Validation of uncertainty reduction by using multiple transfer locations for WRF-CFD coupling in numerical wind energy assessments

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Abstract

This paper describes a method for reducing the uncertainty associated with utilizing fully numerical models for wind resource assessment in the early stages of project development. The presented method is based on a combination of numerical weather predictions (NWP) and microscale downscaling using computational fluid dynamics (CFD) to predict the local wind resource. Numerical modelling is (at least) two orders of magnitude less expensive and time consuming compared to conventional measurements. As a consequence, using numerical methods could enable a wind project developer to evaluate a larger number of potential sites before making an investment. This would likely increase the chances of finding the best available projects.

A technique is described, multiple transfer location analysis (MTLA), where several different locations for performing the data transfer between the NWP and the CFD model are evaluated. Independent CFD analyses are conducted for each evaluated data transfer location. As a result, MTLA will generate multiple independent observations of the data transfer between the NWP and the CFD model. This results in a reduced uncertainty in the data transfer, but more importantly MTLA will identify locations where the result of the data transfer deviates from the neighbouring locations. This will enable further investigation of the outliers, and give the analyst a possibility to corrected erroneous predictions. The second part is found to reduce the number and magnitude of large deviations in the numerical predictions relative to the reference measurements.

The Modern Energy Wind Assessment Model (ME-WAM) with and without MTLA is validated against field measurements. The validation sample for ME-WAM without MTLA consist of 35 observations, and gives a mean bias of -0.10m/s and a standard deviation of 0.44m/s. ME-WAM with MTLA is validated against a sample of 45 observations, and the mean bias is found to be +0.05m/s with a standard deviation of 0.26m/s. After adjusting for the composition of the two samples with regards to the number of sites in complex terrain, the reduction in variability achieved by MTLA is quantified to 11% of the standard deviation for non-complex sites and 35% for complex sites.

Introduction

In the early stages of wind project development, it is common to consider a large number of potential sites. The majority of these potential sites typically do not contain an on-site measurement of climatic conditions. As on-site measurements are both expensive and time consuming, there is a practical limit to the number of sites that a developer can investigate using conventional methods. As a consequence, the number of potential sites considered is reduced at an early stage. This step may reduce the number of sites considered by an order of magnitude (e.g. from approximately 100 down to 10) to achieve a manageable portfolio for further analysis. As these decisions are often taken with limited data available, there is a risk of discarding some of the best projects in the process.

A remedy to mitigate the risk of advancing an incorrect subset of sites for further analysis is to use high quality numerical methods. As numerical methods are potentially (at least) two orders of magnitude less time consuming and expensive compared to conventional on-site measurements used for early project selection, such as SODAR or LIDAR measurements, it allows developers to evaluate a much larger set of projects. As an example, the numerical method presented in the work can be used to investigate on the order of 100 projects spread out over an area the size of Sweden in a timeframe of 10 weeks for the cost of a single measurement campaign. However, a crucial aspect for the feasibility of such methods is the resulting uncertainty in the wind resource estimate. If the uncertainty is too high, compared to the real difference in wind resource between the investigated projects, the developer may reach the wrong conclusions.

As a result of this large potential, the field of numerical wind resource assessment is a mature research topic and there are a multitude of different approaches investigated. The most relevant work in relation to this paper is the methods based on NWP using the Wind Research and Forecast model (WRF) (Skamarock et al. 2008). WRF can be used to produce sufficiently accurate local wind speed estimates for early stage wind resource assessments in flat terrain and for offshore applications (Draxl et al. 2015, Hahmann et al. 2015, Mylonas-Dirdiris et al. 2016, Ohsawa et al. 2016, Standen et al. 2017). However, it has also been observed that the prediction error and uncertainty in local wind speed estimates using WRF is correlated with increasing terrain complexity (Flores-Maradiaga et al. 2019, Giannaros et al. 2017, Prósper et al. 2019). To increase the accuracy in moderate and complex terrain, higher resolution models are desirable to resolve the microscale effects. With respects to conducting wind energy assessments in the early stage of project development, the increased resolution also improves the ability to quantify the spatial extent of the areas with favorable wind conditions, i.e. the size of the potential wind farm, as well as allows the developer to better identify suitable terrain formations and other areas with a relatively small characteristic length scales. Mortensen et al. (2017) discuss a combination of WRF and WAsP (WAsP, 1986) to include the effect of microscale terrain. Standen et al. (2017) describe a linearized microscale correction in their virtual met-mast approach. The microscale effects have also been modelled by coupling WRF with a large variety of non-linear CFD models (eg. Gopalan et al. 2014, Haupt et al. 2019, Quon et al. 2019).

The work presented here is based on the Modern Energy Wind Assessment Model (ME-WAM), which is combination of WRF and a non-linear CFD model. The coupling to WRF is achieved through a virtual met-mast, in which roughness and terrain corrected long term normalized time series from WRF is imported. The ME-WAM model was originally presented at the Wind Europe conference (Keck et al. 2019). In this paper we describe a method for reducing the uncertainty associated with utilizing an NWP-CFD coupled via an internal forcing point for wind resource assessments. We have developed a technique, multiple transfer location analysis (MTLA), where several different locations for performing the data transfer between the NWP and the CFD model are evaluated. Independent CFD analyses are conducted for each evaluated data transfer location. As a result, MTLA will generate multiple independent observations of the data transfer between the NWP and the CFD model. This yields a reduced overall uncertainty, as well as a reduction in the number of large outliers in the distribution.

Description of the ME-WAM model

The Modern Energy Wind Assessment Model (ME-WAM) is a numerical model for assessing the feasibility of early stage wind projects in absence of on-site wind measurements. The method is based on a combination of NWP in WRF, and a steady-state non-linear CFD simulation to capture the microscale terrain. This allows for a fast and computationally effective method which retains the ability to capture mesoscale effects from WRF, as well as the capability to model local terrain, roughness and forest effects at high resolution, see figure 1.

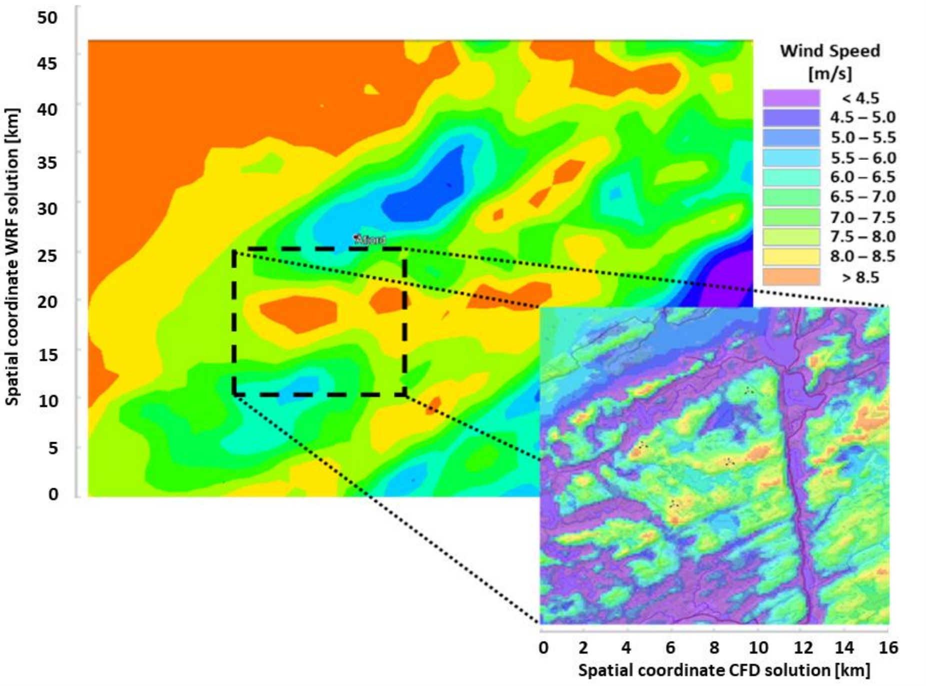

Figure 1, illustration the ME-WAM method. The background contour is extracted mean wind speed from the WRF model. The black dashed box indicates the location where a microscale CFD analysis is conducted to add resolution in the results. By comparing the two velocity fields, which has the same color setting, it is clear that the microscale effects are important to assess the local wind speed and to be able to design a wind farm in the investigated area.

The coupling between WRF and the CFD solver is achieved through a virtual met-mast approach. The WRF data is corrected based on regional roughness and terrain, as well as long term normalized against the ERA5 reanalysis dataset (Copernicus Climate Change Service, 2017). The corrected time series is inserted into the CFD domain. This has the benefit of delivering a stable and straightforward coupling between the models. In the CFD model this is the same process as using a measured time series. A drawback, however, is that the virtual met-mast approach is sensitivity to the location of the data transfer. It is crucial to find an appropriate location where the wind regime is sufficiently similar in the WRF and the CFD simulation to achieve good results.

Figure 2 displays an overview of the ME-WAM modelling process. The method only requires project coordinates as input, and utilize open data sources from WRF and other available GIS data to simulate the mesoscale wind regime. Modern Energy has developed a technique to optimize the data transfer location based on surrounding terrain, slopes, roughness and expected mesoscale effects. We also apply a long-term normalization of the extracted WRF data. These steps occur in the “ME-WAM CORE” step. In the last step of the process, the information from the virtual met-mast is applied in a CFD simulation to generate wind resource files, as well as turbulence and wind shear maps.

In the following sections the WRF and CFD model configurations used in our validation is briefly described. The algorithms for optimizing the data transfer location, as well as the corrections applied, and long-term normalization will not be described in further detail as they are proprietary information.

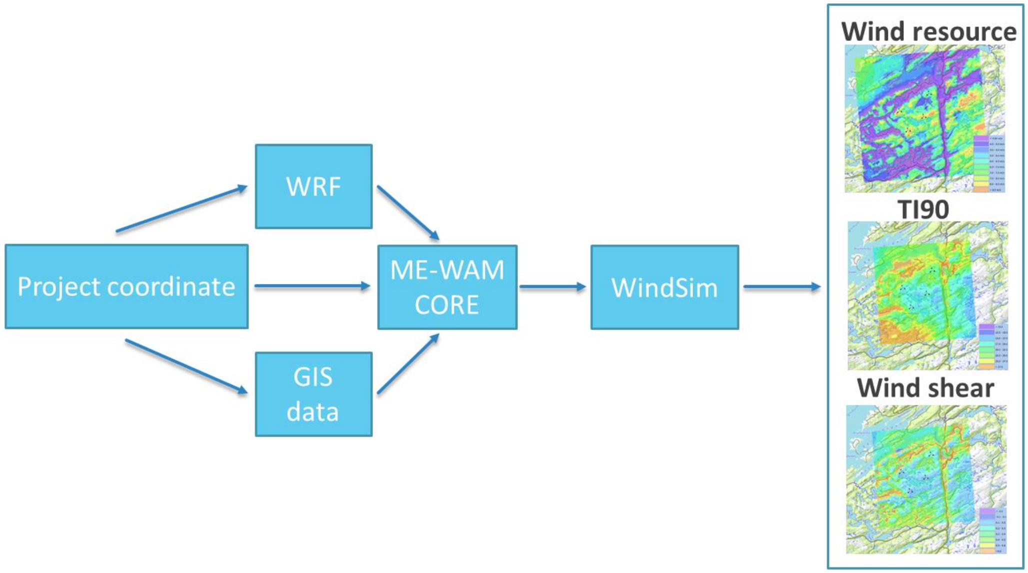

Figure 2, schematic description of the ME-WAM model process

The WRF model

The large-scale wind regime at the simulated sites is predicted using numerical weather simulations conducted in the advanced research version of the Weather Research and Forecasting model (WRF-ARW) (Skamarock et al. 2008). The WRF model is an open-source state-of-the-art weather model which is widely used in both industry and the research environment.

It is a comprehensive model which includes all relevant processes of heat, mass and momentum transfer, and thereby has the fidelity to be used for simulating a wide range of weather phenomena from large synoptic scales down to meso- and even microscale.

The WRF-ARW model is based on the compressible nonhydrostatic Euler equations formulated using a terrain following pressure level as vertical coordinate. The model contains a large number of methods for parametrizations to handle e.g. land-surface properties, surface layer which govern near surface turbulence fluxes, vertical transfer in planetary boundary layer (PBL), short and long wave radiation budget, microphysics and cumulus formation. The appropriate selection of these schemes is dependent on both the numerical setup of the model (most noticeably the spatial resolution of the computational grid), as well as the most important physics for the investigated sites. Care must be taken when selecting the combinations of parametrizations as they interact with each other.

In this work the WRF configuration has been customized to the various sites based on internal best-practice for the different locations and topographies investigated. The details of each case are not considered to be relevant for the research described here. There are some common configurations for all cases. The WRF simulations are conducted with two-way nesting approach on three domains. The horizontal resolution of these domains has been 13.5, 4.5 and 1.5km. The vertical mesh contains 42 vertical levels, with fine meshing near the surface and vertical stretching in higher levels. In Europe the GMTED dataset with 500m resolution as terrain representation and Corine with 100m spatial resolution as the input roughness. The ERA5 reanalysis dataset (Copernicus Climate Change Service, 2017) is used as initial and boundary conditions. The parametrizations vary based on regional verifications, but in general the more advanced options for surface-layer, PBL and micro-physics are applied.

CFD downscaling with WindSim

The microscale effects are incorporated by performing CFD downscaling of the mesoscale wind regime using the commercial CFD software package WindSim (from Vector AS), see figure 1. WindSim is based on the Phoenics solver and solves the three-dimensional incompressible RANS (Reynolds Averaged Navier-Stokes) equations. The equations are solved on a cartesian grid, and multiple grid refinement regions and grid stretching can be applied. The convective terms are discretized using the hybrid differencing scheme (i.e. a combination of the 1st order upwind scheme and the 2nd order central differencing scheme), and the diffusion terms are discretized by the central differencing scheme. The pressure-velocity coupling is achieved using the SIMPLEST algorithm. There are multiple turbulence closures available in the solver. In this work the standard $k-\varepsilon$ model (Launder and Sharma 1974) has been used. WindSim has functionality to model the effect of atmospheric stability by including buoyancy effects using Boussinesq approximation and by modifying the inlet boundary conditions and boundary layer height. WindSim also has functionality for modelling forest effects as distributed volume forces in the CFD domain.

For this application, where WindSim is used to downscale WRF data imposed as a virtual met-mast, one must consider a balance between high representation of details in the flow field and small scale phenomena (such as e.g. terrain induced flow separation in the context) with the requirement for a smooth and predictable flow field which can be coupled to the large scale dynamics represented by the WRF simulation. The imposed WRF timeseries will be scaled based on difference in flow conditions between any location in the CFD domain and that at the mast location to produce a wind resource map over the area. As a consequence, the transfer location between WRF and WindSim is important to achieve a stable and robust output for the ME-WAM modelling-chain as any errors at the transfer location is propagated out to the whole wind resource map. In this work all WindSim simulations has been conducted using a central refinement region of equidistant cartesian mesh with a horizontal resolution of 100m in a 25km by 25km region. The mesh is stretched outwards from the equidistant region in the outer domain. The size and height of the outer domain vary based on local topography. The vertical mesh consists of 40 vertical cells. There are 10 cells within the first 80m to resolve the boundary layer. The y+ value for the near wall modelling is maintained at a value on the order of 50 (the wall model applied is valid in the range between 30-130 according to the Phoenics documentation). The vertical cells size then increase with height from the ground.

Steady-state simulations are conducted for 12 sectors of 30 degrees each. The General Collocated Velocity (GCV) method was used for solving the governing equations and the standard k−ε model for turbulence closure. Forest is described by 18 classes based on height and tree type. The forest resistive value varies between 0.025 and 0.2 in the various classes.

Description of the multiple transfer location analysis (MTLA)

As described above, the modelling chain in ME-WAM is based on a WRF simulation coupled to a CFD model via an internal forcing point. Experience has shown that the data transfer and downscaling between WRF and the CFD model is the link with the highest uncertainty in the ME-WAM method. The multiple transfer location analysis (MTLA) technique is based on conducting the data transfer and CFD downscaling through several different transfer locations, each with independent CFD simulations. As a result, MTLA will generate multiple independent realizations of the data transfer and the CFD downscaling. The hypothesis is that this will result in a reduced overall uncertainty in the modeling chain, but even more importantly it should result in a reduction in the number of large outliers in the distribution. A reduction of large outliers will be probable as the multiple predictions of mean wind speed at a single location will help identify results that deviate from the surrounding analyses. These transfer points and CFD simulations can thereafter be investigated further and root-causes for the deviations can be identified and corrected for.

The hypothesis above is formulated based on observations that ME-WAM is found to give consistent result across the extracted 25x25 km results surfaces. At instances where multiple ME-WAM analyses have been conducted to predict the wind speed at a specific location, it has been found that as long as the ME-WAM core, see figure 2, has been able to identify a suitable location for WRF-CFD coupling, the difference in the predictions are generally small. This ability was also verified for seven wind farms with a total sample of over 300 wind turbines by Keck et al. (2019). As an example, consider the data in figure 3. Three different ME-WAM analyses have been conducted to predict the mean wind speed at the location of the gray marker. The transfer location between WRF and the CFD model is indicated by the black markers. The data transfer has been confirmed to occur at suitable location for all thee analyses. Even though the data transfers have occurred in distances varying from 3 km to 20 km, all three analyses produce estimates within 1% deviation of target mean wind speed in this case (7.06m/s, 7.09 and 7.13m/s).

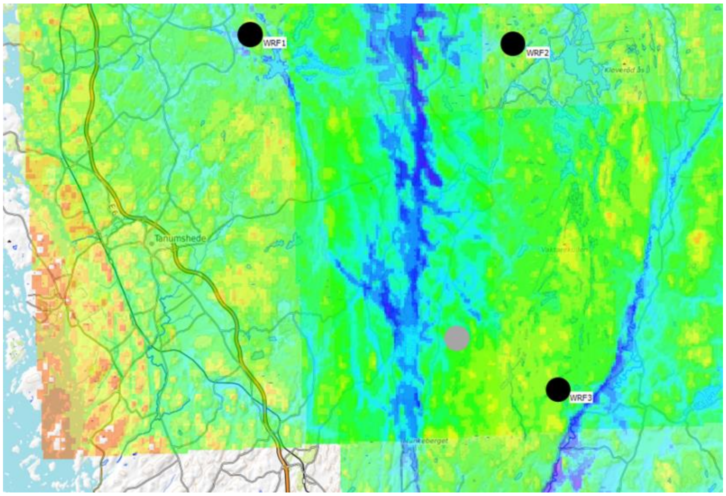

Figure 3, illustration of the MTLA method where the wind speed at the target location (gray marker) is predicted based on three separate ME-WAM analyses. The black markers indicate the data transfer locations. The color scale in the background represent mean wind speed at 100m above ground level, red represent high wind and blue low wind in a range from 5m/s to 8m/s.

One aspect that is important to consider is that the two underlaying models have different capabilities. The WRF model includes mesoscale effects which cannot be captured by the CFD model. As a consequence, care must be taken to consider any gradients in the velocity field caused by mesoscale effects (as discussed by e.g. Haupt et al. 2019). When mesoscale gradients are present in the simulated region, there should be a difference in the predictions of two independent CFD. Examples of such effects to consider is land-sea interactions in coastal areas, capping inversions, or mesoscale stability effects in mountains areas.

In this work, four analyses have been made for each location were the MTLA method is utilized. The drawback of this approach is that the second half of the modelling-chain becomes four times as computationally demanding due to the duplication of work. If a significant reduction in uncertainty can be achieved, however, this method has the potential to increase the applicability for numerical modelling for wind assessments. The added computational cost with the proposed simulation configuration is on the order of 500 CPU-hours.

Description of validation data and method

The validation data used in the work is obtained through collaborations with wind project developers. In total 11 developers have contributed data, and a total of 80 meteorological masts are available for the validation campaign. The available data represents a large variation in topographical conditions and geographical spread. The dataset is considered to cover the range of normal conditions experienced in wind project assessment, as it includes sites with severely complex terrain, coastal conditions, rolling hills and varying degree of forest coverage, see figure 4.

Figure 4, the variations of terrain and roughness covered in the validation dataset. The left figure depicts a site in complex terrain on the Norwegian west coast and the right figure a forested inland site in Sweden.

The evaluation of the ME-WAM model and the MTLA is based on a conducting blind-tests in which the ME-WAM prediction is compared to the measured and long term corrected wind speed. In this process the collaborating company provides a project coordinate somewhere in the vicinity of the metrological mast. Modern Energy subsequently conduct a ME-WAM analysis and send the resulting wind resource files to the collaborating company. The collaborating company finally compares the numerical results to their measured and long term corrected wind speed at the mast location.

A drawback of this validation method is that the field data is not available to the authors for quality control. However, as the measurements are conducted and analyzed to be used for wind farm development, and are often scrutinized by a third party of the collaborating companies, the data is considered to have an industry standard quality and a resulting uncertainty on the order of 3% on mean wind speed at the mast locations.

To verify the effect of the MTLA method, the validation is conducted in three steps. First a baseline is established where the accuracy of the ME-WAM model without MTLA is analyzed against 35 meteorological masts. As a secondly, the accuracy achieved with the ME-WAM after implementing the MTLA method is analyzed by verification against the remaining 45 meteorological masts. As a final step the baseline data is re-evaluate by applying the MTLA method to obtain a validation of ME-WAM with MTLA based on 80 data points.

Results

ME-WAM is validated against a sample of 35 mast measurements to establish a baseline of ME-WAM performance before applying the MTLA technique, see table 1 and figure 4. The average wind speed was found to be 0.10m/s lower than the reference sources with a standard deviation of 0.44m/s. If the data is binned based on terrain class, we can also note that the model performs considerable better in the forested and non-complex sites (black and blue markers in figure 5). The bias is -0.07m/s, and the standard deviation is 0.28m/s for a sample of 15 data points. The corresponding number for the 20 data points in complex terrain is a bias of -0.16m/s and a standard deviation of 0.52m/s.

Table 1, validation statistics for the baseline assessment of ME-WAM without MTLA applied for a sample of 35 datapoints.

	Non-complex terrain	Complex terrain	All data
Number of observations	15	20	35

Bias	-0.07m/s	-0.16m/s	-0.10m/s
Standard deviation	0.28m/s	0.52m/s	0.44m/s

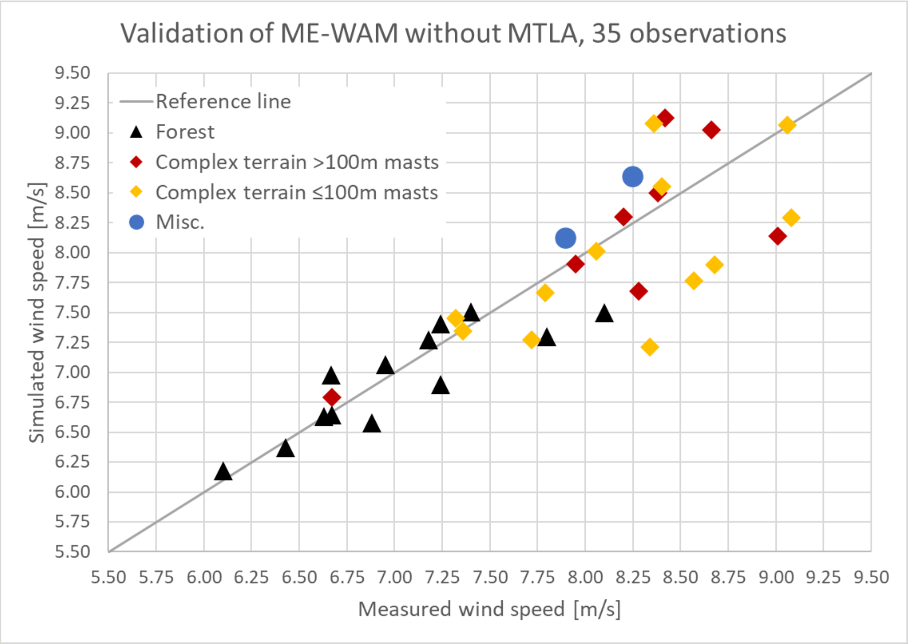

Figure 5, comparison of simulated wind speed (y-axis) and measured wind speed at the meteorological mast (x-axis) for the 35 datapoints where MTLA is not applied.

The validation of ME-WAM with the MTLA correction is conducted against a sample of 45 meteorological masts, see table 2 and figure 5. The average wind speed was found to be 0.05m/s higher than the reference sources with a standard deviation of 0.26m/s. If the data is binned based on terrain class, we find that the forested and non-complex sites (black and blue markers in figure 6) has a bias of +0.07m/s and a standard deviation of 0.25m/s for a sample of 37 data points. The corresponding number for complex terrain is found to be a bias of -0.04m/s and a standard deviation of 0.34m/s for a sample of 8 data points.

Table 2, validation statistics for the assessment of ME-WAM with MTLA applied for a sample of 45 datapoints.

	Non-complex terrain	Complex terrain	All data
Number of observations	37	8	45
Bias	0.07m/s	-0.04m/s	0.05m/s
Standard deviation	0.25m/s	0.34m/s	0.26m/s

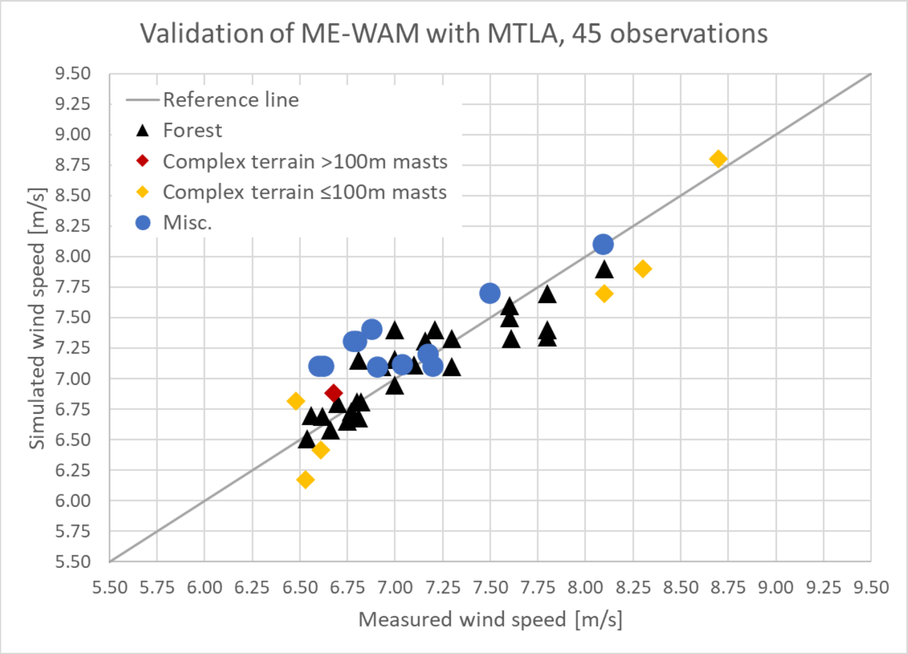

Figure 6, comparison of simulated wind speed (y-axis) and measured wind speed at the meteorological mast (x-axis) for the 45 datapoints where MTLA is applied.

As a final step in the evaluation of the MTLA method, the data from the first ME-WAM validation sample is reanalyzed to include MTLA. This evaluation is performed to gain a better significance in the validation, especially for complex terrain where the second dataset contains only eight observations which makes the conclusions uncertain. Based on 80 data points achieved by combining the two samples, the average wind speed in the ME-WAM analyses is found to be 0.05m/s lower than the reference sources with a standard deviation of 0.28m/s, see table 3. Applying the same binning for terrain class as in the previous analyses, the performance in forested and non-complex sites (black and blue markers in figure 7) has a bias of -0.02m/s and a standard deviation of 0.21m/s for a sample of 52 data points. The corresponding number for complex terrain is found to be a bias of -0.12m/s and a standard deviation of 0.35m/s for a sample of 28 data points.

Table 3, validation statistics for the assessment of ME-WAM with MTLA applied for a sample of 45 datapoints.

	Non-complex terrain	Complex terrain	All data
Number of observations	52	28	80
Bias	-0.02m/s	-0.12m/s	-0.05m/s
Standard deviation	0.21m/s	0.35m/s	0.28m/s

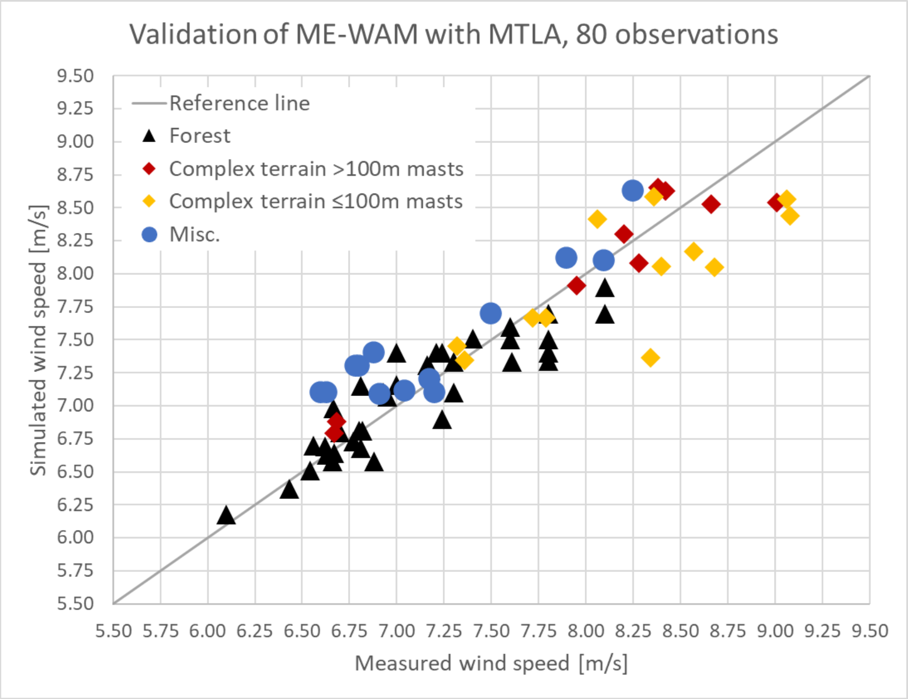

Figure 7, comparison of simulated wind speed (y-axis) and measured wind speed at the meteorological mast (x-axis) for 80 data points after MTLA is applied to all data points (note that this includes a re-analysis of the data points in figure 5 to include MTLA).

An important metric when using numerical methods for wind resource assessment is the occurrence of large prediction errors. Figure 8 below depicts a boxplot of the complete sample of 80 data points using the MTLA method (left) compared to the sample of 35 data points using the ME-WAM model without MTLA (right). It can be seen that utilizing the MTLA method reduce the difference between Q1 and Q3 from 0.53m/s to 0.38m/s. The range between P5 and P95 is reduced from 1.30m/s to 0.95m/s. This represents a reduction of large prediction errors by 27%.

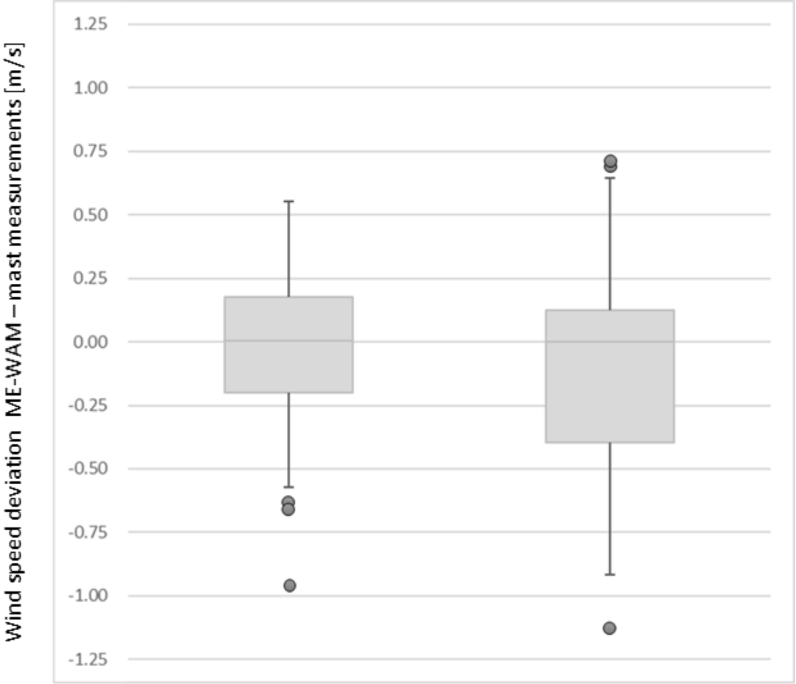

Figure 8, boxplot of the derived statistics for ME-WAM with MTLA (left) and without MTLA (right).

Discussion

The standard deviation of the prediction error for the ME-WAM model compared to field measurements is reduced from 0.44m/s to 0.26m/s by including the MTLA method based on the blind-testing presented above, i.e. a reduction of 40%. However, as the composition of the validation samples differ, where the validation of the WE-WAM model without MTLA has a higher fraction of complex terrain sites, part of this reduction is likely due to the sample composition. To reduce the effect of the sample composition, the data is binned into classes based on high and low terrain complexity. This result in standard deviations of 0.28m/s for non-complex sites and 0.52m/s for complex sites when applying ME-WAM without MTLA. With MTLA the numbers are reduced to 0.25m/s for non-complex sites and 0.34m/s complex sites. The reduction in standard deviation is 11% for non-complex sites and 35% for complex sites. This difference is well aligned with expectations as the uncertainty in the data transfer between the WRF and the CFD model is higher in complex terrain. Including multiple transfer locations should therefore have a larger effect in complex terrain.

A re-evaluation of the model results for the 35 data points without MTLA was conducted to gain significance in the predictive ability of the ME-WAM model after the MTLA is implemented. After applying the MTLA to the analyses, the re-evaluated dataset displays similar statistics as the original MTLA test sample with 45 data points. The difference in standard deviation between the two samples are 0.01m/s for non-complex sites and 0.01m/s for complex sites. This adds confident in the representativeness of the reductions achieved with the MTLA method in the previous test.

Combining the two samples results in a bias of -0.05m/s and standard deviation of 0.28m/s based on 80 data points. The accuracy based on 52 non-complex sites gives a bias of -0.02m/s and a standard deviation of 0.21m/s. The corresponding number for complex terrain is found to be a bias of -0.12m/s and a standard deviation of 0.35m/s for a sample of 28 data points.

The variability in the difference between the ME-WAM predictions and the reference data must also be put in relation to the uncertainty of the field data. The uncertainty in the measured long-term corrected wind speed is estimated to 3%. The mean wind speed of the sample is 7.5m/s, which gives us a standard deviation is on the order of 0.23m/s. Assuming a gaussian distribution, this means that theoretically 68% of the data points should have a measurement error of +/- 0.23m/s or less, and that 90% of the data should have a measurement error of +/- 0.39m/s or less.

The corresponding numbers for the ME-WAM validation with MTLA shows that 68% of the data point has a difference between ME-WAM prediction and measurement in the range of -0.34m/s to +0.25m/s, and that 90% in within the rage +/- 0.48m/s. This indicates a distribution that is similar to a gaussian distribution with a standard deviation of 0.3m/s.

As the metric for ME-WAM accuracy inherently includes the variability from the field measurements, and since it is reasonable to assume that the variability of the ME-WAM predictions and that of the measurement are uncorrelated, the variability of the ME-WAM model itself can be derived. Under these assumptions the standard deviation of the ME-WAM model is on the order of 0.2m/s. This is an important result as it indicates that the ME-WAM model predictions have a variability and a distribution which is similar to that of a long term corrected mast-measurement.

Conclusions

This paper describes a method for reducing the uncertainty associated with employing a virtual met-mast approach to couple an NWP model with a CFD model. This is done via a technique where several different locations for performing the data transfer between the NWP and the CFD model are evaluated independently. This enables the analyst to identify and correct for outliers and to obtain multiple realizations of the data transfer step in the modeling-chain. The validation shows that this technique results in a reduced variability in the prediction error. The reduction is quantified to 11% of the standard deviation for non-complex sites and 35% for complex sites.

The paper also describes a validation of the ME-WAM model with the proposed multiple transfer location (MTLA) method against measurements from 80 meteorological masts. The results show that ME-WAM is able to predict the mean wind speed for the investigate projects with a bias of less than 0.1m/s and a standard deviation of about 0.3m/s. The standard deviation is slightly lower in non-complex terrain (0.21m/s), and slightly higher in complex terrain (0.35m/s). Considering that these numbers include the inherent uncertainty of the reference data, which has an estimated uncertainty of 0.23m/s, the ME-WAM model predictions have a accuracy and a variability which is similar to that of a long term corrected mast-measurement based on this validation.

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