE is found.







Figure A2. Hub-height TI versus ground-level TKE at Perdigão and WFIP2 segregated by stability condition.

When considering the relationship between hub-height TKE and ground-level TKE when segregated by wind direction at Perdigão (Figure B2), TSE04 shows a greater distinction between wind directions than TSE09, likely because there was a greater difference in roughness and vegetation height in the SW and NE flow directions at TSE04, than between the NW and SE directions at TSE09 in the valley.

Hub-height TKE as a function of ground-level TI segregated by stability condition can be seen in Figure B3. Stable conditions consistently predict lower values of hub-height TKE; however, the trend lines vary significantly across the sites, not providing useful information regarding the relationship.

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Finally, hub-height TKE as a function of ground-level TI segregated by wind direction is shown in Figure B4, once again without revealing any clear and universal trend.









Figure A3. Raw (not-binned) data of hub height TI versus ground-level TI at TSE04 tower showing the large spread in the data as compared to the processed data seen in Figure 11.



Figure A4. Hub-height TI versus ground-level TKE at Perdigão towers segregated by wind direction.







Figure B1. Hub-height TKE versus ground-level TKE at Perdigão and WFIP2 segregated by stability condition.







Figure B2. Hub-height TKE versus ground-level TKE at Perdigão towers segregated by wind direction.







Figure B3. Hub-height TKE versus ground-level TI at Perdigão and WFIP2 segregated by stability condition.







Figure B4. Hub-height TKE versus ground-level TI at Perdigão towers segregated by wind direction.





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