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Quality control of the RMI's AWS wind observations

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Abstract. Wind observations are important for a wide range of domains including among others meteorology, agriculture and extreme wind engineering. To ensure the provision of high quality surface wind data over Belgium, a new semi-automated data quality control (QC) has been developed and applied to wind observations from the automated weather stations operated by the Royal Meteorological Institute of Belgium. This new QC applies to 10 m 10 min averaged wind speed and direction, 10 m gust speed and direction, 2 m 10 min averaged wind speed and 30 m 10 min averaged wind speed records. After an existence test, automated procedures check the data for limits consistency, internal consistency, temporal consistency and spatial consistency. At the end of the automated QC, a decision algorithm attributes a flag to each particular data point. Each day, the QC staff analyzes the preceding day's observations in the light of the assigned quality flags.

1 Introduction

This paper describes the quality control (QC) procedures developed at the Royal Meteorological Institute of Belgium (RMI) to ensure the accuracy and reliability of the wind observations performed within the Automatic Weather Stations (AWS) network operated by RMI. Indeed, while high quality wind measurements are critical for many fields of science and engineering, only little attention has been paid in literature to quality control (QC) of wind-related variables. DeGaetano (1997) was the first to introduce complex automated QC checks for hourly wind records. In a subsequent study (DeGaetano, 1998), the author went a step further by proposing a distinct treatment for calm and non-calm wind speed values in the detection of wind speed bias. Later, Graybeal (2006) proposed to evaluate the reliability of extreme wind values using a relationship between daily wind speed and daily wind gust peaks (Weggel, 1999). In more recent years, Jiménez et al. (2010) extended the automated QC procedures of wind speed and wind direction values to wind data collected at higher temporal resolutions of 10 or 30 min. Lastly, Chávez-Arroyo and Probst (2015) presented a set of eleven QC procedures applied to the wind velocity records of the automated surface observation network of the Mexican National Weather Service. In the present approach, the automated QC functions are included in a larger QC protocol involving manual inspections.

Wind data are evaluated daily by automated screening and manual inspection. Every morning a comprehensive suite of QC algorithms is applied to the previous day's data and a report summarizing the results for each station is produced for the RMI's QC staff. The purpose of the automated data screening is to objectively identify anomalous data values for subsequent review by an experienced data analyst. Note that false positives (i.e. type I error) increase the burden on the manual QC and false negatives (i.e. type II error) reduce the data quality. The review is necessary to determine whether an anomaly results from a problem with the instrument – and what maintenance action may be necessary – or whether it accurately reflects unusual meteorological conditions.

The paper is organized as follows. In Sect. 2, we briefly describe the wind measurements performed within the AWS operated by RMI. In Sect. 3, the automated quality control procedures are presented. Manual QC is discussed in Sect. 4. Finally, conclusion and perspective are given in Sect. 5.

2 Wind measurements within the RMI's AWS network

Wind speed and direction are recorded in 14 AWSs operated by RMI (see Fig. 1 for the stations' location). Wind

Table 1. List of the 14 RMI's Automatic Weather Stations performing wind observations and the associated measurements. Group of stations with similar measurements are defined by "QC group".

AWS		Wind measurement(s)					QC group
Synop code	Name	Wind (gust) speed 2 m	Wind (gust) speed 10 m	Wind (gust) speed 30 m	Wind (gust) direction 10 m	Wind (gust) direction 30 m	
6414	Beitem	X	X (X)		X (X)		2
6418	Zeebrugge		X (X)		X (X)		3
6431	Zelzate		X (X)		X (X)		3
6434	Melle	X	X (X)	X	X (X)		1
6438	Stabroek	X	X (X)		X (X)		2
6439	Sint Katelijn Waver	X	X (X)		X (X)		2
6447	Uccle	X		X (X)		X (X)	4
6455	Dourbes	X	X (X)		X (X)		2
6459	Ernage	X	X (X)		X (X)		2
6464	Retie	X	X (X)		X (X)		2
6472	Humain	X	X (X)	X	X (X)		1
6477	Diepenbeek	X	X (X)		X (X)		2
6484	Buzenol	X	X (X)		X (X)		2
6494	Mont Rigi	X	X (X)		X (X)		2

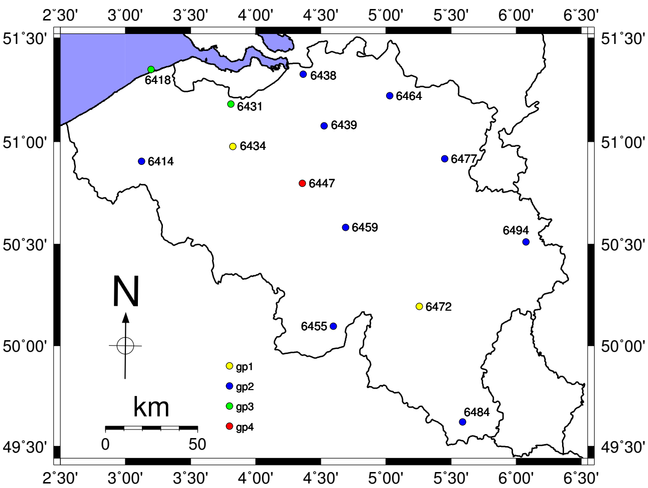

Figure 1. Location of wind measurements performed within the RMI's AWS network and the associated QC groups (see Table 1 for QC group definition).

speed is measured by the Siggelkow's wind velocity sensor LISA excepted for the 2 m wind speed in Uccle (AWS 6447), Ernage (AWS 6459) and Beitem (AWS 6414) where the Wind Transmitter "First Class" Advanced sensor of Thies clima is used. For the wind direction, all AWS are equipped with the Siggelkow's wind direction sensor RITA i WR08 Gray/Analogoutput except in Humain (AWS 6472) and Zeebrugge (AWS 6418) where the Wind Direction Transmitter "First Class" sensor of Thies clima is used. At a given station, wind speed can be measured at up to 3 different levels (i.e. 2, 10 and 30 m high). By contrast, wind direction is recorded at 10 m high in all stations excepted in Uccle where it is measured at 30 m high. Table 1 provides an overview of the wind measurements performed in each AWS and the associated QC group. Indeed, due to the large heterogeneity within the RMI's AWS, four groups based on the recorded wind parameters have been distinguished for the automated data QC.

RMI's AWS are built around a programmable data logger that acquires the sensors' measurements, then processes, stores and transmits the data to the central RMI database (DB) in Uccle, Brussels. Once converted to digital values a first processing is performed at the raw data level allowing calculation of 10 min wind speed and direction averages from the 1 s measurements together with the computation of the gust speed and direction (the gust speed being defined as the maximum 3 s wind speed running average over the 10 min time period).

3 Automated data quality control

Similarly to what is done for the air and soil temperatures measurements from the RMI's AWS (Bertrand et al., 2013, 2015), a first basic QC is performed on all wind records once acquired centrally to ensure that gross errors are found before being further transmitted in the central DB. Automated procedures monitor the data to make sure they are collected and that the system performance is acceptable. After an existence test, a module checks for physical limits and flags the data violating these limits (erroneous when data lie outside physical limits and suspect when lying outside basic long-term climatological extremes that do not take into account the time of

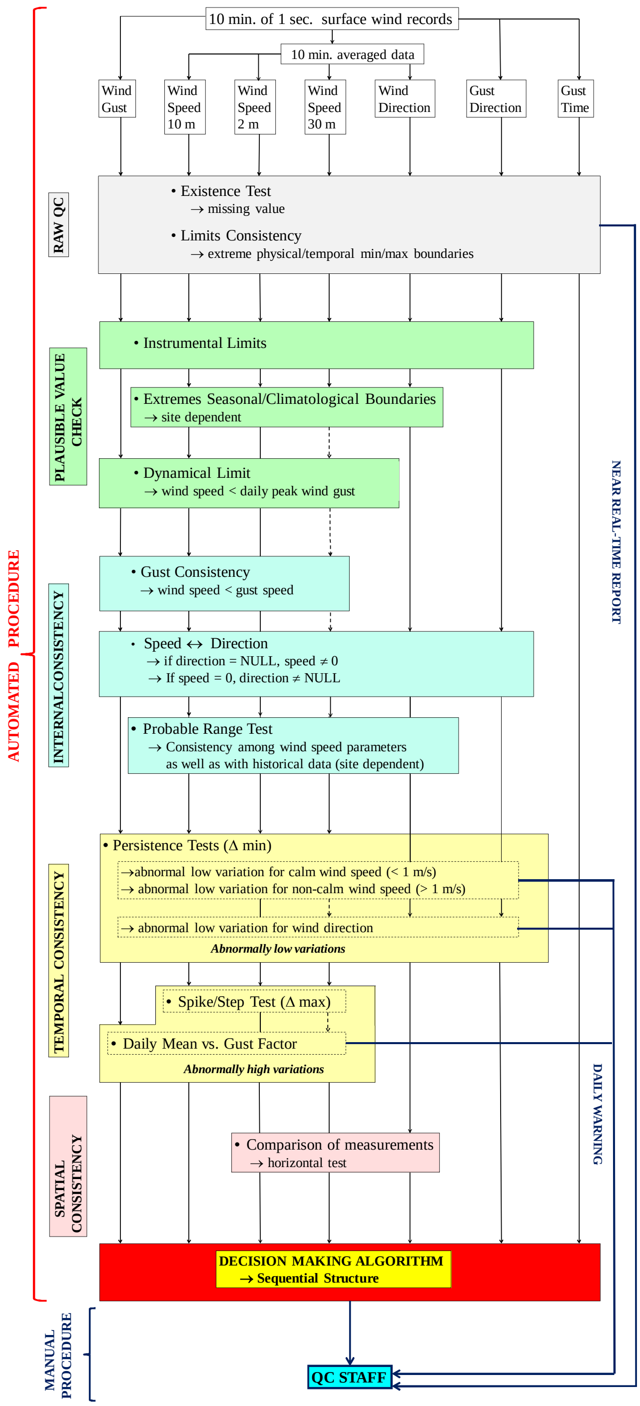

Figure 2. Flowchart of the wind quality assurance process implemented at RMI. (Dashed arrow only applies to 30 m wind measurements in Uccle – AWS6447.)

year and location). A list of missing and flagged data is automatically produced after each control cycle and transmitted to the AWS network maintenance team for further intervention (see Fig. 2). Note that values flagged as erroneous fail immediately and do not need to undergo additional checks.

Second, each night automated procedures check the previous day wind records for more subtle errors. Based on previous works by, e.g., DeGaetano (1997), Graybeal (2006), Liljegren et al. (2009), Jiménez et al. (2010) and Chávez-Arroyo and Probst (2015), the developed data quality tests fall into four categories ranging from simple to complex, from less restrictive to more restrictive. More specifically, the quality assessment process (see Fig. 2) starts with the identification of the records of all wind parameters which show readings beyond plausible values, both fixed and defined dynamically. Afterwards, wind speed, wind direction and gust speed and direction are evaluated for internal consistency. Thereafter, a temporal consistency check is applied. It aims at detecting abnormally low and high variations in wind speed and direction records. Finally, a spatial check is applied to the wind direction records.

To interpret the results of the automated tests, a decision algorithm has been developed that is applicable to all wind parameters and all sites. The algorithm proceeds sequentially through each step until a failure mode is identified. If no failure mode is identified, the measurement is judged to be valid. At the end of the process, a report is automatically generated for each AWS and sent to the QC staff.

3.1 Plausible value check

Implausible values are first defined according to the ranges specified by the manufacturer of the measurement equipment. Here, the fixed range is from 0 to 360° for the average 10 min wind direction and gust direction, and from 0 to 60 or 75 $\mathrm{m\,s^{-1}}$ for the Siggelkow or Thies clima systems, respectively, both for the average 10 min wind speed and wind gust parameters. Second, to verify whether the 10 min wind speed values are within acceptable limits depending on the climatic conditions of the measurement site, individual values are compared with upper seasonal bounds derived at each station from each measuring height from several years of manually controlled wind speed records. To minimize the possibility of a false positive identification, the decision algorithm does not report a range anomaly in case where 10 min wind speed measurements performed at different heights in the same site are larger than their corresponding seasonal limit. Finally, based on DeGaetano (1997), the daily peak gust (computed as the maximum value of the 10 min gust speed records over the given day), u_g, is used as daily limit for the averaged 10 min wind speed measurements recorded at the same height than the gust speed. Similarly to what is done in Chávez-Arroyo and Probst (2015), this dynamical limit test is performed only if more than 85 % of the daily 10 min gust speed records (i.e. more than 122 values a day) are available.

3.2 Internal consistency check

The internal consistency check consists of three different stages; in the first stage gust consistency is verified while in the second stage it is required that zero wind (gust) speed records must have zero and non-changing associated wind (gust) direction records. The third stages involve vertical comparisons of the 10 min wind speed measurement at different heights on the same AWS/site. This test provides a more stringent constraint than simple valid maximum/minimum limit tests by requiring consistency among the measurements as well as consistency with historical data. In order to implement such a QC procedure, 10 min wind speed record measured at a given height is related to 10 min wind speed value at another height using a simple linear regression model. At each station location, parameters of the regression model were estimated using the resistant least trimmed squares (LTS) regression method (e.g., Rousseeuw, 1984) due to the expected existence of outliers in the historical station data considered to fit the model. The biweight mean and standard deviation (Lanzante, 1996) were then used to calculate the confidence intervals around the regression line. Note that prediction intervals were constructed on the basis of a target-flagging rate of 1 per 1000 (e.g. a 99.9 % interval) for erroneous and of 10 per 1000 (e.g. a 99 % interval) for suspicious, respectively (e.g., Eischeid et al., 1995; Graybeal et al., 2004; Graybeal, 2006; Liljegren et al., 2009). Because two comparisons are necessary to unambiguously identify which level is problematic, at least two vertical tests (comparing three levels) must fail for the decision algorithm to report an anomaly. Consequently the decision algorithm will never report a vertical anomaly for AWS where only two wind speed measurement levels are available. However, a single vertical test is still valuable because a single failed vertical test can confirm a range test failure and cause the decision algorithm to report a range anomaly. For this reason, wind speed vertical comparisons are performed not only at stations of QC group 1 (where the test is the more efficient as it involves three measuring levels) but also at stations of QC groups 2 and 4 (see Table 1 for group QC definition).

3.3 Temporal consistency check

The temporal consistency check aims at detecting abnormally low and high variations in wind speed and direction records. Because the frequency distribution of repetitive readings under calm conditions for a given AWS has a far heavier tail than the distribution for non calm condition (i.e. both true calms and total sensor failures produce a sequence of repetitive values, while a similar situation is quite improbable for valid non-calm values) a distinct treatment is applied to calm and non-calm wind speed records, respectively. Ideally the limit between calm and non-calm wind speeds should be given by the anemometers cut-in wind speed (typically in the order of 0.3 m s^{-1} for both the Siggelkow's LISA sensor and the Thies Clima wind transmitter). Here, for the sake of simplicity, we conservatively assume a typical cut-in value of 1 m s^{-1} similarly to what is done in Jiménez et al. (2010) and Chávez-Arroyo and Probst (2015).

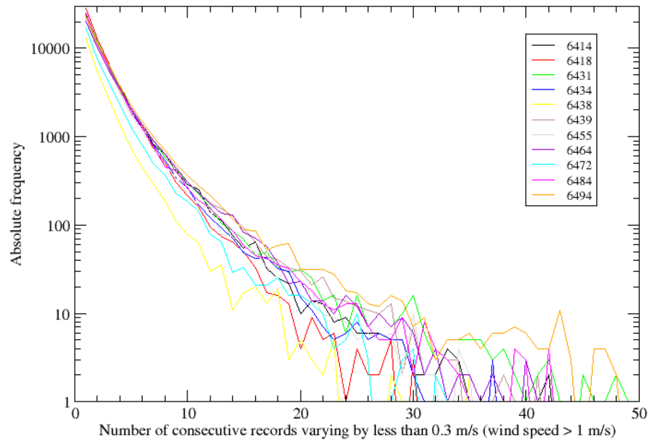

Figure 3. Frequency of occurrence of different consecutive 10 m wind speed repetitions at given AWS (non-calm wind speed) gathered over five years (i.e., 2010–2014) of 10 min wind speed records (see Table 1 for the AWS names).

To identify the maximum number of consecutive unchanging records that can be assumed to be valid, an analysis of the frequency counts for different numbers of consecutive repetitions was performed at each station's location for each wind parameter at each recording height using manually quality controlled historical data. For short durations, constant wind periods are reported with a high frequency of occurence. As duration increases, an abrupt decrease in frequency of constant wind periods appears in all stations although each site has a different decay rate. As an example, Fig. 3 displays the number of consecutive records of 10 m wind speed measurements varying by less than 0.3 m s^{-1} for non-calm wind speed situation at various AWS locations. The threshold value for suspect (erroneous) periods of constant wind speed was selected as being the number of repetitions reached by 99 % (99.9 %) of cumulated frequencies. A methodology similar to the one used for abnormally low variations of wind speed was used for the wind direction (for non-calm wind speed situation).

Besides the persistence test, a spike/step test compares the magnitude of change between 10 min wind speed records with the maximum probable change for a 10 min, 1h, 2h, 3h, and 6h time step periods. As for the persistence test, the maximum probable change is based on the 99th (99.9th) percentile change for several years of quality controlled prior data. The maximum probable change for wind speed depends on the location and sensor mounting height. To minimize the possibility of a false positive identification, a given 10 min wind speed record must fail in at least three of the five tested time steps prior to be flagged as suspect or erroneous. More-over, because wind speed associated with thunderstorms can produce large changes in successive data values, the decision algorithm does not report a spike/step anomaly if more than one sensor mounted at different height on the same location fails the spike/step test. Note that the wind speed spike/step test is performed in all our AWS. Indeed, even if a failure in only one height is insufficient to report an anomaly, it can support other kind of detected failure mode during the algorithm decision making process.

The step/spike test is however not well suited when missing values are found in the time series as the difference between records cannot be calculated. Using different time steps allow to partly overcome such a limitation but does not solve the handling of abnormally high wind speed records surrounded by missing values (which tend to be systematically detected as invalid; Jiménez et al., 2010). Therefore, based on Graybeal (2006) an additional QC procedure evaluates the reliability of extreme wind values using the empirical relation of Weggel (1999) between daily mean wind speed, U, and the gust factor, G, to fit a linear regression model and establish prediction intervals around the regression line:

$$G = A\,U^n \quad \text{or} \qquad (1)$$
$$\log G = \log A + n \log U,$$

where A is a constant and log the natural logarithm. G the gust factor is defined as

$$G = \frac{u_\mathrm{g}}{U} - 1 \qquad (2)$$

with u_g the daily peak gust (i.e., the maximum daily gust value). For each location, the parameters of the linear regression in Eq. (1) were estimated at the sensor mounting height where both 10 min wind speed and gust speed are recorded. As previously done for the vertical comparisons of the same measurement (see Sect. 3.2), the LTS regression method was used to fit the model and the biweight mean and standard deviation to calculate the variance of the predictions. The procedure is illustrated in Fig. 4 which presents the regression plot for the logarithm of the gust factor, G, versus the logarithm of the daily mean wind speed, U, for the station of Dourbes (AWS 6455). The LTS fit is given in blue and the 99 % (99.9 %) confidence level region in green (red), respectively.

It is worth pointing out that when abnormal low or high (excepted for the spike/test) variations are detected by the automated procedures, a daily warning is sent to the QC staff for requesting a visualization of the entire daily time evolution of the identified problematic wind parameter during the manual QC.

3.4 Spatial consistency check

In the horizontal test, the differences between a measurement and the corresponding measurements on other locations are compared. Here, the spatial check only applies to the 10 min averaged wind direction records (for non-calm wind speed situations). It compares the station's direction to the mean wind direction in a radius of 75 to 100 km around the analyzed station's direction value. Basically, the station fails the neighboring test if the difference between the recorded station's direction and the computed direction in the radius is larger than 100°. It is worth pointing out that this test does not apply to the wind direction records performed at AWS 6484 and 6494 (see Fig. 1 for the stations location with the Belgian territory) as a minimum of five neighboring stations in radius is required to perform the test. An illustration of the spatial consistency check is given in Fig. 5. In this example, the wind direction recorded at the Zelzate's station (AWS 6431) and represented by the red arrow differs by more than 100° from the mean direction of the five nearest stations directions (represented by the black arrows).

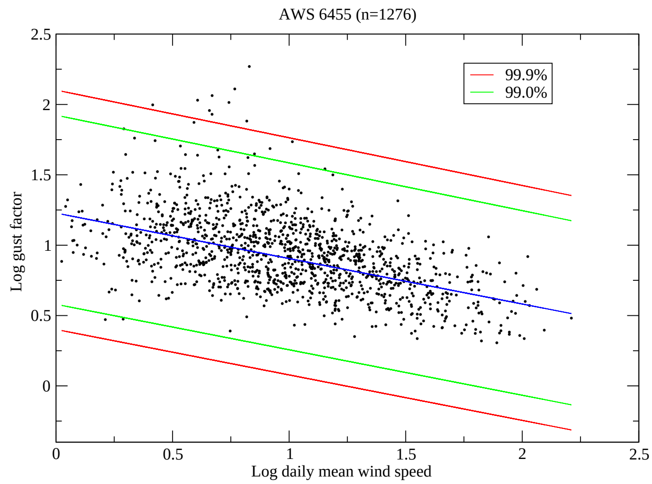

Figure 4. Log daily peak-gust factor plotted against daily mean wind speed, for an arbitrary sample of $n = 1276$ consecutive days (AWS 6455), with regression (blue line) and resistant prediction bounds (99 % in green and 99.9 % in red, respectively).

4 Manual QC

Each day, the QC staff analyses the preceding day's wind records in the light of the assigned quality flags from the automated system. Results of the automated system can be graphically plotted on the operator terminal screen. In that case, all the analyzed wind speed records (including the gust speed) of the inspected day at a given station are presented in a graphic window with erroneous or suspect values indicated in the corresponding parameter daily time series. Similarly, the daily time series of the wind and gust directions are reported in separate window together with wind direction recorded at neighboring stations (e.g. daily time series of wind direction measurements from stations included in a domain surrounding the analyzed station – domain delimited by

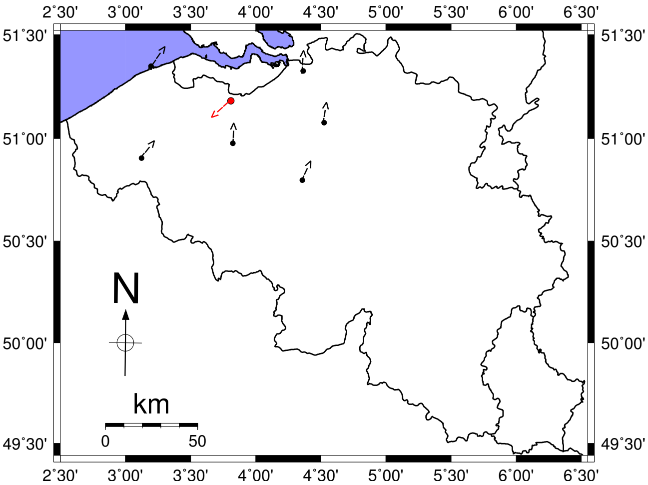

Figure 5. Illustration of the spatial consistency check applied to the 10 min averaged direction records. Date: 2015-08-23 15:00 UTC. Station flagged: Zelzate (AWS 6431). Station's speed: 2.5 m s^{-1}. Station's direction: 52.74°. Radius: 75 km. Stations in the radius: 6. Speed in the radius: 3.02 m s^{-1}. Direction in radius: 201.70°.

the operator). Visual inspection of all records flagged by the automated decision making algorithm is done to distinguish instrumental problems from plausible behaviors. It is the human decision whether or not a value is accepted. When errors are verified or visually detected, faulty records are eliminated and "trouble tickets" are issued where needed to the maintenance team so that sensors can be replaced or repaired. More than simply deleting erroneous measurements, human operators supply corrections and estimations (i.e., when values are missing) where possible. They have the opportunity to visualize different automated corrections on the problematic time series in order to determine the most appropriate in their specific case while it is always possible for individuals to apply their own corrections. When the correction/estimation process is completed, all modifications introduced by the operator are automatically recorded in the central RMI's DB. Note that the original parameters values are kept in the database and still accessible by the QC staff if required.

5 Conclusions

Automation of the RMI's AWS data quality control is in progress. After the automated quality control of 10 min air and soil temperatures records (Bertrand et al., 2013, 2015), automated quality assurance procedures devoted to wind records have been operationally implemented to support the QC staff in their work. Validation exercises have revealed that unsurprisingly the automatic QC system performs better for stations of the QC group 1 than for those of the QC group 3 as the increased wind speed recording heights allow to refine the final decision of the algorithm. Nevertheless, it has been found that the automated QC is able to correctly identify problematic parameters in a particular station on a given day irrespectively of the AWS QC group. However, the spatial consistency check applied to the 10 min wind direction tends to produce type I error (i.e. false positives) at some stations (located in the North-East part of Belgium). This occurs when the station's direction while being close to the direction recorded at nearest neighboring station differs by more than 100° from the mean wind direction in radius. Enlarging the acceptable direction difference threshold does not satisfactory solve the problem as the direct counterpart is an increasing number of type II error (false negatives). Current investigations tend to indicate that incorporating the wind measurements performed in the 7 AWS operated by the Belgian army on military airports (three being located within the problematic area) into the automated QC and limiting the number of neighboring in the radius to the five or four nearest stations in the spatial consistency check will substantially reduce the occurrence of type I error. Another advantage of using the wind records from the military AWS is that the increased stations density will authorize to extend the spatial consistency check to the wind directions recorded in our eastern AWS (Mont Rigi station, AWS 6494).

Finally, while the validation exercise has not revealed a particular weakness in the step/spike test, we are planning to investigate if it could be relevant or not to adapt the procedure using the daily mean wind speed and the gust factor to detect abnormally high variations in presence of missing data records (Eq. 1 in Sect. 3.3). The idea is that similarly to Jiménez et al. (2010) the daily peak gust (u_g) could be replaced by the daily maximum 10 min wind speed to calculate the gust factor (G) in Eq. (2). In that case, only historical daily time series with no missing 10 min values will be considered to determine the linear regression parameters in Eq. (1).

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