




**RESEARCH ARTICLE**

# Assessing the potential and application of crowdsourced urban wind data

Arjan M. Droste<sup>1</sup>  | Bert G. Heusinkveld<sup>1</sup> | Daniel Fenner<sup>2</sup>  | Gert-Jan Steeneveld<sup>1</sup> <sup>1</sup>Meteorology & Air Quality, Wageningen University, Wageningen, the Netherlands<sup>2</sup>Institute of Ecology, Technische Universität Berlin, Berlin, Germany**Correspondence**A.M. Droste, Meteorology & Air Quality, Wageningen University, 6708 PB, Wageningen, the Netherlands.  
Email: arjan.droste@wur.nl**Funding information**

Deutsche Forschungsgemeinschaft, Grant/Award Number: SCHE 750/15-1; Nederlandse Organisatie voor Wetenschappelijk Onderzoek, Grant/Award Number: 846.14.007

**Abstract**

The use of crowdsourcing – obtaining large quantities of data through the Internet – has been of great value in urban meteorology. Crowdsourcing has been used to obtain urban air temperature, air pressure, and precipitation data from sources such as mobile phones or personal weather stations (PWSs), but so far wind data have not been researched. Urban wind behaviour is highly variable and challenging to measure, since observations strongly depend on the location and instrumental set-up. Crowdsourcing can provide a dense network of wind observations and may give insight into the spatial pattern of urban wind. In this study, we evaluate the skill of the popular “Netatmo” PWS anemometer against a reference for a rural and an urban site. Subsequently, we use crowdsourced wind speed observations from 60 PWSs in Amsterdam, the Netherlands, to analyse wind speed distributions of different Local Climate Zones (LCZs). The Netatmo PWS anemometer appears to systematically underestimate the wind speed, and episodes with rain or high relative humidity degrade the measurement quality. Therefore, we developed a quality assurance (QA) protocol to correct PWS measurements for these errors. The applied QA protocol strongly improves PWS data to a point where they can be used to infer the probability density distribution of wind speed of a city or neighbourhood. This density distribution consists of a combination of two Weibull distributions, rather than the typical single Weibull distribution used for rural wind speed observations. The limited capability of the Netatmo PWS anemometer to measure near-zero wind speed causes the QA protocol to perform poorly for periods with very low wind speeds. However, results for a year-long wind speed climatology of the wind speed are satisfactory, as well as for a shorter period with higher wind speeds.

**KEYWORDS**

citizen weather station, crowdsourcing, urban wind, personal weather station, urban climate, Weibull distribution

## 1 | INTRODUCTION

The urban climate is a subject of increasing interest in science and society. With ongoing climate change and urbanisation, the need for accurate urban weather information has never been more urgent. In order to combat the effects of heat waves, air pollution or urban flooding, knowledge of urban weather can assist in identifying risk prone areas, to which urban planners can find a solution. The urban climate is of particular importance to human thermal comfort and air quality, and their associated health risks (Moonen *et al.*, 2012).

The lack of urban weather observations is a major challenge in characterising the urban climate. Several cities have dedicated observational networks, for example, Birmingham (England, Warren *et al.*, 2016), Berlin (Germany; Fenner *et al.*, 2014), Novi Sad (Serbia; Savić *et al.*, 2019), Ghent (Belgium; Caluwaerts *et al.*, 2020) or Amsterdam (the Netherlands; Ronda *et al.*, 2017), but the majority of cities across the world lack such a detailed network. WMO regulations prevent official weather stations being located in cities, since they require relatively open surroundings. Though obstructions characterise the urban climate, their heterogeneity complicates taking representative measurements of the city as a whole. From street to street, vast differences can occur, especially in wind speed, but also in temperature and, to a lesser extent, humidity (Heusinkveld *et al.*, 2014).

To compensate for this lack of data, the urban meteorological research community has embraced the use of crowdsourcing. Muller *et al.* (2015) define crowdsourcing as “*Obtaining data or information by enlisting the services of a (potentially large) number of people and/or from a range of public sensors, typically connected via the Internet.*” An increasing number of crowdsourcing studies have been conducted recently, mainly to study the urban heat island effect (Wolters and Brandsma, 2012; Chapman *et al.*, 2017; Fenner *et al.*, 2017; Feichtinger *et al.*, 2020), urban rainfall (de Vos *et al.*, 2017) and air pressure (Mass and Madaus, 2014). Urban air temperature and rainfall are well-captured by so-called Personal Weather Stations (PWSs): small weather stations designed for use by citizens, which can be installed on balconies, in gardens or on roofs.

Wind has so far not been researched through crowdsourcing. Urban wind speed and direction are hard to quantify due to the strong turbulent nature of wind. Observational studies have usually been confined to single streets, where canyon profiles of wind speed and direction are measured with masts (Rotach *et al.*, 2005; Eliasson *et al.*, 2006). Urban wind studies often rely on wind tunnel experiments or computational fluid dynamics models to study wind loads on buildings, at pedestrian

level, and for urban pollutant dispersion (Carpentieri and Robins, 2015; Ramponi *et al.*, 2015; Toparlak *et al.*, 2017). Knowledge of the urban wind is important for topics such as air pollution dispersion (Pascal *et al.*, 2013), mechanical wind loads on buildings (Ramponi *et al.*, 2015), human thermal comfort (Hsieh and Huang, 2016; Heusinkveld *et al.*, 2017), and urban wind energy potential (Kent *et al.*, 2017).

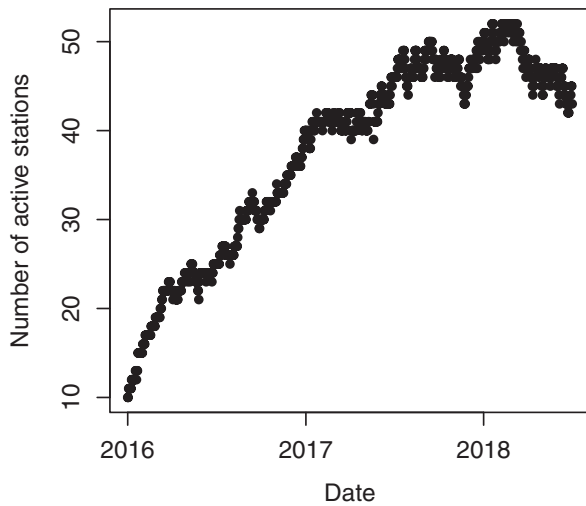
Crowdsourcing might be useful to investigate the urban wind climate. Crowdsourced data are available in great quantities, but quality is often relatively low, so serious scrutiny of data is required. The station set-up and site representativeness are generally less well-known (Muller *et al.*, 2015), which impacts data interpretation. In this study, we aim to learn whether crowdsourced wind speed data from “Netatmo” PWSs are suitable for analysing urban wind speed. We perform this research in Amsterdam (the Netherlands), where the Meteorology & Air Quality group of Wageningen University operates an urban network of automated weather stations with high-quality wind measurements (Ronda *et al.*, 2017), to serve as reference against which the crowdsourced stations can be tested. First, the Netatmo wind module is compared to reference sonic anemometers records in the field, in both a rural and an urban setting. Subsequently, from these field tests a bias correction and Quality Assurance (QA) protocol is established, which is then applied to the crowdsourced urban wind speed measurements. Finally, these data are used to analyse the wind speed characteristics of different Local Climate Zones (LCZs; Stewart and Oke (2012)) in Amsterdam, and to compare the results to the reference network.

Section 2 introduces the data (crowdsourced and reference stations), as well as the QA protocol used to filter the crowdsourced data; section 3 shows the results, which are discussed in further detail in section 4, before final conclusions are drawn in section 5.

## 2 | DATA AND METHODOLOGY

### 2.1 | The Netatmo wind module and data gathering

We focus on the Netatmo brand PWS, because of its popularity as a PWS brand in Europe. As an illustration, in large cities such as Berlin or Paris, hundreds to thousands of Netatmo PWSs are set up (Meier *et al.*, 2017), but even smaller cities such as Amsterdam or Toulouse appear to be equipped with hundreds of stations measuring urban weather (de Vos *et al.*, 2017; Napoly *et al.*, 2018). All Netatmo PWSs contain the same hardware, which limits



**FIGURE 1** Number of actively measuring Netatmo wind stations over the course of the study period in Amsterdam

discrepancies between stations, and allows development of a uniform bias-correction and QA procedure. Meier *et al.* (2017) have developed such a QA procedure for PWS air temperature data, and we will follow their example to develop such a system for PWS wind speed data, using reference measurements during QA. The Netatmo company started distributing their wind sensor midway through 2015, as the latest addition to their weather station. For Amsterdam, 60 PWSs measuring wind speed were present within the period January 2016–July 2018. Not all stations were active for this whole period: at most 52 stations actively measured in a single day, but we see a general increase of the number of stations measuring over time (Figure 1). At the beginning of 2016, few PWS owners will have had the new wind module, though the PWS itself has been gaining popularity over the years as well. The wind module is a cylindrical sonic anemometer, 11 cm tall and 8.5 cm in diameter, using four nodes in an opening in the middle of the cylinder to measure the zonal and meridional wind components (Figure 2). Measurements are taken every 6 s and aggregated to mean and maximum output values every 5 min. Accuracy of the wind speed measurements is  $0.5 \text{ m}\cdot\text{s}^{-1}$  for speed, and  $5^\circ$  for wind direction (Netatmo, 2019). The data of this study are obtained through the Netatmo online API (Application Programming Interface) method *getstationdata*. This method provides wind data at roughly 5 min resolution (variable time-frame) in rounded integer  $\text{km}\cdot\text{hr}^{-1}$  for wind speed and degrees for wind direction. The API requires station and module identifiers, which are requested from the *getpublicdata* API method. This method outputs a list of station identifiers and their corresponding weather modules (outdoor module, wind, or rain meters) which can be used in *getstationdata*.

## 2.2 | Data evaluation

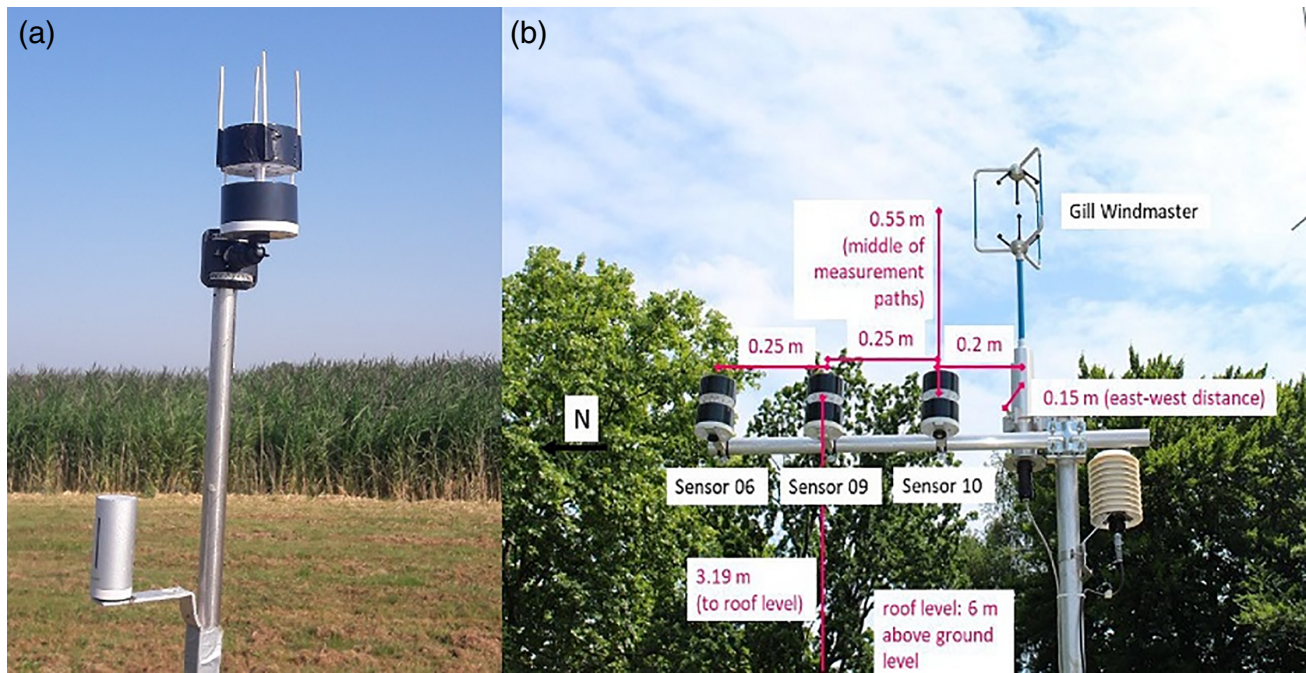
To evaluate the PWS wind speed measurements against a known reference, without the complexity of an urban environment, one Netatmo station was installed at the experimental rural weather field in Wageningen, the Netherlands ( $51.981^\circ\text{N}$ ;  $5.622^\circ\text{E}$ ; 5.0 m.a.s.l.). This weather field is a well-watered flat grass field that conforms to WMO regulations for weather observations. The Netatmo wind module was installed at 2 m height (Figure 2a), allowing for direct comparison with the Gill/Campbell Scientific CSAT3 3D sonic anemometer (measurement rate 10 Hz; resolution:  $0.001 \text{ m}\cdot\text{s}^{-1}$ ; 2% accuracy), also installed at 2 m, distanced roughly 10 m away from the Netatmo sensor. Rain and relative humidity are also measured at the weather field and used in the development of the QA procedure (Section 2.3). The field comparison at the weather field ran from April 2018 to December 2018.

As a second reference, located in an urban setting, we utilise observations of three Netatmo anemometers (Figure 2b) installed on the rooftop of the Chair of Climatology building of the Technische Universität Berlin, Germany ( $52.457^\circ\text{N}$ ,  $13.316^\circ\text{E}$ ). Here the reference sonic is a Gill Windmaster Ultrasonic Anemometer installed on a pole, measurement height (middle of path): 9.74 m above ground level (3.74 m above roof level). Wind speed range:  $0\text{--}45 \text{ m}\cdot\text{s}^{-1}$ , resolution:  $0.001 \text{ m}\cdot\text{s}^{-1}$ , sampling at 10 Hz to give 1-min data. The three Netatmo sensors were installed on a boom 0.55 m below the reference sensor, in a north–south configuration, sensors each 0.25 m apart (Figure 2b). These comparison measurements ran from June 2018 to March 2019.

The reference to which we compare the crowdsourced urban PWS observations is the Amsterdam Atmospheric Meteorological Supersite (AAMS), which consists of 25 stations covering the city centre and suburbs, measuring wind, temperature, and relative humidity. The air temperature and humidity sensor (Decagon VP-3, U.S.A.) is mounted inside a 184 mm aspirated radiation shield (Davis, U.S.A.). The ventilation fan is powered by two small solar panels mounted on top of the shield. The fans work at global radiation levels  $>100 \text{ W}\cdot\text{m}^{-2}$ . The radiation screens are mounted on lantern posts, 0.46 m away from the edge of the lantern post, 4.0 m above ground level. The ultrasonic anemometer (Decagon DS-2, U.S.A.) has an accuracy of  $0.30 \text{ m}\cdot\text{s}^{-1}$  or 3% (whichever is larger). The anemometer is mounted above the radiation screen 0.50 m away from the lantern post edge and at a height of 4.30 m above ground level.

Rain and humidity observations from the WMO station at Amsterdam airport (Schiphol, WMO 06240, situated 10 km to the southwest of the city centre) are used in the





**FIGURE 2** (a) Netatmo wind module (top sensor) at the Wageningen weather field, fitted with spikes to prevent birds resting and disturbing the position. The silver cylinder is the outdoor temperature and humidity module, which is not used in this study. (b) Netatmo set-up at Technische Universität Berlin. The sensor numbers refer to the identifiers of the Netatmo wind modules

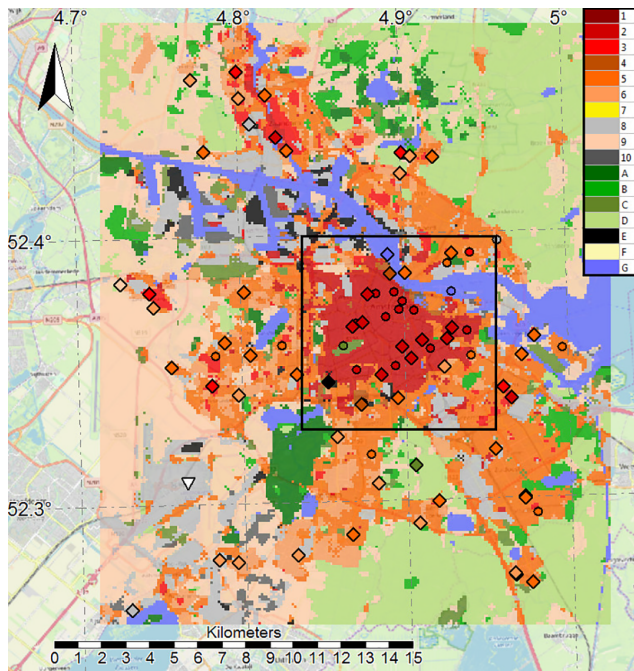
bias correction for the PWS wind data. By using the WMO data as input for the bias correction (rather than the AAMS reference network), the correction protocol can be used for any city with a nearby WMO station, and does not require an extensive urban network. The WMO wind speed data are not used as a reference.

The LCZ framework allows for an objective division of a city and its surroundings into zones with equal morphological properties, such as building heights, vegetation fraction, and building material. According to the LCZ framework, sites are classified in 17 classes, ten “built” and seven “natural” classes (which can also be combined). So far, the framework has mainly been applied in studies investigating air temperature differences (e.g., Alexander and Mills, 2014; Stewart *et al.*, 2014; Leconte *et al.*, 2015; Skarbit *et al.*, 2017; Beck *et al.*, 2018). Others showed that different LCZs also possess different characteristics in terms of humidity (e.g., Unger *et al.*, 2018a; Yang *et al.*, 2020) or human thermal comfort (e.g., Geletič *et al.*, 2018; Unger *et al.*, 2018b; Kwok *et al.*, 2019). To the authors’ knowledge, no investigation concerning wind characteristics of LCZs has been carried out so far. For wind, the building height and the building density are the most important factors to determine the influence of the urban fabric on wind behaviour. In the LCZ framework, these can be distinguished in three categories of height (high, mid and low-rise) and two categories of density (compact and open) for the urban LCZs typically found in the city

centre of Amsterdam. The LCZ map (Figure 3) constructed for Amsterdam, following the World Urban Database and Access Portal Tools (WUDAPT) guidelines (<http://www.wudapt.org/>; accessed 7 May 2020) shows the location of the AAMS and Netatmo PWSs, their respective LCZs, as well as the location of the WMO station. Table S1 contains the full table of AAMS station locations and LCZs.

Most PWSs are concentrated around the city centre (LCZ2 and LCZ5; compact/open midrise, and LCZ6, open low-rise), with some very close to the river and canals (LCZG, water), and three stations in sparsely built areas (LCZ9), near farmland. We use LCZs as an indicator for urban morphology, which has a strong impact on wind speed (especially the ratio between building height and street width), so comparing stations with similar LCZs is required. We assume that morphology strongly determines a certain wind speed distribution, and by pooling the individual station data into one overall distribution per LCZ we are more likely to sample the ‘true’ wind speed distribution for a given LCZ, and not the microscale wind climate of one particular station. In section 3.4.1, the PWS data will be compared to the AAMS data over the period January 2017 to June 2018, which has high data availability for both AAMS and PWS. Only stations roughly in the city centre (between 52.33 and 52.4°N, and 4.837 and 4.95°E; black box in Figure 3) are used. Using the entire PWS network would give a biased image of the fit to the AAMS reference, since a large number of PWSs are outside the





**FIGURE 3** Local Climate Zone map of Amsterdam. The diamonds indicate the PWSs, the circles the AAMS stations, and the white triangle the WMO Amsterdam Airport station. The black rectangle encloses the “city centre” stations used for analyses

city centre. The applicability of the data in calm or windy conditions is examined in Sections 3.4.2 and 3.4.3, for a relatively calm period (August–September 2017) and a relatively windy period (February–April 2018) respectively. Both periods contain a high data density of the PWS network. Both sections also address the effect of morphology on the wind speed distribution, analysing stations in LCZ2 and LCZ5.

### 2.3 | Quality Assurance protocol

To set up a QA protocol to improve the quality of the crowdsourced wind observations, we follow Meier *et al.* (2017), who developed a rigorous QA procedure for air temperature measurements from crowdsourced data. We adapt and extend their QA protocol to be suitable for wind data, as follows:

- A. **Location requirement** and morphology (QA A1 in Meier *et al.*, 2017). This criterion is based on the provided location as present in the PWS data (latitude and longitude). Stations with equal latitude and longitude are excluded. Additionally, we did a visual assessment using Google Earth to filter out unusual locations (such as a station in the middle of a canal). The initial crowdsourced dataset was filtered according to these

criteria, leaving 60 PWSs. These stations are classified into LCZs, using the LCZ map of Figure 3.

- B. **Data averaging and filtering.** The PWS data are provided in integer  $\text{km}\cdot\text{hr}^{-1}$ , at roughly 5-min resolution. This step aggregates all data (PWS, WMO, test field, AAMS) into hourly means. According to the Netatmo website, the minimum wind speed measurement is  $0\text{ m}\cdot\text{s}^{-1}$ , with an accuracy of  $0.5\text{ m}\cdot\text{s}^{-1}$  ( $1.8\text{ km}\cdot\text{hr}^{-1}$ ). However, having placed the wind module indoors for a period of time, we found the minimum measurement tended to be  $1$  or  $2\text{ km}\cdot\text{hr}^{-1}$  rather than  $0$ , meaning that very low wind speed or calm conditions are probably not well captured by the sensor. This is also often reported by users at the official Netatmo forum (<https://forum.netatmo.com/>; last accessed 5 May 2020). The histograms of the raw PWS data indeed show a peak at precisely  $1.0\text{ km}\cdot\text{hr}^{-1}$ , much more than seen in reference sonic anemometer data (not shown). The crowdsourced urban data especially suffer from the large uncertainty at low wind speeds, which comprise a significant part (up to 20% for some locations) of the wind distribution. To eliminate the large bias in wind distribution, all hourly means below  $1.0\text{ km}\cdot\text{hr}^{-1}$  are excluded from the analysis. A peak at  $2.0\text{ km}\cdot\text{hr}^{-1}$  remains visible, but is less pronounced (not shown).
- C. **Filtering for meteorological conditions.** From the field experiments, we determine whether meteorological circumstances, such as rain or humidity, negatively influence the measurements. Netatmo users report that rain disturbs the measurements, and that the stations are prone to collecting moisture inside the sonic module. We investigate any significant influence of rainy (rain in the past 3 hours) and humid ( $\text{RH} > 95\%$ ) conditions, and whether filtering for these circumstances can improve data quality.
- D. **Systematic bias correction.** Any systematic deviation from the actual wind speed as measured during the comparison measurements at the experimental sites will be corrected for. The bias correction based on the experimental set-up will be applied to the (filtered) crowdsourced data from Amsterdam.

### 2.4 | Wind statistics

A direct comparison between the crowdsourced data and the professional AAMS data, as was performed for Wageningen and Berlin, is complicated by the urban heterogeneity and the contrasting set-up between PWSs and the AAMS stations. Whereas the AAMS stations are installed on lampposts within the street canyon (public space), the PWSs are installed in private space. The exact PWS set-up is unknown, which adds uncertainty. Hence,

the wind statistics, rather than instantaneous values, are compared. Under idealised, undisturbed conditions, wind speed follows a two-parameter Weibull distribution (Justus *et al.*, 1978; Takle and Brown, 1978; Conradsen *et al.*, 1984). This distribution is invalid below 0, has a peak at low values, and a long tail. The distribution is determined by shape ( $a$ ) and scale ( $b$ ) factors:

$$f(x) = \frac{a}{b} \left(\frac{x}{b}\right)^{a-1} e^{-(x/b)^a}. \quad (1)$$

However, the observations do not always match the Weibull distribution for sites with disturbances, for instance where the wind speed distribution shows a bimodal pattern, or where there is a high probability of null (near-zero) wind speeds. This may occur in mountainous regions, but also in complex environments such as cities. This especially holds for PWSs, which have a relatively low accuracy, and are therefore very likely to have high peaks at the lower end of the wind speed distribution. Carta *et al.* (2009) have investigated several statistical distributions to capture a variety of wind regimes in the Canary Islands, including stations in mountainous regions. They found that a mixture Weibull distribution can represent a wind speed regime with a large probability of null winds, which is what we would expect in a city. Such a distribution combines two Weibull distributions into one overall mixture distribution: one representing the peak, and one representing the tail end of the distribution. Equation (1) then turns into Equation (2):

$$f(x) = \omega_1 \frac{a_1(x)^{a_1-1}}{b_1^{a_1}} \exp\left[-\left(\frac{x}{b_1}\right)^{a_1}\right] + \omega_2 \frac{a_2(x)^{a_2-1}}{b_2^{a_2}} \exp\left[-\left(\frac{x}{b_2}\right)^{a_2}\right]. \quad (2)$$

Here  $a_{1,2}$  and  $b_{1,2}$  are shape and scale parameters, respectively, for the first and second components.  $\omega_{1,2}$  are the proportions of the two components, which sum to 1. In this case, as for Equation (1),  $x$  represents the measured wind speed ( $\text{km}\cdot\text{hr}^{-1}$ ), and  $f(x)$  is the probability density function.

We use the R-package *mixdist* to fit a mixture distribution to the PWS and AAMS data (Macdonald and Du, 2018). This method iteratively fits the shape and scale parameters, and estimates the proportion of the two distributions, through a maximum likelihood procedure. This requires an initial estimate of the first-order statistical moments and proportions of the two distributions. These are estimated from the data share below  $3.0 \text{ km}\cdot\text{hr}^{-1}$ , which also provides an estimate of the proportionality.

We assess the performance of the PWS data against the AAMS reference data through the resulting probability

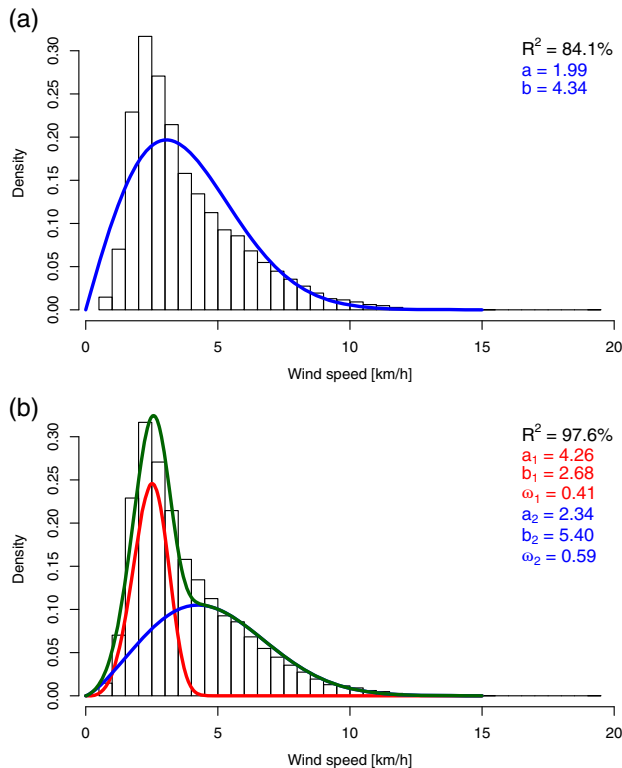
density distribution (PDD). We do this graphically, and numerically using the coefficient of determination ( $R^2$ ) between the two PDDs, as is common practice in the wind energy field (Garcia *et al.*, 1998; Celik, 2004; Carta *et al.*, 2009). In order to compare the wind speed distributions between the AAMS and PWSs, mixture Weibull PDDs are constructed for both data sources for similar LCZs, for an equal time period. All shown histograms of the measurements are made with  $0.5 \text{ km}\cdot\text{hr}^{-1}$  bins: the PDDs are constructed from the fitted distribution parameters using  $0.1 \text{ km}\cdot\text{hr}^{-1}$  intervals, up to the maximum range of the data (often  $20 \text{ km}\cdot\text{hr}^{-1}$ ).

## 3 | RESULTS

### 3.1 | Evaluating the mixture Weibull distribution

To examine whether the mixture Weibull distribution indeed outperforms a regular Weibull distribution for representing urban wind speed, we fit various distributions to a single AAMS station, located in the city centre (station 2194, Spuiplein; Table S1). This site is a square, surrounded by midrise buildings (LCZ2). Since the site is not in a narrow street canyon, the influence of turbulent flows will likely be smaller than at a sheltered PWS site. Data were filtered for rain and humidity (QA step C), but not for low wind speeds (QA step B), since the AAMS sonic anemometer is well capable of measuring very low wind speeds. Fitting a normal two-component Weibull distribution to the observations (Figure 4a) offers a fairly poor result: the peak at the low wind speeds is poorly captured whereas the right tail tends to overestimate the frequency of higher wind speeds. On the other hand, the fitted mixture distribution (Figure 4b) captures the peak and the tail end, though a slight under-representation of the transition between the peak and tail seems to occur (at  $\approx 4 \text{ km}\cdot\text{hr}^{-1}$ ). While graphically the mixture Weibull distribution fits well to the observations, the  $R^2$  confirms that the mixture distribution ( $R^2 = 98\%$ ) outperforms the regular Weibull ( $R^2 = 84\%$ ). Note that  $R^2$  values of Weibull distribution fits tend to be relatively high, since the 0 and the furthest tail generally match (always very close to 0) because of the shape of the distribution. Alternatively, we can evaluate the bulk of the wind speed, below  $5 \text{ km}\cdot\text{hr}^{-1}$ , while excluding  $0.0 \text{ km}\cdot\text{hr}^{-1}$ .  $R^2$  for the mixture Weibull distribution for this lower end still amounts to 93%, but for the regular Weibull distribution drops down to 66%, confirming the superiority of the mixture Weibull distribution.

While these results show that in general the mixture Weibull distribution represents the disturbed urban wind environment well (other AAMS stations show similar



**FIGURE 4** (a) Regular and (b) mixture Weibull distributions fitted to the data of AAMS station 2194 (data used runs from January 2016 to June 2018). Shape ( $a$ ), scale ( $b$ ) and proportionality ( $\omega$ ) parameters are given for all (mixture) components. In (b), the green line indicates the resulting mixture distribution made from the two component distributions (red and blue lines)

results, not shown), for some stations the single Weibull distribution performs equally well, for instance in relatively open environments. However, the mixture Weibull distribution is a viable tool to use for the typically urban, sheltered PWSs.

### 3.2 | Bias analysis through comparison measurements at Wageningen weather field

For the Wageningen comparison measurements, the unfiltered PWS data (Figure 5a) show a systematic underestimation of the wind speed which increases with the actual wind speed. Also, the PWS frequently measures  $1.0 \text{ km}\cdot\text{hr}^{-1}$  when the actual wind speed is higher. Thus, hourly mean wind speeds of  $1.0 \text{ km}\cdot\text{hr}^{-1}$  and lower are excluded from all crowdsourced datasets (QA step B).

Moisture can collect inside the device, which is not completely watertight, and which can influence the measurements (a common issue according to the users' forums). This problem appeared after three months when our installed PWS stopped measuring, at which

point we dismantled the module, cleaned and dried it, and re-installed it in the field. Sonic anemometer measurements are known to be disturbed by rain and water droplets, which can affect the sonic path and the instrument itself (Campbell Scientific, 2017). To investigate the effect of humidity and rain, rain events are classified as hours with more than  $0.1 \text{ mm}$  accumulated rainfall, measured by the Wageningen pluviometer, as well as two hours afterwards, to also take into account possible collection of droplets on the anemometer path. In a similar way, humidity events are hours with  $>95\%$  relative humidity, measured by the reference. High humidity events mainly coincide with positive wind bias by the Netatmo station in the lower wind speed regions, whereas rain events are distributed over the entire wind speed distribution (Figure 5a).

After rain and humidity filtering, and removing the  $1.0 \text{ km}\cdot\text{hr}^{-1}$  data, 64% of the data remain for analysis (2,294 hrs from 3,570). We correct for the systematic bias based on the wind speed measured by the PWS, not on the 'ground truth' of the reference sonic. Hence, the correction is independent from reference data and can be used universally. The data are corrected with a linear regression model, optimised for the median absolute error (MDAE) of resulting corrected wind speed, to give high outliers less weight. Other regression models, including higher polynomial models and multiple linear regression models including other variables such as humidity or rain, have been tested, but a linear regression model explained most variance whilst maintaining model simplicity:

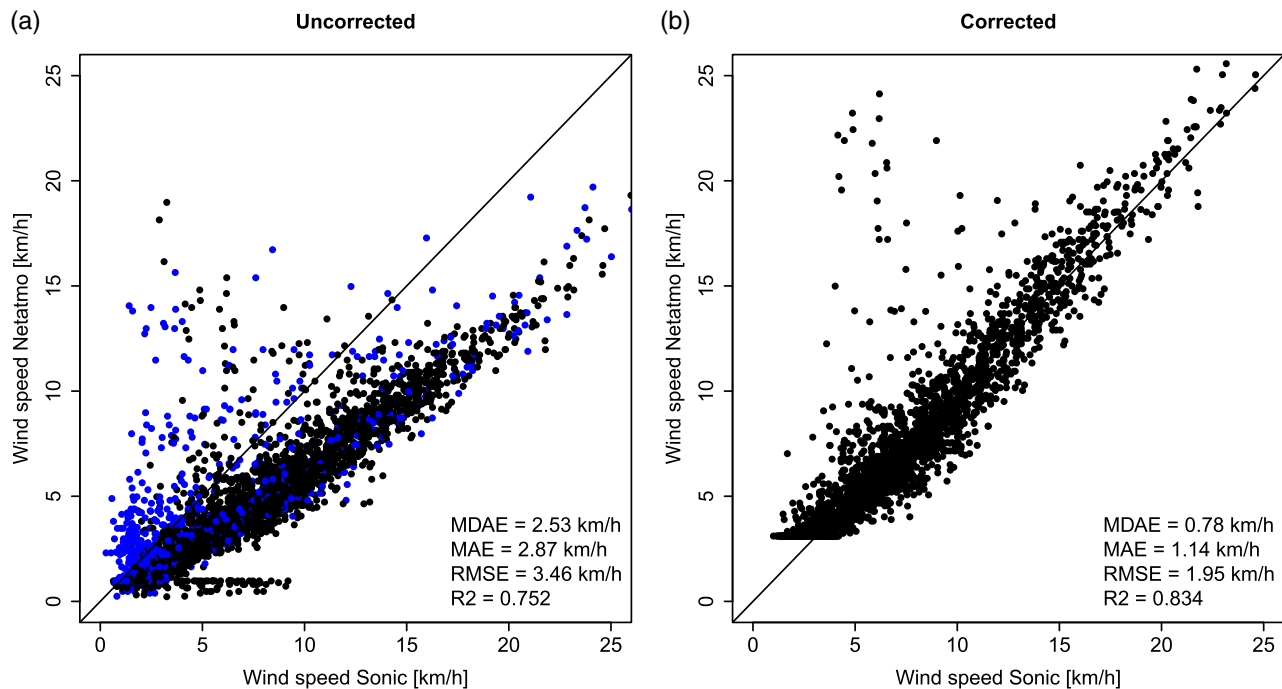
$$v = N(1 + c). \quad (3)$$

In Equation (3),  $v$  is the resulting, corrected wind speed ( $\text{km}\cdot\text{hr}^{-1}$ ),  $N$  the uncorrected (but filtered) wind speed measured by the Netatmo anemometer, and  $c$  is the regression coefficient ( $c = 0.559$  in this case). The majority of the corrected data follows the 1:1 line (Figure 5b), though a portion of positive outliers remains. MDAE amounts to  $0.78 \text{ km}\cdot\text{hr}^{-1}$ , down from  $2.5 \text{ km}\cdot\text{hr}^{-1}$  in the uncorrected set. However, the root mean square error (RMSE) of the corrected data is still  $1.95 \text{ km}\cdot\text{hr}^{-1}$ , compared to  $3.46 \text{ km}\cdot\text{hr}^{-1}$  in the uncorrected dataset, indicating that spread is still visible in the corrected dataset.

### 3.3 | Bias correction of comparison measurements in Berlin

To investigate the robustness of the correction coefficient obtained at the Wageningen site, it is applied to correct the Berlin Netatmo data, after QA step B. Data for rain and humidity are obtained from the WMO station





**FIGURE 5** Scatterplots of hourly averaged wind speeds ( $\text{km}\cdot\text{hr}^{-1}$ ) as observed by the sonic reference instrument (x-axis) and the Netatmo station (y-axis) at the Wageningen weather field. (a) shows the unfiltered, uncorrected data, with rain and/or humidity events marked in blue. (b) shows the resulting data after filtering and bias correction. The correction factor  $c$  used is 0.559. MDAE is the Median Absolute Error; MAE the Mean Absolute Error; RMSE the Root Mean Square Error and R<sup>2</sup> the coefficient of determination R<sup>2</sup>

Dahlem (WMO 10381), close to the measurement location ( $52.454^{\circ}\text{N}$ ,  $13.302^{\circ}\text{E}$ , 51 m.a.s.l.).

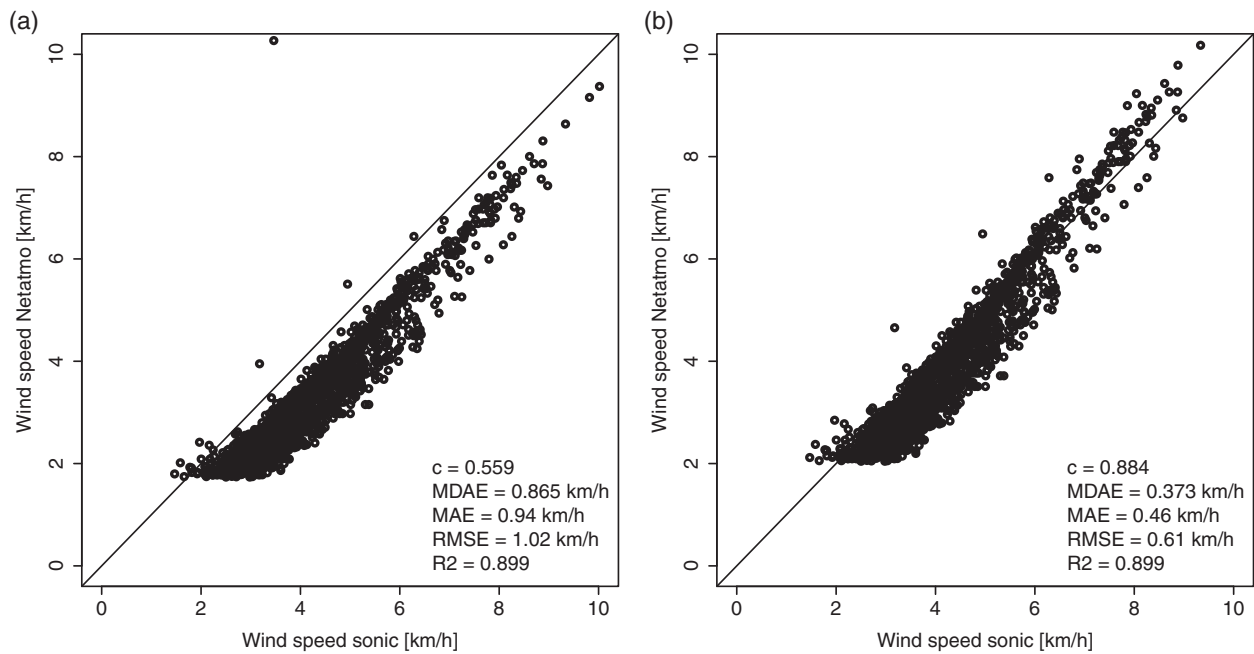
The Berlin wind speed data (Figure 6) are notably lower than the Wageningen data, with hourly averages reaching only  $8\text{ km}\cdot\text{hr}^{-1}$ , with some rare outliers to  $14\text{ km}\cdot\text{hr}^{-1}$ . This is partly due to the lower wind speed in urban areas in general but can also be caused by the trees surrounding the building, sheltering the station. In this sense, the Berlin data represent what we can expect in terms of Netatmo set-up: sheltered environments in gardens or on balconies. Consequently, around 40% of the hourly values are  $1.0\text{ km}\cdot\text{hr}^{-1}$ , which are filtered out in QA level B. Filtering for rain and humidity events in QA level C (of which rain is the main contributor; humidity hardly ever reaches 90% for this site), brings the total data reduction to 45.1%. This indicates that the main expected contributor to error is the underperformance of the hardware at low wind speeds.

The correction factor obtained from the Wageningen dataset ( $c = 0.559$ ) is initially applied to the (filtered) Berlin dataset (Figure 6a). Results are good, with the output statistics showing a better response than for Wageningen: MDAE is only  $0.55\text{ km}\cdot\text{hr}^{-1}$ , RMSE is  $0.64\text{ km}\cdot\text{hr}^{-1}$  and R<sup>2</sup> is 83%. However, some underestimation still seems to be present, although not as prominent as in the initial data. Therefore, we repeated the optimisation procedure for the Berlin dataset to derive a new correction constant.

This new correction constant is higher ( $c = 0.884$ ), indicating that the underestimation of the Netatmo is stronger in Berlin than at Wageningen. Especially at relatively low wind speeds, the fit to the reference observations is better, and model statistics improve overall (Figure 6b). At the upper end of the measurements, some overestimation appears due to the higher correction factor which weighs heavier on higher wind speeds (Equation (3)). Since this new correction factor is tuned towards a wind speed distribution characterised by lower (urban) wind speeds, this might be a preferred tool to correct the urban PWS measurements than the correction coefficient derived from the rural Wageningen data, which covers a much wider wind speed spectrum. In Section 3.4, both will be tested to see which one results in a better fit to the reference network. A separate calculation of the correction coefficient on the Wageningen data, using only wind speeds below  $10\text{ km}\cdot\text{hr}^{-1}$ , did not significantly change the previously found value for  $c$ .

### 3.4 | Application of QA to Amsterdam data

The previous sections showed that the Netatmo anemometer is capable of measuring wind speeds, but requires a substantial correction for rain/humidity events and portrays a



**FIGURE 6** Hourly averaged wind speeds of the three Berlin Netatmo stations (y-axis) against reference sonic observations (x-axis). Netatmo data have been filtered and corrected. (a) shows the correction using  $c = 0.559$  obtained from the Wageningen dataset, and (b) shows the corrections using  $c = 0.884$ , obtained from optimising the Berlin data. Abbreviations are as in Figure 5

systematic negative bias. The following sections apply the QA protocol from Section 2.3 to the urban PWS data, comparing the data after each QA step to the rain and humidity filtered AAMS data as the reference, with the  $R^2$  of the PDDs as a measure of goodness of fit. In Sections 3.4.2 and 3.4.3, the data are separated into periods of relatively low and high wind speeds to analyse the dependency of the QA protocol on mean wind speed.

### 3.4.1 | QA effect on the entire dataset (January 2017–July 2018)

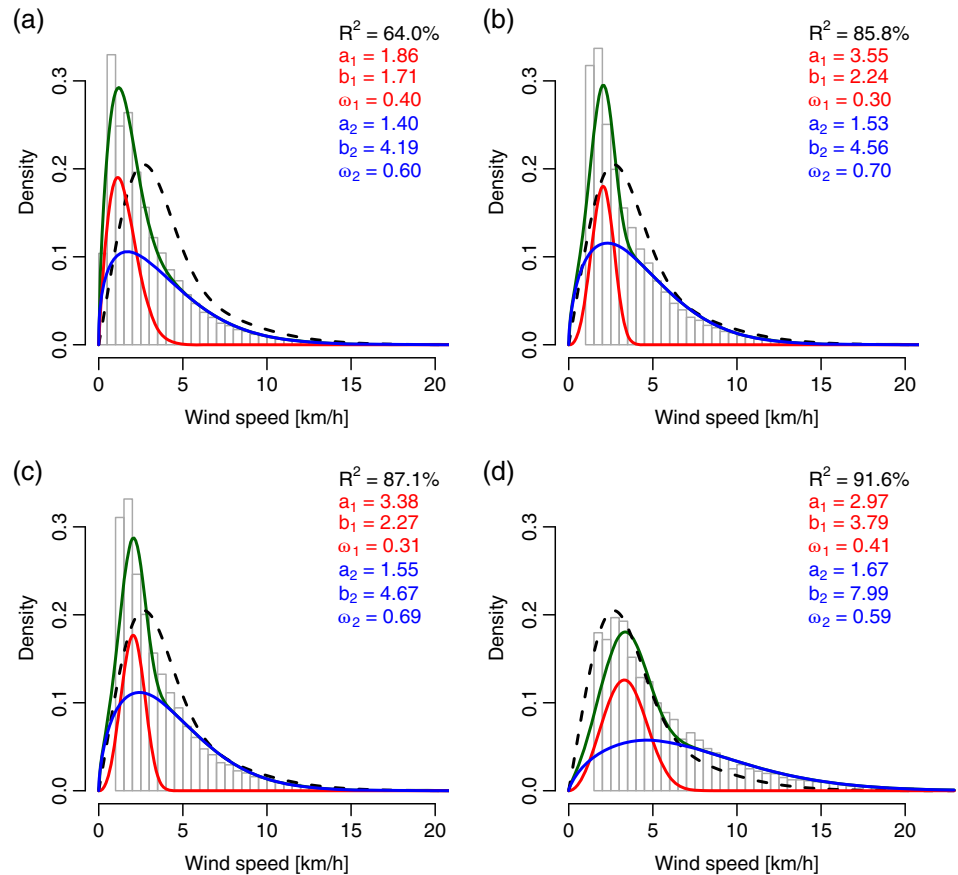
The AAMS dataset contains 99,950 records over 17 stations, after filtering for rain and humidity (which removed 34.7% of the originally available data with the number of stations to be used for analysis at a given time fluctuating between 5 and 15). This filtered dataset serves as the reference against which the PWS data are tested across the various QA steps. For the PWS data, the total unfiltered data available (prior to any QA) are 164,267 records over 17 stations (Figure 7a). At QA level B, which removes the  $1.0 \text{ km}\cdot\text{hr}^{-1}$  values, the dataset is reduced by 21.6% to 128,655 records (Figure 7b). At QA level C, filtering for rain and humidity, total data reduction is 45.9%, or 88,897 records (Figure 7c). The disturbing effect of the  $1.0 \text{ km}\cdot\text{hr}^{-1}$  measurements can be seen in Figure 7a, where the peak is prominent and strongly influences the PDD of the PWS data.

The fit to the reference AAMS data is decent ( $R^2 = 64\%$ ), since the centre of the PWS PDD is much lower than the reference. Removing these  $1.0 \text{ km}\cdot\text{hr}^{-1}$  values strongly improves the fit (to  $R^2 = 85.8\%$ ; Figure 7b) but the peak at low wind speeds is still prominent. Filtering for rain and humidity (Figure 7c) does little to improve the peak values, since rain events tend to coincide with relatively high wind speeds, and as such the main data reduction occurs at the tail end of the PDD. The fit only marginally improves with respect to the previous QA step (to  $R^2 = 87.1\%$ ). Applying the bias correction (using  $c = 0.559$ ) results in a strong improvement ( $R^2 = 91.6\%$ ), which eliminates the high peak value, and the PWS PDD fits that of the AAMS data much better. However, due to the linear nature of the correction, some overestimation of the higher wind speeds is introduced. Using  $c = 0.884$  degrades the result since low wind speeds are under-represented in that case, and  $R^2$  is only 77.7% (not shown). From this point onward, the value of  $c$  is always 0.559, the Wageningen value, since it gives better results.

### 3.4.2 | Calm period (August–September 2017)

August and September 2017 were characterised by generally calm conditions in Amsterdam: 78% of hourly wind speed values measured at Amsterdam airport were below  $5 \text{ m}\cdot\text{s}^{-1}$ . During the period, nine PWSs were

**FIGURE 7** QA protocol applied to all city centre PWSs (January 2017–July 2018). Bars indicate the PWS data in  $0.5 \text{ km}\cdot\text{hr}^{-1}$  bins; red and blue lines are the two Weibull components that make up the mixture Weibull distribution (green). The black dashed line is the rain- and humidity-filtered AAMS reference probability density distribution (PDD).  $a_{1,2}$ ,  $b_{1,2}$  and  $\omega_{1,2}$  are shape, scale, and proportionality parameters of the components, respectively, as in Equation (2).  $R^2$  is the squared correlation between the PWS PDD and the AAMS PDD. (a) is the unfiltered, hourly averaged data, (b) the data with  $1.0 \text{ km}\cdot\text{hr}^{-1}$  values removed (QA level B), (c) the data filtered for rain and humidity (QA level C), and (d) the bias-corrected data using  $c = 0.559$  in Equation (3) (QA level D)

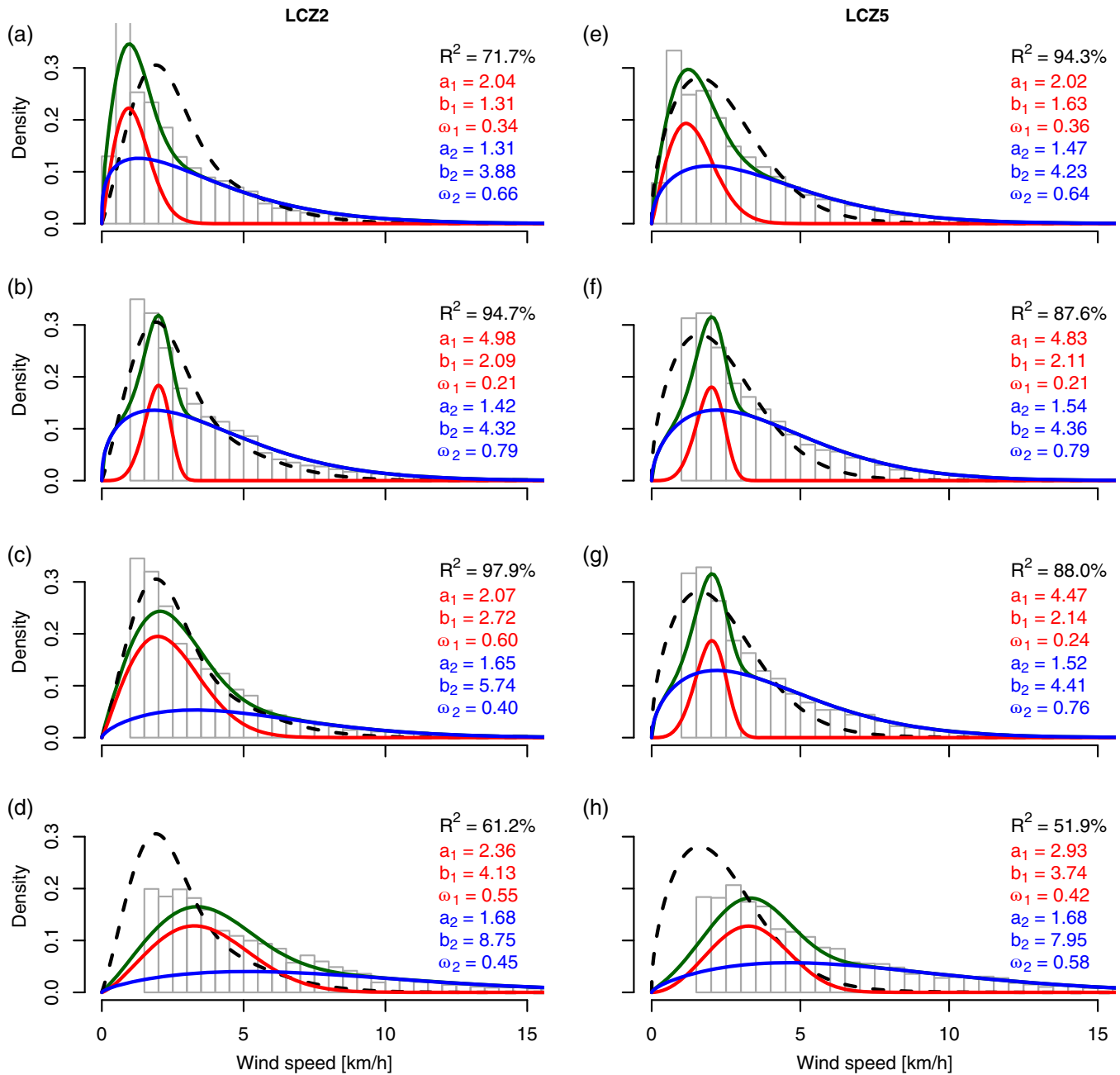


operational in LCZ2, compared to twelve AAMS stations. Prior to any filtering (QA level A), the PWS data contains 10,243 observations across all nine stations. The twelve AAMS stations only have two missing hours in this period, but the rain and humidity filters remove 36.4% of the data (leaving 11,182 records). The histograms of the wind data demonstrate the calm conditions in this period (Figure 8): both the unfiltered PWS data and the AAMS data (Figure 8a) peak at very low wind speeds, and the  $1.0 \text{ km}\cdot\text{hr}^{-1}$  peak of the PWS data makes up for over 20% of the histogram. Indeed, at QA level B (Figure 8b), 27.6% of the data are filtered out, leaving 7,418 records. This shifts the centre of the distribution to almost exactly the value of the peak in the AAMS distribution, resulting in a very good fit to the reference even at QA level B ( $R^2 = 94.7\%$ ). The tail of the PWS PDD slightly overestimates the occurrence of high wind speeds, but by filtering for rain and humidity (Figure 8c) this is corrected, and the fit to the AAMS reference is further improved ( $R^2 = 97.9\%$ ). When applying the bias correction (with  $c = 0.559$ ), results become worse ( $R^2$  drops to 61.2%; Figure 8d), since low wind speeds are over-corrected towards higher values. The bias correction does not seem to perform well during these circumstances with very low wind speeds, and just data filtering is enough to obtain a good fit to the reference network. The PWS's tendency to underestimate wind speed seems to become

an issue only when wind speeds are not low (median wind  $\sim 2 \text{ km}\cdot\text{hr}^{-1}$ ), so QA step D for these situations is not recommended.

To ensure this result is not only valid for LCZ2, stations from LCZ5 are evaluated for the same period (Figure 8e–h). Here we have six AAMS stations with the same relative data reduction after rain and humidity filtering (5,576 observations left), and 18 PWSs. There are a total of 18,515 hourly PWS observations across the 18 stations prior to any filtering. The low winds seem even more prominent in LCZ5: the AAMS observations peak at  $2.0 \text{ km}\cdot\text{hr}^{-1}$  (Figure 8e). Removing the  $1.0 \text{ km}\cdot\text{hr}^{-1}$  measurements (QA level B) reduces PWS data by 20.6% (14,700 measurements left). The rain and humidity filter (QA level C) brings the total data reduction to 49.6% (9,329 measurements left), comparable to LCZ2. This mainly filters the higher wind speed observations at the right tail, though some over-representation of high wind speed remains. Oddly enough, here the best results have been made by just the hourly, unfiltered data (QA step A,  $R^2 = 94.3\%$ ), since the AAMS wind speed values themselves are very low. Understandably, applying the bias correction (QA level D) degrades the fit to the AAMS values further since the distribution is shifted to the right (Figure 8h). Some differences in the characteristics of the Weibull distribution appear between the two LCZs. Especially the scale ( $b$ )

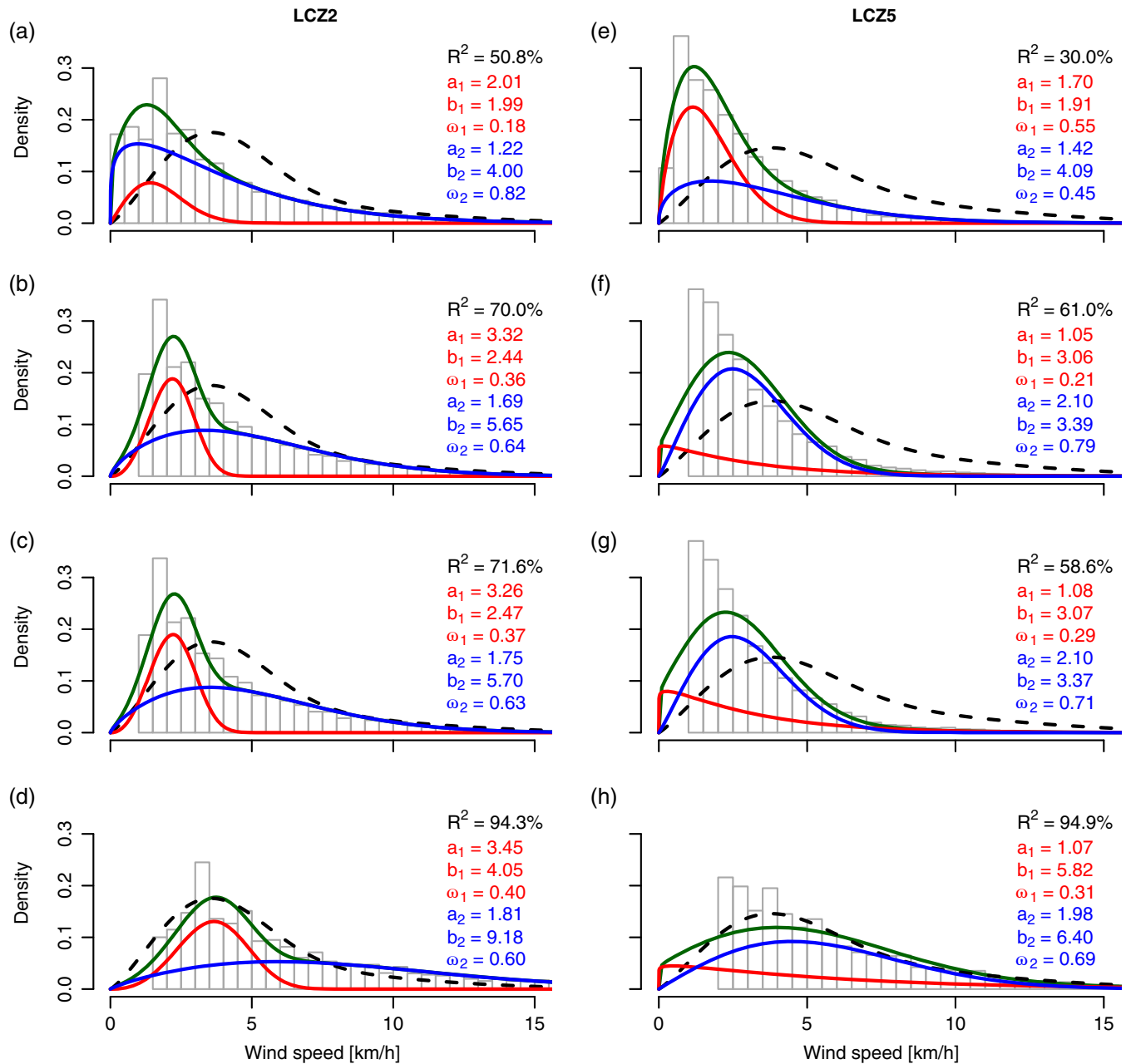




**FIGURE 8** QA applied to the calm wind period (August–September 2017), for (a–d) LCZ2 based on nine PWSs (bars) and twelve AAMS reference stations (dashed black lines), and for (e–h) LCZ5 based on 18 PWSs (bars) and six AAMS reference stations (dashed black lines). The set-up is similar to Figure 7. In (d) and (h), QA level D, the value for  $c$  is 0.559

parameter is lower for both mixture components in LCZ5, indicating lower wind speeds altogether (the scale parameter scales with mean wind speed). The shape ( $a$ ) parameter is only different for the first mixture component (red lines in Figure 8): at 4.83 in Figure 8f it shows a very narrow distribution with a clear peak, related to the narrow shape of the overall distribution, indicating low wind speed values and low spread. Regardless of the LCZ, the QA protocol is not fully able to improve wind speed estimations from PWSs under calm conditions, only up to a certain point

(QA level C, and arguably not even that for LCZ5), and bias correction degrades results. Applying QA step D should therefore be dependent on the mean wind speed. However, applying a different type of correction model, consisting of two separate corrections (for wind speed either above or below  $3 \text{ km}\cdot\text{hr}^{-1}$ ) did not significantly improve the results compared to the model used here (results not shown). The underperformance is therefore likely due to the strong relative error introduced by the integer data resolution and the measurement accuracy of  $1.8 \text{ km}\cdot\text{hr}^{-1}$  ( $0.5 \text{ m}\cdot\text{s}^{-1}$ ).



**FIGURE 9** QA applied to the windy period (February–April 2018), for (a–d) LCZ2, based on nine PWSs (bars) and ten AAMS reference stations (dashed black lines), and for (e–h) LCZ5 based on 18 PWSs (bars) and six AAMS reference stations (dashed black lines). The set-up is similar to Figure 7. In (d) and (h), QA level D, the value for  $c$  is 0.559

### 3.4.3 | Windy period (February–April 2018)

The period February–April 2018 was relatively windy, with 54% of the hourly wind speeds at Amsterdam airport above  $5 \text{ m}\cdot\text{s}^{-1}$ . 15,497 AAMS records are available in LCZ2 after filtering, out of ten AAMS stations, of which one reported no data for one month. There are 16,945 unfiltered hourly PWS records available for LCZ2, over nine PWSs. Data reduction is 17.9% at QA level B (13,910

records left); 38.0% for QA level C (10,507 records left). Compared to Figure 8, Figure 9 shows a wider distribution of wind speed, and the peak of the data is not at  $1.0 \text{ km}\cdot\text{hr}^{-1}$  this time, but at  $2.0 \text{ km}\cdot\text{hr}^{-1}$  (Figure 9b). The AAMS data are centred around  $5 \text{ km}\cdot\text{hr}^{-1}$ , indicating that the average wind speed measured by the reference network is higher than in the previous case. Here, the bias correction is clearly valuable, resulting in a very good fit at the centre of the distribution (Figure 9d;  $R^2 = 94.3\%$ ). Comparing the proportionality parameters of the tail

distribution ( $\omega_2$ ) between Figures 8d and 9d reveals that the tail end of the distribution contributes relatively more than the peak:  $\omega_2$  always exceeds 0.5.

LCZ5 contains 6,407 reference observations across six AAMS stations, and 30,413 PWS observations after excluding missing data, across 18 PWSs. 23.4% of the data are removed at QA level B (23,290 records left); 43.5% for QA level C (17,176 records left). The AAMS data are similar to LCZ2, but with a longer tail end (observed wind speeds also exceed  $15 \text{ km}\cdot\text{hr}^{-1}$ ). Initial unfiltered PWS data are still focused on the strong peak at  $1 \text{ km}\cdot\text{hr}^{-1}$  (Figure 9e) resulting in a poor fit ( $R^2 = 30\%$ ) with the higher-tailed reference data. Removing the  $1.0 \text{ km}\cdot\text{hr}^{-1}$  peak improves the fit by shifting the distribution to the right, but still suffers from a large number of low wind speed observations around  $2 \text{ km}\cdot\text{hr}^{-1}$  (Figure 9f,g). Applying the systematic bias correction strongly improves the fit to the AAMS data ( $R^2 = 95.4\%$  with  $c = 0.559$ ;  $R^2 = 94.9\%$  with  $c = 0.884$ ). The shape of the first Weibull component is rather curious owing to its low shape ( $a$ ) parameter. A shape parameter close to 1 approaches the exponential distribution (where  $a = 1$ ) which carries a strong weight at the low end of the distribution. The wider tail of LCZ2 is the most remarkable difference in wind speed distribution between the two LCZs, suggesting a higher likelihood of higher wind speeds, which could be caused by funnelling through street canyons (Macdonald, 2000). For LCZ5 we conclude that, as for LCZ2, the QA protocol strongly improves the raw PWS data to the point where they can provide an estimate of the wind speed distribution for a windy case. The poor result of Section 3.4.2 can therefore be attributed to the very low wind speeds which make up the bulk of the distribution, at which the Netatmo anemometer is not capable of measuring due to hardware limitations and the coarse output in integer  $\text{km}\cdot\text{hr}^{-1}$ .

## 4 | DISCUSSION

### 4.1 | Use of PWS data in other studies

The use of citizen science is not new in meteorology, and has even aided in the birth of the field (Eden, 2009). The emergence of PWSs has contributed to various studies, especially in urban areas lacking traditional measurements (Steenefeld *et al.*, 2011; Wolters and Brandsma, 2012; Chapman *et al.*, 2017; de Vos *et al.*, 2017; Fenner *et al.*, 2017; Chapman and Bell, 2018), but also at the level of national weather authorities (Krennert *et al.*, 2018; Nipen *et al.*, 2020). While PWS data provide valuable insights into undersampled urban regions, the data remain of relatively low quality compared to WMO standards. The nature of the technique means there is little information regarding

the set-up of the station, which will not have been performed by an expert, and can thereby lead to substantial errors in the data. Additionally, the hardware itself can be a cause of error, such as unventilated screens heating up during the day to strongly overestimate outside air temperature (Bell *et al.*, 2015; Meier *et al.*, 2017). Our study shows that hardware can play a significant role in wind speed errors as well, here related to the effect of humidity and rain on the anemometer. For meaningful results, extensive quality checks need to be made, and have been constructed for PWS air temperature data (e.g., Meier *et al.*, 2017; Napoly *et al.*, 2018; Nipen *et al.*, 2020) and rain (de Vos *et al.*, 2017; 2019). These account for the different error sources associated with crowdsourced PWS data by statistical checks and/or using data from surrounding (reference) stations to determine and filter out potentially erroneous data. For wind speed this is not applicable due to the microscale character of the measurements, but grouping stations into LCZs is an appropriate solution, reducing the impact of potentially wrong individual station data.

Since our overall aim is to develop a QA procedure that does not rely on WMO wind data, we have also made use of the precipitation dataset of de Vos *et al.* (2019), who have studied Netatmo rain data over Amsterdam during the same study period as our work. We constructed a precipitation filter based on their PWS precipitation data, which showed a very strong similarity to the WMO-constructed precipitation filter we have used for our QA protocol (filter results were identical for 94% of the time). The combination of crowdsourced data to generate broad datasets can thus be a helpful tool for urban meteorology, as shown by de Vos *et al.* (2020).

Using crowdsourcing or non-traditional data sources for wind measurements is comparatively rare. Agüera-Pérez *et al.* (2014) utilise several data sources to construct a global wind field for Andalusia (Spain), and the Spanish Meteorological platform (<https://www.meteoclimatic.net/>; last accessed 7 May 2020) offers data, though without QA. Furthermore, the density of the network is scarce in comparison to our work (one station every  $\sim 450 \text{ km}^2$ ), and only some metadata such as measurement height is known. An interesting effort has been made to use mobile phones to measure wind, using an add-on device to create crowdsourced handheld wind observations (Hintz *et al.*, 2017), but the dataset is limited and seems focused towards the coast (and is mainly used by windsurfers).

### 4.2 | Causes of error in PWS wind

The greatest issue with crowdsourcing data is its lack of metadata (Muller *et al.*, 2015). The aforementioned



scarcity of studies exploring crowdsourced or otherwise unorthodox measurements can be ascribed to the large uncertainties inherent in (urban) wind measurements. Wind is strongly variable in time and space, more so than air temperature and rainfall. The station set-up is a crucial factor: air temperature measurements are affected by radiation from nearby walls or direct sunlight in the case of unshielded thermometers; rain is sensitive to the orientation and level of shelter of the station (which can cause underestimation of rainfall), but wind speed is affected not only by orientation (the sonic anemometer needs to be level), and strongly by shelter and obstacles (which induce turbulence and block the flow), but also the height of the measurement, which is unknown. While it is unlikely that an anemometer is used for anything other than measuring outside wind speeds, it is easy for inexperienced users to make small mistakes during station set-up, such as angling the sonic anemometer. The wind module is a separate purchase, and therefore a conscious one by each Netatmo owner, which could suggest that the owner has some understanding on how to properly install such a device, but this cannot be reliably quantified. Only the most basic location information is given by Netatmo, which does not contain any information regarding set-up, calibration, or height of the measurements. Citizens have the option to provide more information about their station on the Wunderground platform (<https://www.wunderground.com/>; last accessed 7 May 2020) or the Weather Observations Website (<https://wow.metoffice.gov.uk/>; last accessed 7 May 2020), but this is entirely voluntary and is provided by only a few owners. PWS owners on rare occasions have their own weather website, which often provides very detailed information about the station, but these tend to be the higher-end stations such as Davis Vantage stations (Steenefeld *et al.*, 2011; Wolters and Brandsma, 2012), not the cheaper Netatmo devices.

A large uncertainty lies within the Netatmo PWS itself: our bias analysis and experimental set-up shows that the station has a tendency to underestimate relatively high wind speeds, and substantially underestimates very low ( $< 2 \text{ km}\cdot\text{hr}^{-1}$ ) wind speeds due to the coarse output resolution. We know that the measurement frequency is roughly 0.16 Hz and that these measurements are then aggregated into the  $\sim 5$  min output obtained through the API, so potentially the raw unprocessed data could provide a solution to the low wind speed errors. Other PWS brands might not suffer from the issues at low wind speeds combined with coarse output, which could make QA level B unnecessary for these cases.

Wind speed in the open field follows a logarithmic profile increasing with height; in the urban area the usual boundary-layer similarity theory is not valid, but wind still increases with height (Rotach, 1995; Castro, 2017; Kent

*et al.*, 2018). We expect the PWSs to be usually mounted at some height above the ground, at best 2 m, but also on balconies, window sills, or wherever it is most suitable for the instrument owner. A more ambitious weather hobbyist might install the anemometer on a pole or on top of a shed, for example, to better measure the actual wind. Stations installed on balconies or rooftops will give a completely different signal over time than a station in a sheltered garden. When installing the anemometer, the software offers the opportunity to report the station's height above ground. However, this information cannot be extracted from the Netatmo data obtained through the API, so we cannot check whether any correction towards a standard value (e.g., 10 m) is performed prior to data storage. This uncertainty also follows from the bias correction parameter, which is different between the open test field at Wageningen (Section 3.2) and the sheltered rooftop environment of Berlin (Section 3.3). While the comparison measurements in Berlin were carried out within the urban area, the rooftop measurement at the top of the canopy layer is apparently not ideal to use, since the Amsterdam Netatmo stations are likely situated in the urban canopy, thus experiencing a different wind regime. This is possibly why the Wageningen correction factor seems to yield better results for the Amsterdam data, despite it being obtained from a rural site, but at 2 m height.

### 4.3 | Application and perspectives

Due to the uncertainty of station set-up, the data obtained from individual PWSs cannot give an accurate representation of the wind speed climate; the station might be located on a balcony, a shed, near a wall, etc. A 1-to-1 time series for individual PWSs compared to their closest matching AAMS stations displayed large deviations around the mean (not shown), even for daily averages, indicating the strong microscale character of the measured wind speed. The mixture Weibull distribution successfully captures the variability of wind within a city, and provides insight into the wind speed differences between neighbourhoods and LCZs. For a more quantitative temporal assessment of wind speed, PWSs appear not to be the right tool, and specialised measurement networks set up by professionals are still necessary. For instance, the effect of wind speed on thermal comfort during heat waves is better researched using stations situated in street canyons with a higher accuracy (such as the AAMS network); the effect of wind on thermal comfort is substantial, and strongly dependent on the local conditions (Heusinkveld *et al.*, 2017). While a technique like Generalized Extreme Value statistics of thermal comfort as in Steenefeld *et al.* (2011) would be possible using the substantial length of the crowdsourced

dataset, this is usually not applied by policy makers, but could be in the future with increasing number of PWSs in cities worldwide.

The use of a PDD is very common in the field of wind energy, where these functions are used to assess the wind energy potential of given areas (Celik, 2004; Carta *et al.*, 2009; Drew *et al.*, 2013). It would therefore be interesting to research the value of the crowdsourced wind data for identification of possible urban wind energy generation given the difficulties in estimating urban wind resource (Walker, 2011). A potential issue here could again be the unknown height of the stations; a (Weibull) PDD is typically constructed at a certain level and transposed to the hub height of the expected wind turbine. A possible way to circumvent this issue is to assume a likely range of heights (between 2 and 5 m seems the most logical given the residential character of the PWS locations, though balcony stations can be much higher) and construct the transposed PDDs for the minimum and maximum height to see the spread in the results. Geographic Information System data on building height could also provide some information for rooftop and balcony stations.

The sensitivity of the station to set-up errors (i.e., tilting, sheltering, measurement height) needs to be investigated in a systematic way, as Bell *et al.* (2015) did for air temperature and humidity. Wind tunnel experiments using several Netatmo anemometers could investigate the influence of the angle of tilt of the station on the reported wind speed values, and perhaps determine a threshold wind speed when the measurements are of sufficient quality. A long-term urban experimental set-up of the Netatmo anemometer next to a known reference station could give some insight into expected sensor drift, the cause of errors for the low urban wind regimes and a more robust estimate of the bias correction parameter needed.

## 5 | CONCLUSIONS

This study makes use of wind speed data from 60 Netatmo Personal Weather Stations (PWSs) collected between January 2016 and June 2018 in the area of Amsterdam, the Netherlands, as well as data from an urban reference network and two experimental set-ups. From these data, we have established a Quality Assurance (QA) protocol to filter incorrect data, remove the effects of rain and humidity, and correct for a systematic underestimation of wind speed measured by PWSs. The quality-controlled PWS wind speed data can be used to construct a mixture Weibull probability density distribution (PDD) which conforms to the reference network. The wind distribution of different Local Climate Zones (LCZs) can be investigated by aggregating the data from all stations in those

LCZs. While we conclude that for extended periods with very low ( $<2 \text{ km}\cdot\text{hr}^{-1}$ ) wind speeds, the QA protocol does not improve the raw data, and the bias correction even degrades results, we acknowledge that other PWS devices might not suffer from hard- and software issues associated with the Netatmo PWS anemometer, which needs to be investigated in further studies. Based on the results obtained, we conclude that Netatmo PWS wind speed data are useful for urban climate research under the following conditions:

- The record is of sufficient length ( $> \approx 2$  months) to have a large amount of data and to document meaningful probability density distributions.
- The mean wind speed in this period is not low ( $>2 \text{ km}\cdot\text{hr}^{-1}$ ): inherent issues with the Netatmo hardware induces substantial errors at low wind speeds, and the output of the stations in integer  $\text{km}\cdot\text{hr}^{-1}$  only increases the relative error made.
- External WMO data of rain and humidity are available to apply the QA protocol, which filters out rain and high relative humidity ( $\text{RH} > 95\%$ ) events. Humidity impacts the sonic anemometer and reduces its quality. Humidity and rain data could also be collected from (QA-controlled) PWSs.
- The research in question is interested in the distribution of wind, rather than the wind at one given moment in time or space.

## ACKNOWLEDGEMENTS

The authors wish to acknowledge all contributors to the Netatmo web platform, without whom the vast dataset this article uses would not have existed. We thank Lotte de Vos (KNMI) for her help with the Netatmo API set-up. We acknowledge the Amsterdam Institute for Metropolitan Solutions for their financial support of the AAMS observational network. Arjan Droste and Gert-Jan Steeneveld acknowledge funding from the Netherlands Organization for Scientific Research (NWO) VIDI grant “The Windy City” (file 864.14.007). Daniel Fenner acknowledges funding from the Deutsche Forschungsgemeinschaft (DFG) under grant no. SCHE 750/15-1. Hartmut Küster, Ingo Suchland, Fred Meier, and Carl Benz are thanked for support with the comparison measurements at the Chair of Climatology at the Technische Universität Berlin.

## SUPPORTING INFORMATION

**Table S1.** Amsterdam Atmospheric Meteorological Super-site station details.

## ORCID

Arjan M. Droste  <https://orcid.org/0000-0003-0218-5160>

Daniel Fenner  <https://orcid.org/0000-0003-0967-8697>

Gert-Jan Steeneveld  <https://orcid.org/0000-0002-3365-0283>

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**How to cite this article:** Droste AM, Heusinkveld BG, Fenner D, Steeneveld G-J. Assessing the potential and application of crowdsourced urban wind data. *Q.J.R. Meteorol. Soc.* 2020;1–18. <https://doi.org/10.1002/qj.3811>