

Author's response

December 18, 2016

- 5 The discussion paper has been revised based on the comments from the reviewers and the editor. This document lists those comments, each followed by the response of the authors. This is followed by a marked-up manuscript, indicating the changes between the previous and last version of the paper. Revisions are indicated with color, where deleted and added text is indicated with respectively red and blue.
- Page and line numbers in the author's response refer to those in the marked-up version of the manuscript in this document.
- 10 Page and line numbers from the original comments referring to the previous manuscript have not been altered.

5 *REVIEWER 1: The paper discusses the advantages of crowdsourced weather station data (rainfall measurement) to obtain rainfall information suitable for hydrology studies in urban areas, i.e., rainfall measurements that the need to have high temporal and spatial resolutions. The paper is, to the best of my knowledge, the first attempt to quantify the errors of rainfall data made available from local, distributed and crowdsourced weather stations, which makes it an interesting study. In the paper the crowdsourced rainfall data are compared with dedicated rain gauges and rainfall radar data as these are the common rainfall data sources used in urban hydrology.*

10 AUTHORS: We thank the reviewer for the valuable review of this paper. We appreciate the constructive comments, and address each of them below.

REVIEWER 1: Here some suggestions:

15 (1) *Some sentences are too vague and need to be rephrased to convey a clear message: e.g., what do authors mean by “... return time of less than a few years”?*

AUTHORS: The section discussed here was intended to highlight the limitations of the filter that was used on the Amsterdam dataset. “a return time of less than a few years” refers to the return times of Dutch rainfall amounts found by Buishand and Velds (1980), Overeem et al. (2008) and Buishand and Wijngaard (2007), as documented by the latter.

20 The filter that is discussed in this section contains a dynamic maximum threshold, which filters out intervals with values higher than 50 mm h^{-1} above the median rainfall intensity of the surrounding stations. For example, in case of 10 min time series the filter works as follows; If for a certain 10 min interval the median rain intensity of surrounding stations is 4 mm h^{-1} , the upper threshold for rainfall intensity becomes 54 mm h^{-1} for this particular interval. According to the values found in the research, this corresponds with a return time between 1 and 2 years (Buishand and Velds, 1980; Buishand and Wijngaard, 2007).

25 As these return time values are different for other interval lengths and median values of surrounding stations, the statement was phrased in a general way.

30 In conclusion, realistic rainfall measurements could be excluded by the filter. We would like to stress that visual comparison with gauge adjusted radar data indicates that this was not the case for the dataset used in this paper. However, for operational application of a filter with an upper threshold, this should be taken into consideration.

Other sentences throughout the manuscript have been adjusted to make their message more clear.

35 (2) *The structure of the manuscript deserves to be revised. See for example: (a) the order figure numbers appear in the manuscript is cumbersome and makes the manuscript confusing (why Fig. 5 appears earlier than Fig. 3?)*

40 AUTHORS: In Sect. 2.1.3 the experimental set-up is described, and the reader is referred to the inset in Fig. 5 where the set-up is visualized. This reference precedes references to Fig. 3 and Fig. 4, as the results that are also visualized in Fig. 5 are discussed in Sect. 3.1. The authors acknowledge this may be cumbersome to the reader, though prefer to not split up Fig. 5 in two figures.

45 (3) *Lines 18-24 in Page 12 are not conclusions. The authors may want to move these sentences to another section of the manuscript. Also, lines 29-33 page 12 are not conclusions.*

AUTHORS: The sections that did not belong in the Conclusions section have been removed.

(4) Figure 5 does not show “a dedicated experimental set-up” (page 6, lines 2-3), i.e. the text does not match what is seen in the Figure. The authors may want to adjust the text of the Figure.

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AUTHORS: With this sentence the authors refer to the photo in Fig. 5 that shows the experimental set-up of the rain gauges. In page 6, line 22, the reference has been changed to "Fig. 5, photo inset".

(5) Figure 1. The “black dot” KNMI radar product is not visible in the plot (only in the legend). Authors may want to adjust the plot /or legend).

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AUTHORS: The symbols in Fig. 1 have been adjusted.

(6) There is room for improving the English language; incomplete sentences (e.g., Page 5, line 6) and minor typos (e.g., “criterion” should read “criterion” in Page 11, line 19) can be found in the manuscript; “CV” is only defined in Fig. 10 legend.

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AUTHORS: The overall text has been reevaluated for English language.

REVIEWER 2: Summary

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This study discusses a new technique for measuring rainfall. This consequently would satisfy the need for hydrological analyses like urban hydrology, where high temporal and spatial resolution rainfall data are required. Although several studies have addressed alternative ways for measuring rainfall such as using microwave links, this study specifically investigates rainfall information from automatic personal weather stations (PWSs) for point-measurement purposes. I found the topic quite interesting as such approaches may indeed provide valuable information.

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AUTHORS: We want to thank the reviewer for the review of this paper. We appreciate all the suggestions to improve this manuscript, and address each of them below.

30 *REVIEWER 2: General comments:*

I found the manuscript a bit hard to follow. The authors may consider the following points for improvements. The structure of the manuscript may need some modifications. For example, you may introduce the “Methodology” the “Data and study area” in separated sections, and not combined. Providing some important details would make getting the message of the manuscript easier. More information is required explaining the functionality of the devices used in this study. Although some devices do not have the sought information, providing available information, e.g. for Netatmo, would help to better follow the text. You may even add some figures for that reason. The message of some sentences is not clear. Furthermore, some sentences have minor/major language problems and/or they are too long. You may consider English proofreading. Another point is the objective of this study. The last paragraph in introduction addresses the objective of this study. You may clearly add the fact that using these measurements is economically reasonable comparing to conventional techniques. At the end I would like to add

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that there are some facts given without proper references.

5 AUTHORS: We thank the reviewer for the suggestions on how to improve the manuscript. We have reevaluated the structure of the sections in order to improve readability. It was preferred to not split up the Methodology section, and keep the division between data collection and data analysis. The text has been scanned for sentences that are unclear and/or without proper reference. The argument of the reviewer regarding the objective of this study has been added to the last paragraph of the Introduction (page 4, lines 21 -23).

10 Section 2.1.1. contains product specifications (as provided by the manufacturer) on the Netatmo rain gauge devices. More information has been provided on the data transfer between devices in a station; the rain module, i.e. the tipping gauge, communicates in a wireless manner to the indoor module over distances up to 100 m. Every 5 minutes (time step may vary) the number of tips in that interval is communicated from the indoor module to the online dashboard via a WiFi-connection. (page 5, lines 8 - 12)

15 *REVIEWER 2: Scientific comments:*

You addressed a study where they used “average value of 12 pixels”, and furthermore, you addressed the difficulties radar data have, especially when comparing to “groundbased measurements”. You used in this study 1 radar pixel as the reference at the end. You may elucidate the reason for that.

20 AUTHORS: Though radar provides rainfall estimates with a large coverage, they are indirect measurements of rainfall averages over a spatial area (pixels 0.92 km² for our C-band Doppler radar product) representative for a significant altitude above the ground (~1.5 km). Because radar measures in a volume aloft, there will always be differences with point measurements at the ground. This difference will not decrease by averaging rainfall in multiple radar pixels. Although averaging over radar pixels may smooth such an error, it also implies that rainfall from a much larger area is compared to a point measurement, which will introduce an additional difference. Figure 5 shows the scatter plots of Netatmo measurements with radar data as well as with the pit gauge reference. This figure is meant to highlight that even though the Netatmo rain gauges show good correspondence with the pit gauge reference (both are point measurements), a larger spread is found when comparing with gauge-adjusted radar rainfall. This is helpful in the interpretation of the analyses of PWS rainfall data in Amsterdam. For these time-series no ground-based point reference is available, which is why we compare with the gauge-adjusted radar data.

REVIEWER 2: Also, you may explain the method (you) used for correcting (adjusting) radar data.

35 AUTHORS: Section 2.1.2. describes the radar dataset used in this research. Data from two C-band Doppler weather radars in De Bilt and Den Helder have been adjusted with ground-based rainfall measurements. This adjustment was already done and has not been performed as part of this study. The dataset has been made available by KNMI. For information on the methods used we refer more clearly to previous research (Overeem et al., 2009a, b, 2011) in Sec. 2.1.2 (page 6, line 15).

40 *REVIEWER 2: The same is valid for the experimental set-up. You may add how exactly the reference device “KNMI pit gauge” measures rainfall.*

AUTHORS: The KNMI pit gauge has been introduced in Sect. 2.1.3., which also includes information on the pit gauge configuration. It is an electronic rain gauge, measuring cumulative rainfall every 12 s. A potentiometer connected to a floating unit measures the amount of liquid water. A heating element makes it possible for the device to accurately measure solid precipita-

tion.

REVIEWER 2: I could not really understand the reason why you used Pearson correlation coefficient for your analyses. You may add some other criteria like bias, root mean square error, etc.

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AUTHORS: The Pearson correlation coefficient is a widely used statistic to describe correspondence between rain gauge measurements, in order to characterize the complex spatial structure of rainfall patterns. The dependence of the Pearson correlation coefficient with distance between gauges has been evaluated Habib et al. (2001), Krajewski et al. (2003), Ciach and Krajewski (2006), Villarini et al. (2008), Tokay and Öztürk (2012) and Peleg et al. (2013). In order to compare with results in these papers, a similar method was chosen.

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Figure 6 describes the accumulation interval dependence of the correlation between gauges and the pit gauge reference. The same figure has been made for the coefficient of variation (CV) of the residuals. The CV values decrease with increasing accumulation interval where they approach zero (indicating a perfect match) at 15 minute intervals. The values of the Wunderground timeseries approach zero at a slower pace than the Netatmo original data. As this CV -analysis did not provide any additional information beyond that communicated by Fig. 6, it has not been included in the manuscript.

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The Pearson correlation coefficient and the CV give information on the random error. Figure 5 and Fig. 7 give information on the bias.

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REVIEWER 2: Regarding the “inter-station correlation”, you may add the way you estimated the parameters.

AUTHORS: The parameters in Fig. 12 have been determined by fitting Eq. (2), where the correlations between stations and the inter-gauge distances were used as input. Fitting was done by determining the nonlinear (weighted) least-squares estimates of the parameters. This will be included in Sect. 3.4 (page 11, lines 14-15).

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REVIEWER 2: Some of the specific comments for the abstract and introduction section is provided in the following:

P.1 - L.7: are you referring by “63 stations” to the Netatmo network in Amsterdam?

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AUTHORS: The 63 stations do not exclusively refer to Netatmo stations. Figure 2 shows which of these stations are of type Netatmo (square symbols) and which are of other types (triangle symbols). The time-series are obtained from the Wundermap website, as described in detail in Sect 2.1.1.

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REVIEWER 2: P.1 – L.10: “the method of data transfer to the online platform causes considerable errors in the datasets obtained.” This phrase may need some modifications.

AUTHORS: The sentence will be rephrased in “The sensor performance in the experimental set-up and the density of the PWS-network are promising. However, features in the online platforms cause changes in the time-series, resulting in considerable errors in the datasets obtained.” (page 1, lines 9-11)

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REVIEWER 2: P.1 – L.16: Does “data conversion” refer to “data transfer” you provided some lines earlier? The word “conversion” sounds a bit strange in this context.

5 AUTHORS: This refers to adjustments made to the measurement time-series by features of the online platforms. Data conversion occurs within the data transfer. This has been rephrased in order to avoid confusion.

REVIEWER 2: P.2 – L.3: Why “Rainfall” starts with capital letter? And “from the radar”; you may change to “from the radar station”.

10 AUTHORS: This should indeed not be a capital. “from the radar” was changed into “from the radar station” as suggested (page 2, line 7).

REVIEWER 2: P.2 – L.4: “and which may..” I suppose one may not put “and” and “which” together.

15 AUTHORS: This has been corrected.

REVIEWER 2: P.2 – L.7: Does “spatial resolution” mean “network density”?

20 AUTHORS: Spatial resolution is directly related to network density, only if all stations in the network are measuring constantly. In most PWS-networks, spatial resolution is lower than the actual network density because of station outages and periods of fewer measurements in time.

REVIEWER 2: P.2 – L.10: You may add a comma after “Hydrological models” and a comma before “have minimized”.

25 AUTHORS: This has been corrected.

REVIEWER 2: P.2 – L.15: What is the spatial resolution of 3 km? Is it a 3 km x 3 km?

30 AUTHORS: A spatial resolution of 3 km generally corresponds with a 3 km x 3 km square. Here it means that measurements are taken on average 3 km apart. For crowdsourced measurements, the inter-gauge distance is likely to vary slightly, as the placement of stations is irregular and not in a regular grid.

REVIEWER 2: P.2 – L.21: Bruni et al. (2015) “addressed”.

35 AUTHORS: All the tenses in the document regarding such references to literature have been changed.

REVIEWER 2: P.2 – L.24: When explaining “Smearing”; “the ratio of the resolution”: are you referring to temporal, spatial or tempo-spatial resolution?

AUTHORS: Here we refer to spatial resolution ratios. This has been clarified in the text, as well as the highest resolution of the radar data (page 2, lines 25-31).

REVIEWER 2: P.2 – L.30: *Ochoa-Rodriguez et al. (2015) “evaluated the”*

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AUTHORS: This has been corrected.

REVIEWER 2: P.2 – L.31: *You may add a comma after “1 km” and a comma before “was found”.*

10 AUTHORS: This has been corrected.

REVIEWER 2: P.2 – L.34: *Not all radar products are in 5 min temporal resolutions. Some X-Band radars work in 30-sec temporal resolution.*

15 AUTHORS: The phrase will be changed to “Temporal resolutions should ideally be below the 5 min intervals currently available in most operational weather radar-products,” (page 3, line 5).

REVIEWER 2: P.2 – L.35: *“impact on the accuracy than coarsening spatial scales does.” I would change the word scale to “resolution”. Furthermore, you may omit “does” at the end of the sentence.*

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AUTHORS: This has been corrected (page 3, lines 7-8).

REVIEWER 2: P.3 – L.2: *“evaluate” to “evaluated”. You may rephrase the entire sentence.*

25 AUTHORS: This has been corrected.

REVIEWER 2: P.3 – L.9: *What type of sensors are you referring to? Rain gauges?*

AUTHORS: The sensors we refer to are any type of sensors that measure rainfall. We will clarify this in our revised manuscript.

30 This could be rain gauges, though it could also refer to disdrometers (page 3, line 17).

REVIEWER 2: P.4 – L.10: *But you did not investigate for any urban applications. Your study area is located in an urban area.*

AUTHORS: The existing PWS-network is tested on the demands specified in the literature for urban hydrological applications.
35 The required spatial and temporal resolutions of measurements are considered. Based on the number of stations and frequency of data upload, the resolution approached the required values stipulated in literature. However, there were errors in the datasets originating from data transfer as well as other sources. These errors can be compensated by averaging rainfall measurements in space and time. This decreases the effective resolutions of the network.

ADDITIONAL AUTHOR'S COMMENTS:

5 In the previous version of the manuscript some conclusions were made regarding processing errors in obtaining data via the Netatmo Weathermap platform, that later proved to be due to a faulty API. Also, it was found that the original Netatmo time-series were not only available in real-time via this platform, but also as historic data. The conclusions in the manuscript have been adapted according to this new information, in the last alinea of section 3.1 (page 9, lines 13-34), and the Conclusions section (page 15, lines 1-5).

10 Figure 4 was made with an analysis that included some faulty assumptions. The figure has been corrected, this time with the original unfiltered data. In order to avoid confusion the points that indicate on which dt and dx combinations the fraction calculation has been performed were excluded. The overall conclusions from the figure have not been changed dramatically, though now they make more sense as they include some temporal dependence at short time steps.

15 Figure 12 has been made, with thicker dotted lines to improve readability.

References

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The potential of urban rainfall monitoring with crowdsourced automatic weather stations in Amsterdam

Lotte de Vos^{1,2}, Hidde Leijnse², Aart Overeem^{1,2}, and Remko Uijlenhoet¹

¹Hydrology and Quantitative Water Management Group, Department of Environmental Sciences, Wageningen University, 6708 PB Wageningen, the Netherlands

²Research and Development Observations and Data Technology, Royal Netherlands Meteorological Institute, 3732 GK De Bilt, the Netherlands

Correspondence to: lotte.devos@wur.nl

Abstract. The high density of built-up areas and resulting imperviousness of the land surface makes urban areas vulnerable to extreme rainfall, which can lead to considerable damage. In order to design and manage cities to be able to deal with the growing number of extreme rainfall events, rainfall data is required at higher temporal and spatial resolutions than those needed for rural catchments. However, the density of operational rainfall monitoring networks managed by local or national authorities is typically low in urban areas. A growing number of automatic personal weather stations (PWSs) link rainfall measurements to online platforms. Here, we examine the potential of such crowdsourced datasets for obtaining the desired resolution and quality of rainfall measurements for the capital of the Netherlands. Data from 63 stations in Amsterdam (~575 km²) that measure rainfall over at least 4 months in a 17-month period are evaluated, **in addition to** . **In addition**, a detailed assessment **that** is made of three Netatmo stations, the largest contributor **of the to this** dataset, in an experimental set-up. **Although the** **The** sensor performance in the experimental set-up and the density of the PWS-network are promising, **the method of data transfer to the online platform causes** . **However, features in the online platforms, like rounding and thresholds, cause changes from the original time series, resulting in** considerable errors in the datasets obtained. These errors are especially large during low intensity rainfall, although they can be reduced by accumulating rainfall over longer intervals, **improving the correlation** . **Accumulation improves the correlation coefficient** with gauge-adjusted radar data from 0.48 at 5 min intervals to 0.60 at 15 hourly intervals. Spatial rainfall correlation functions derived from PWS data show much more small-scale variability than those based on gauge-adjusted radar data and those found in similar research using dedicated rain gauge networks. This can largely be attributed to the noise in the PWS data resulting from both the measurement setup and the **data conversion by the processes occurring in the data transfer to the online PWS-platform**. A double mass comparison with gauge-adjusted radar data shows that the median of the stations resembles the rainfall reference better than the real-time **available** (unadjusted) radar product. Averaging nearby raw PWS measurements **already further** improves the match with gauge-adjusted radar data in that area. **The These** results confirm that the growing number of internet-connected PWSs **holds a promise could successfully be used** for urban rainfall monitoring.

1 Introduction

Urban catchments are characterized by a high proportion of impervious surfaces, leading to a large fraction of rainfall producing direct runoff and a fast hydrological response. This makes cities especially vulnerable to flooding. The temporal and spatial resolutions of rainfall data required for urban applications exceed those needed for rural catchments (Schilling, 1991).

- 5 The rainfall information at spatial and temporal resolutions of typically 1 km by 1 km and 5 min generated by **weather radar most operational weather radars** is considered valuable for urban hydrological analysis, **and even and** forecasting (Liguori et al., 2012). However, radar has significant limitations; **Rainfall rainfall** is determined indirectly, over an atmospheric volume with a size depending on the distance from the radar **and station**, which may not be representative for rainfall at ground-level (Einfalt et al., 2004; Peleg et al., 2013). Errors in rainfall estimates from radar due to sampling uncertainties can be significant.
- 10 In addition, there is an optimum **in** spatial resolution corresponding to a given temporal resolution (Fabry et al., 1994; Bell and Moore, 2000). Rain gauges, if well maintained, provide accurate ground-based measurements, although they are limited in their spatial representation. ; Villarini et al. (2008) showed that approximations of true **rainfall spatial rainfall fields** with rain gauges requires a dense network and/or large temporal measurement intervals.
- 15 Hydrological models, designed to deal with high resolution input **have minimized rainfall accumulation errors**, **provide the best simulation results** not just when the temporal resolution or the spatial resolution is high, but particularly when the combination thereof is optimal. The required spatio-temporal resolutions for urban applications have been studied extensively. Berne et al. (2004) determined a relation between the space-time resolution required for hydrological applications as a function of the catchment size for Mediterranean conditions. It was found that for urban catchments in the order of 10 km², rainfall data is
- 20 needed at a temporal resolution of 5 min and a spatial resolution of 3 km. For urban catchments of 1 km² these resolutions were 3 min and 2 km, respectively. The **space-time** scales of four types of rainfall are evaluated by Emmanuel et al. (2012). With the use of variograms of 24 storm events, the **required spatial resolution spatial resolutions** required to capture these types of rainfall at urban **scale scales** range from 0.8 to 3 km for instantaneous monitoring and from 2.5 to 8 km for 30 min intervals.
- 25 Gires et al. (2012) found **a catchment an** outflow uncertainty of up to 20% **in an urban catchment of 9km²** due to rainfall variability at **smaller scales than scales smaller than the** typical C-band radar resolution of 1 km by 1 km and 5 min. Bruni et al. (2015) **address addressed** the loss in urban hydrodynamic model accuracy due to smoothing and smearing **in an analysis of radar data from** . Radar data of 4 **different storms in storm events in 1 min temporal resolution** were aggregated to various **spatial and temporal resolutions (highest range resolution of 30 m) and used as precipitation input in** a 3.4 km² Dutch urban
- 30 catchment. Smoothing occurs when the ratio of radar resolution over catchment size becomes larger than 0.2 and storms that move near the catchment boundary are averaged partly out of the catchment. Smearing becomes significant when the ratio of the **spatial** resolution of radar measurements over the rainfall correlation length exceeds 0.9, leading to averaging of rainfall over the coarse spatial grid and resulting in underestimation of rainfall rates in areas **in within** the storm cells and overestimation in the surrounding areas. Also, a runoff peak time shift of up to 6 minutes was found due to temporal aggregation (from 1

minute to 5 and 10 minutes) of rainfall input.

Ochoa-Rodriguez et al. (2015) evaluate evaluated the required spatial and temporal resolutions of rainfall in a simple spatio-temporal scaling framework. A spatial resolution of 1 km, typically found in radar, was found to give good hydrodynamic model results, although some extremes will be were missed. Temporal resolutions should ideally be below the 5 min intervals currently available in most operational weather radar-products, although . Nevertheless, the accuracy of 5 min radar data accuracy can be improved with the use of an accumulation procedure that assumes constant velocity of the rainfall field and rainfall intensity to vary linearly in time (Fabry et al., 1994). Coarsening temporal scales resolution has more impact on the accuracy than coarsening spatial scales does resolution. Initial results from an ongoing study by the authors indicate that this impact is reduced when temporal resolutions are coarsened through aggregation (i.e. similar to rain gauges) instead of sampling. Lobligois et al. (2014) evaluate in which circumstances evaluated the circumstances where hydrological model performance is enhanced by higher spatial resolution of rainfall. They did so by comparing lumped and semidistributed models with subcatchment sizes of 64, 16 and 4 km². From comparisons between the various model outputs and observations in 181 catchments in France, it was found that model accuracy improvement depends on scale, catchment and event characteristics, and that the spatial representation of rainfall can be a highly important factor in the model performance.

From these works it becomes evident that an increase of the number of measurements would yield a higher accuracy of rainfall fields and would improve hydrological applications. Adding sensors (rain gauges or others) to a network is costly, although there are alternatives. For instance, rain maps can be produced from received signal strength in cellular communication networks, as the microwave signals transferred over the linkpaths propagating over the link paths are attenuated by rainfall (Overeem et al., 2016). Weather data can also be provided directly by crowdsourcing measurements from amateurs in various ways (Muller et al., 2015). A growing number of weather enthusiasts measure their local weather with automatic personal weather stations (PWSs). PWS accuracy on measuring temperature, relative humidity, radiation, pressure, rainfall, wind speed and direction has been evaluated for popular high-end expensive weather stations (Jenkins, 2014; Bell et al., 2015), as well as for the cheaper, user-friendly Netatmo type (temperature only) (Meier et al., 2015), which have grown rapidly in number over the past years. So far, weather stations have been used to obtain air temperature data to examine the Urban Heat Island effect (Steenveld et al., 2011; Wolters and Brandsma, 2012), although other meteorological variables, such as rainfall, are measured by some of these stations as well.

A large number of PWSs share data on online platforms, both on the owner's own initiative (Gharesifard and Wehn, 2016) or automatically as an intrinsic software feature of the product (i.e. for Netatmo). Netatmo has its own online platform collecting and visualizing data from all operational Netatmo stations. The Wundermap of company Weather Underground is a similar online platform. Data from Netatmo stations are automatically linked to the Wundermap, and owners . Owners of other PWS-types can actively transmit their measurements to this platform themselves as well. A growing number of automatic weather stations are linked to these platforms; in May 2016 there were 258 personal weather stations linked to Wundermap

in the Amsterdam metropolitan area (~575 km²) alone (239 of type Netatmo), of which 83 stations measured rainfall (64 of type Netatmo). By contrast, the official national automatic weather station network in the Netherlands (~35,000 km²) consists of 31 stations, and these are, as a rule, always located outside of urban areas. Figure 1 shows the relative resolutions in the Netherlands of networks discussed in this paper. At many locations, the density of PWS-stations collecting rainfall data far exceeds that of any realistic operational network implemented by national weather services or local authorities beyond experimental campaigns. As the online platforms collecting and sharing PWS weather data are not nation-bound, global rainfall measurements have become easily available, with especially high densities in Western-Europe, USA and Japan.

Although rainfall data availability with PWS-networks is cause for optimism for urban hydrological applications, errors are expected to be larger than those in traditional measurements. PWSs come in many types, a large fraction of which are low-cost with expected low sensor quality. In most cases there is no information available on the PWS type, the installation set-up, maintenance of the sensor, or data post processing while transferring measurements to the online platform. Bell et al. (2013) examine the potential improvement on the UK's observational network with the real-time and local weather measurements of air temperature, relative humidity and pressure collected from Wundermap, where the . The most critical issue was found to be the estimation of data-quality data quality. Validation procedures like range tests (i.e. a check whether the measurement is within predefined extremes limits) and internal consistency tests should be applied to precipitation data from automatic weather stations (Estévez et al., 2011). Integrating The integration of crowdsourced data with variable temporal resolutions in hydrological monitoring systems discharge modeling by accounting for different uncertainties for data of various sources is already has been addressed in recent research (Mazzoleni et al., 2015).

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It becomes clear that urban applications would benefit from high resolution rainfall measurements. The potential of crowdsourced PWS rainfall data for this purpose has not previously been explored. Using the existing PWS-network requires minimal financial investment, and would therefore be an economically reasonable alternative to conventional techniques to increase measurement resolutions. This study aims to determine the added value of crowdsourcing automatic weather stations for urban rainfall monitoring. For this purpose the most common PWS is tested in an experimental set-up with a high quality rain gauge reference. Additionally, a dataset of 63 crowdsourced PWS stations in Amsterdam is validated with a gridded dataset based on radar data, a manual network and a WMO certified automatic rain gauge network. These combined results provide insight in the rainfall measurement accuracy of the most commonly used PWS, as well as any issues that occur in operational crowdsourcing of PWS rain measurements. Following this Introduction is the Methods section, where Sect. 2.1 describes the data and Sect. 2.2 gives an outline to determine the achieved measurement scales and quality of PWS, respectively. The results of an experimental PWS set-up, a comparison of a larger dataset in Amsterdam with gauge-adjusted radar data, and an analysis on inter-gauge spatial correlation of this dataset are given in Sect. 3. Finally, a Discussion on the state and future role of PWS networks in (urban) hydrological applications and Conclusions are given in Sect. 4 and Sect. 5, respectively.

2 Methods

2.1 Data collection

2.1.1 Personal weather stations

From the Wundermap website, a dataset of 63 automatic weather stations located in the Amsterdam area (~575 km²) has been retrieved. Stations were selected based on the availability of rainfall measurements, which should cover at least 4 months between December 2014 and April 2016. Of these stations, 49 are of brand Netatmo, 7 are of brand Davis, and 7 are of other unspecified brands. No details on the devices are given. According to the product specifications provided by the manufacturer, the Netatmo rain gauges have a measurement range of 0.2-150 mm h⁻¹ with an accuracy of 1 mm h⁻¹. The plastic tipping buckets have a volume of 0.1 mm and a collecting funnel with a diameter of 13 cm. The network is rain gauge module communicates in a wireless manner to the Netatmo indoor module over distances up to 100 m. The number of tips in the previous interval is communicated every ~5 minutes from the indoor module to the online dashboard via a WiFi-connection, where it can be monitored by the weather station owner. Simultaneously, the measurement is linked to the Netatmo Weathermap from which it is sent every ~10 minutes to the Wundermap. The Wundermap stations that contribute to the dataset are visualized in Fig. 2. The Wundermap platform collects the rainfall measurements and rewrites them into rainfall over the past hour and cumulative rainfall for that day. Daily rainfall only becomes non-zero once the 0.3 mm threshold is reached and subsequent rainfall is only reported if the rounded daily rainfall increases by at least 0.2 mm.

While Netatmo hardware can store measurements for a period of time in case of bad connectivity with the server, only real-time available data is automatically transferred to the Wundermap. This causes gaps in the Wundermap datasets where there may be none in the original Netatmo data, which are only accessible to the weather station owner. Wundermap time series are therefore characterized by characterized by (large) gaps in the dataset and irregular measurement frequencies, though often 5, 10 or 15 minutes, and (large) gaps in the dataset. Also, the locations of Netatmo weather stations on the Wundermap are obtained from the settings at the Netatmo platform without notice to or confirmation from the PWS owner. Relocations of the station that are communicated to the Netatmo platform are not simultaneously adjusted on the Wundermap, leading to potentially potentially leading to large errors in sensor location.

We process the data obtained via Wundermap by calculating the difference in cumulative daily rainfall compared with the previous time step. Since these time steps are not fixed, this results in rainfall accumulations over time intervals of varying lengths. In order to obtain compatible time series, the rainfall is interpolated on a fixed time-line with constant steps, where constant rainfall within the original intervals is assumed. Original intervals longer than 20 min are discarded. Faulty values in precipitation data from automatic weather stations can be identified with range tests and internal consistency tests (Estévez et al., 2011). As a first quality check, values of the interpolated time series are compared with the median rainfall of all stations for each time interval. Values exceeding this median by more than 50 mm h⁻¹ are excluded. Dry periods in the dataset are

identified as periods of at least 24 hours where the median of all PWS measurements indicate zero-rainfall zero rainfall. If a PWS reports continuous zero-rainfall zero rainfall for at least 12 hours outside of this dry reference, the dry period is measurements in this dry period are considered as faulty dry measurements and is zero rainfall measurements and are discarded. Finally, inter-gauge correlations are determined. If a low correlation (i.e. average and median < 0.21) is found between a station and all other stations the entire time series for that station is excluded. Visual comparison with corresponding radar rainfall time series showed that the filter that selected the data a filter based on these criteria , was suitable in excluding obviously incorrect data from the datasets. This filter could be applied in real-time, although for operational uses outside of beyond this dataset, adjustments are will be required.

2.1.2 Radar

As rainfall reference we use gauge-adjusted radar data from a climatological rainfall dataset by the Royal Netherlands Meteorological Institute (KNMI) (Overeem et al., 2009a, b, 2011), freely available via as "Radar precipitation climatology" via <http://climate4impact.eu>. This dataset is based on data from two C-band Doppler weather radars in De Bilt and Den Helder, has a temporal resolution of 5 min and a spatial resolution of 0.92 km², covering the entire land surface of the Netherlands. Radar This radar makes volumetric scans in all directions, measuring instantaneous rainfall at a location every 5 minutes. In this product, radar composite images have been adjusted with rainfall measurements from the KNMI rain gauge networks (31 automatic and 325 manual gauges). For details on the method of adjusting, we refer to Overeem et al. (2009a, b, 2011). It should be noted that, due to their different representativeness, there can be significant differences between radar pixel areal rainfall and point rainfall (Schilling, 1991; Einfalt et al., 2004; Villarini et al., 2008; Peleg et al., 2013). As this radar product Using a radar product that is adjusted with ground measurements, this difference is likely to be reduced will likely reduce this difference.

2.1.3 Netatmo experimental set-up

As the majority of the weather stations linked to the Wundermap are is of type Netatmo, we examine the quality of Netatmo rain gauges in a dedicated experimental set-up (Fig. 5, photo inset). As reference we use a high quality KNMI pit gauge at the Cabauw Experimental Site for Atmospheric Research (CESAR) (Leijnse et al., 2010), that measures cumulative rainfall in intervals of 12 seconds. This electronic rain gauge is placed in a so-called pit gauge configuration; : a small hill of diameter 6.2 m with a circular pit with diameter 3 m and a depth of 40 cm in the middle. Precipitation is collected in the instrument (collecting funnel with a diameter of 16 cm, i.e. 200 cm²) and in case of solid precipitation melted by a heating element in the funnel. The amount of liquid water is measured by the position of a floating unit connected to a potentiometer. Rainfall is measured every 12 seconds within the range of 0-0.7 mm , with a resolution of 0.1 mm and an accuracy of 0.2 mm. The Netatmo sensors are placed at ~40 cm around the electronic sensor in the center of the pit in such a way that the top of each sensor is level with the edges rim of the pit. The period considered is from February 12th to May 25th 2016. The datasets as collected directly from the Netatmo personal account in mm rainfall per interval of typically 5 minutes, as well as via the

Wundermap platform, are compared to the pit gauge reference. One of the stations was offline between April 20th and May 1st and one station could not be accessed via Wunderground.

2.2 Analysis

2.2.1 Station measurement density

5 As mentioned previously, the original PWS data temporal resolution from Wundermap is quite irregular. Figure 3 shows time series with time steps of The number of stations containing rainfall measurements for time series per 5 and 10 minutes where the number of stations containing rainfall values (smoothed to daily averages) are represented. From the figure it becomes evident shows that the data availability is quite variable . (Fig. 3). Moreover, the fraction of the measurements over the period that is filtered out does not seem to vary significantly in time. Figure 4 shows the fraction of total pixels covering Amsterdam with a certain pixel size and time step It is not straightforward how to attribute a certain measurement resolution to a network that has highly irregular measurement frequencies and station locations at irregular distances from one another. When the Amsterdam area is divided into grid cells, or pixels, of a certain size, the number of pixels that contain at least one measurement is an indication of the network resolution. The fraction of total pixels that contain at least one measurement has been calculated for all time steps over the entire period. This figure shows clearly that for this dataset , increasing the frequency of measurements of , for various combinations of pixel sizes and time step lengths in the scale range relevant for urban applications. It is found that for the Amsterdam dataset (before filter has been applied), the PWSs will yield a far smaller improvement in resolution than an increase in the number of measurement locations. As the current number of operational PWSs is larger than the examined dataset and growing, the data resolution from the PWS network is likely to improve significantly fraction of pixels containing at least one measurement is more limited by the number of stations than the measurement frequency (Fig. 4). Only when dividing the period in time steps shorter than 10 minutes, an increase of measurement frequency will result in a higher fraction. This is unsurprising as most stations in the dataset link their measurements to the Wunderground platform approximately every 10 minutes. Adding stations will result into an increase in fraction at all time step sizes in this range. The PWS network consists of more stations than the number examined in this dataset, and continues to grow, which will have a positive effect on the PWS network measurement resolution.

25 2.2.2 Station measurement quality

With the Netatmo experimental set-up, the performance of this type of PWS and the consequences of transferring its data to the online platform are examined. The measurements are compared to the high resolution pit gauge as well as to the radar rainfall at the corresponding pixel. These two comparisons should give an indication of the differences due to sensor performance and those due to differences in representativeness of radar and rain gauges.

30

Rainfall measurements of the PWS dataset in Amsterdam are compared with the radar rainfall measurement at their corresponding radar pixels. When comparing station data with gauge-adjusted radar data, the coefficient of variation of the residuals

(CV) is calculated. The standard deviation of the differences between the datasets is divided by the mean of the gauge-adjusted radar data. A low value of CV indicates a good match between the datasets. Additionally, spatial correlations between stations are estimated with the use of Pearson's product-moment correlation coefficient (rr):

$$r = \frac{E[XY] - E[X]E[Y]}{\sqrt{(E[X^2] - E[X]^2) \cdot (E[Y^2] - E[Y]^2)}} \quad (1)$$

- 5 where $E[\cdot]$ is the expectation (estimated as the arithmetic mean) and (X, Y) are corresponding time series of rainfall measurements. Because of the spatial and temporal variability of rainfall, the correlation of two point-locations decreases with distance between these points. A three-parameter exponential function is suggested by Habib et al. (2001) to describe this spatial dependency relation between inter-station correlation (r) and distance (d):

$$r = r_0 \exp \left[- \left(\frac{d}{X_0} \right)^{S_0} \right] \quad (2)$$

- 10 where r_0 is the nugget parameter, X_0 is the correlation distance and S_0 is the shape factor. The nugget parameter r_0 is a measure of small scale variability and/or measurement error and is equal to 1 for perfect zero-distance correlation. Correlation distance X_0 indicates the distance at which the rainfall decorrelates (i.e. the distance beyond which the correlation drops below e^{-1}), which should be interpreted with caution when exceeding it exceeds the investigated spatial extent.

- 15 The relationship in Eq. (2) is sensitive to rainfall extremes (Habib et al., 2001), climatic regimes (Krajewski et al., 2003) and seasonality (Van de Beek et al., 2011; Tokay and Öztürk, 2012) as well as strongly dependent on time interval (Krajewski et al., 2003; Ciach and Krajewski, 2006; Van de Beek et al., 2011; Tokay and Öztürk, 2012; Van de Beek et al., 2012; Peleg et al., 2013). For the PWS-dataset in Amsterdam, correlograms are constructed and compared with spatial dependencies found in literature. Special consideration is given to the correlations between Netatmo stations as compared to the other types of rain
20 gauges.

3 Results

3.1 Netatmo comparison with pit gauge

- The original data of three Netatmo stations (measurement frequency of ~5 min) are compared with pit gauge data (measurement frequency of 12 s) and gauge-adjusted radar data (measurement frequency of 5 min), over the period February-May 2016.
- 25 **Figure 5 shows Over this period, the cumulative rainfall by each, as well as scatter plots of rainfall in 10 minute intervals. The large cumulative differences in N2 and W2 as compared to the other graphs are the of station 2 was lower than that of the others (Fig. 5, left panel). This was the result of station outage, although . In general, the Netatmo stations measure less rainfall in general than the pit gauge and radar reference over this period. The scatter plots are not influenced by station outage(Fig. 5, right panel) do not include the intervals where one or both of the time series contains no measurements (in case of station outage), and show a good r^2 of 0.94 between Netatmo measurements and the pit gauge reference. Even though this r^2 suggests**
- 30

a small measurement error in Netatmo, the comparison with radar shows significant scatter away from the perfect fit. This is inherent to comparisons between point locations and pixel averages, and the scatter plot resembles those reported in Peleg et al. (2013), though the radar value used there was an average value of 12 pixels instead of 1.

5 The correlation between Netatmo and the **electronic rain pit** gauge is calculated for a multitude of accumulation intervals (Fig. 6). This correlation reflects small-scale rainfall variability and thus is closely related to the nugget parameter in Eq. (2). As expected, an increase of correlation is found for larger accumulation intervals. However, the correlations of data from the same devices obtained via Wundermap with the same **reference shows pit gauge reference show** far lower values, see Fig. 6. The original Netatmo data **from the personal account** has typical time steps of 5 min against 10 min for the Wundermap data. If
10 this was the only difference between the time series, the correlation graphs should overlap for accumulation intervals above 10 min. As they only approach one another for hourly accumulations, it can be concluded that besides this effect, additional information is lost in the transfer of data between platforms.

**In this study, the daily cumulative rainfall values from Wundermap are rewritten as the difference in rainfall as compared to
15 the previous timestep. As Wundermap cumulative daily rainfall can only become non-zero when at least 0.3 mm rainfall has been collected, and later increases are only registered if they amount to at least 0.2 mm, large differences with the original time-series are caused. Especially in case of light rain, rainfall could occur for a longer period than the interval length in which the daily cumulative rainfall increases. The rainfall is then attributed to a single interval period instead of all previous intervals in which it may have been raining too. This will lead to significant differences in datasets originating from the same sensor,
20 especially during the homogeneous light rainfall typical for Dutch winters.**

**Rainfall values from Netatmo stations can also be obtained with API Besides the Netatmo dashboard (available to the station owner) and Wundermap, Netatmo data is also accessible from the Netatmo platform in daily accumulations of 10 min frequency. The same procedure as with the Wundermap platform data can be applied, which showed no such rounding occurring in this data-transfer. As cumulative rainfall can vary with steps of 0.1 mm, it is expected that more accuracy is retained. Netatmo platform datasets during April 2016 of the three experimental Netatmo stations , as well as a set of Netatmo stations in
25 Amsterdam were examined. In these time series the time Weathermap platform. In this research, real-time measurements from the three stations in the experimental set-up were obtained with from this platform with an API. It was found that rainfall measurements from this dataset were attributed with a time stamp of the measurements seemed to be related to the measurement collection time at the platform moment the data was collected, instead of the measurement time of the sensor, and in time stamp
30 of the measurement itself. In case of sensor outage, the last available measurement was collected repeatedly. These artifacts result resulted in faulty interval attribution of rainfall and negatively affected the correlations with the original dataset (in case of the experimental stations) as well as with gauge-adjusted radar data. An API containing such processing errors will result in datasets that contain considerable errors, though these errors are easily overlooked without the original data. Fortunately, the original data can also be obtained from the Netatmo platform. These time series are identical to the data from the Netatmo
35 dashboard (N1, N2 and N3 from the experimental set-up) and can be obtained in real time.**

3.2 Amsterdam weather station comparison with radar

Figure 7 shows the double mass plot of the filtered PWS dataset in Amsterdam, as well as the unadjusted (real-time) radar with the gauge-adjusted radar reference, where the at the same locations. The only intervals considered are those where both time series contain measurements. Even though individual stations often do not follow the diagonal line representing a perfect match, the median of all available stations only shows a slight underestimation as compared to the gauge-adjusted radar rainfall data. This underestimation is far greater in the radar product that would be (almost) real-time available real-time radar product. Though large deviations occur, the median of the stations resembles the reference quite well.

The scatter density plots in Fig. 8 show the correspondence of When comparing station rainfall against corresponding gauge-adjusted radar rainfall data over the entire period for time steps of 5, 30 and 60 minutes during periods where the with the condition that the radar measures non-zero rainfall. , a better correspondence is found for longer time steps (Fig. 8). A similar scatter as in Fig. 8 is found in Peleg et al. (2013). Not unexpectedly, the amount of scatter decreases for larger time steps. by Peleg et al. (2013). At longer accumulation intervals, the averages resemble each other more, the CV decreases and the r increases, indicating a better resemblance between gauge adjusted radar and station datasets.

3.3 Amsterdam center average comparison

In order to investigate whether the generally poor quality of individual PWS measurements can (partly) be compensated by the generally high quantity of measurements, averages of unfiltered PWS measurements are compared with radar pixel averages in over a small area in Amsterdam. The selected area is the region with highest parking rates; the densely populated and touristic area of the city center and Museum square, as floods in this area will heavily impact residents, businesses and tourism alike. This region of $\sim 20 \text{ km}^2$ is shown in Fig. 9, where the cumulative rainfall of each station relative to the mean of the 12 stations is shown. From Fig. 9 the variation between station measurements becomes evident, as well as the stations measuring. Some stations measure highly unlikely values considering their nearby measurements the measurements of their nearby stations, such as station 3, 9 and 12.

The means of various all possible subsets of the 12 PWSs are compared with the average of the 20 radar pixels over the selected Amsterdam center region. For each subset, the correlation, standard deviation and coefficient of variation of the residuals (CV) of rainfall intensity is calculated over all intervals where each station contains measurements. The resulting values outcomes of each subset are represented with boxplots in Fig. 10 per number of stations contributing to the PWS-mean. Figure 10 shows that the The correlation increases and the standard deviation and CV CV decrease when averaging multiple stations, even when some of the station time series consist of obviously faulty measurements. (Fig. 10). By averaging the unfiltered measurements of a dozen stations, crowdsourced measurements turn out seem to be able to describe rainfall in the city center. As expected,

the values based on 60 minute rainfall intensities show a better correspondence with gauge-adjusted radar data than 5 minute rainfall intensities.

3.4 Amsterdam weather station spatial correlations

Rainfall variability is often described with correlograms, see Sect. 2.2.2, describing Pearson's product-moment correlation between station pairs as a function of distance. Figure 11 shows the correlograms for the PWS-dataset, where the inner 50 percentiles of those scatter points related to Correlograms of PWS-data at longer accumulation intervals show higher inter-station correlations between Netatmo stations are indicated in red, and those between non-Netatmo stations are indicated in blue and the decrease with distance is not as steep (Fig. 11), similar to the results reported by Villarini et al. (2008), Peleg et al. (2013) and Tokay and Öztürk (2012). Especially in winter (Fig. 11, upper panels) and for short accumulation intervals, the non-Netatmo pairs show higher correlation with one another. For longer accumulation intervals, inter-station correlations are higher and the decrease with distance is not as steep, similar to the results reported However, the goodness-of-fit of the correlograms differs significantly than those found by Villarini et al. (2008), Peleg et al. (2013) and Tokay and Öztürk (2012). However, the goodness-of-fit of the correlograms differs significantly.

The correlations of all station pairs in the dataset are fitted with the relation in Eq. (2). Fitting was done by determining the nonlinear (weighted) least-squares estimates of the parameters with the Gauss-Newton algorithm. The resulting parameters for the total dataset, as well as winter and summer individually, are given in Fig. 12. The graphs for winter show the most deviating response, suggesting irregularities in this subset in particular. The nugget parameter r_0 of the total dataset varies between 0.50 and 0.67 for this accumulation interval range. Villarini et al. (2008) finds found a similar nugget parameter of 0.51 for 1 minute accumulations, though far larger values at higher accumulation intervals. The nuggets found by Krajewski et al. (2003), : 0.95-0.97 for 15 minutes and longer, Ciach and Krajewski (2006), : 0.995 and higher for 1 minute and longer, Tokay and Öztürk (2012), : 0.97 and higher for 5 minutes and longer and Peleg et al. (2013), : 0.92 and higher from for 1 minute and longer, are all considerably higher than the nugget parameters found here. This is unsurprising not surprising as the gauges in the networks evaluated in those papers are carefully controlled and of higher sensor quality than typical PWSs.

The correlation distance of the total PWS dataset increases with interval size in a similar manner as in previous research (Fig. 12). The erratic response of the winter graphs suggests a poor fit resulting from other factors than rainfall variability. Likely the correlation distance of stratiform winter rainfall is larger than the spatial scale examined here. The shape parameters do not seem to follow an obvious movementdependence, similar to Peleg et al. (2013), though other research finds found this parameter to increase with interval size (Krajewski et al., 2003; Ciach and Krajewski, 2006; Villarini et al., 2008; Tokay and Öztürk, 2012).

4 Discussion

In the experimental set-up in Cabauw, the immediate overlying radar pixel that was first considered as reference turned out to show a significant bias as compared to gauge-adjusted radar rainfall data in all neighboring pixels. The next nearest pixel to the set-up was then used as reference instead. The distance between radar pixel center and experimental set-up thereby increased slightly from 428.9 m to 473.5 m. **Even though Faulty measurements can occur in the gauge-adjusted radar data dataset, which should be kept in mind when it is used as a reference, faulty measurements can occur in this dataset as well.** When comparing the Amsterdam area radar pixels used in this research to their combined mean value over the 17-month period, individual time series showed up to 10% consistent higher or lower values. Biases in gauge-adjusted radar could result in a larger spread in Fig. 8, although they have a far smaller influence on the results found in Fig. 10 as **in that case** the values are averaged.

Each aspect of this research, i.e. the Netatmo experimental set-up, the analysis of the station data obtained with **the** Netatmo API and the Amsterdam PWS dataset from Wundermap, concerned time series over a different, though partly overlapping, **time-periodtime period**. As the shorter time series were examined with the purpose of identifying artifacts in the data, those conclusions can be carried over to the longer more robust analyses. The results on PWS data availability (Fig. 1 and Fig. 4) do not take measurement quality into account. Because of the faulty attribution of rainfall to measurement intervals due to rounding in the data transfer, the measurements in the current form should be accumulated to larger intervals to reduce errors, although this reduces the temporal resolution appreciably. More desirable would be to address the collection method of the PWS data in the platforms in order to maintain the quality of the original PWS rainfall measurements before data transfer.

The filter applied on the PWS dataset in this paper was based on all stations in the dataset. For operational purposes, the median value that is used as a selection **criterium criterion** should be based on nearby stations only. Large rainfall values were excluded based on a limit on maximum rainfall of 50 mm h^{-1} above the median **amount of rainfall** , **although this rainfall at all PWSs at that interval. This** potentially excludes rainfall with **a return time of less than a few years (plausible return times: depending on the accumulation interval and the median value) , the filter excludes measurements that could occur every 1.5 years.** (Buishand and Wijngaard, 2007). For operational purposes, faulty high values in the data should be identified without the risk of automatically excluding all extreme rainfall events. Because of the small spatial scales and the lack of extremely heavy precipitation in this dataset, the current filter was applicable, as confirmed by visual comparison with gauge-adjusted radar data.

Although a large fraction of the PWS-networks consists of Netatmo stations, this does not imply similar performance of these datasets, **as factors** . **Factors** like placement and maintenance are unknown and not necessarily **equalequally interfering with the measurements**. Even less meta-data is available on the other PWS-types in the dataset, since information on data transfer and the sensors used are not provided for those PWSs. It is expected that there is a positive correlation between the purchase costs of the PWS and the importance of maintenance and high quality measurements to its owner, although this assumption could not be examined **based on with** our dataset. Furthermore, the location of the station is based on the setting provided by the

PWS-owner, although these may be faulty due to inaccurate localization, rounding of the longitude and latitude or relocation of the station at a later time. Even when relocations of PWSs are accurately provided to the Netatmo platform, this is not automatically communicated to Wundermap, resulting in inaccurate time series for that location. This issue is found to arise in the PWS-dataset, though the filter **critierium criterion** regarding minimum correlation with the other stations excludes time series of those stations entirely.

Different spatial correlation parameters between studies are to be expected due to different climates, rainfall types, gauge network density and **-qualityquality**. However, the nugget-parameter r_0 (**1 for perfect correlation between time series**) found here is significantly lower than in other studies. Additionally, the nugget values of the Amsterdam dataset are significantly lower than the correlation found between the Netatmo datasets with the electronic rain gauge reference in the experimental set-up when the data was obtained via the Wundermap platform (see also Fig. 6). This suggests the interference of additional factors besides sensor measurement errors and data transfer rounding when rainfall measurements are gathered in a less controlled manner. Such factors could be measurement errors due to station placement and poor maintenance.

It is important to note that, even though gauge-adjusted radar rainfall is used as a rainfall reference, differences with point measurements are to be expected because of representativeness errors. Ideally, a high-density gauge network could be used to improve this rainfall product in the future. A non-identical match should therefore not directly be interpreted as negative. However, as the nugget parameter from the station analyses was considerably lower than could be explained by rainfall variability alone, differences with gauge-adjusted radar data here are likely mainly caused by errors in the PWS-dataset. Besides **data-transfer data transfer** errors that heavily influence the nugget parameter, the **localization installation** errors (e.g. due to shielding), that are minimized in the experimental set-up, further decrease the nugget in the **dataset analysisAmsterdam dataset**. When comparing nuggets from the experimental set-up and the Amsterdam dataset in the left panel in Fig. 12, the correlations found in the former do indeed reach higher values than those influenced by **localization installation** errors in the latter.

5 Conclusions

The resolution and quality of crowdsourced PWS rainfall measurements **from the platform with the most dense PWS-network** were analyzed to establish whether this data source allows urban hydrological applications. Although the required resolutions (as described by Schilling (1991), Berne et al. (2004), Emmanuel et al. (2012) and Ochoa-Rodriguez et al. (2015)) are not yet achieved by the current PWS-networks, the density of these networks is expected to increase. As the resolution of the current network in Amsterdam is more limited in the spatial **scale resolution** than the temporal **scaleresolution**, the expected continued growth of PWSs that share rainfall measurements via online platforms will yield a network approaching the desired resolutions. This offers a vast contrast compared to KNMI's automatic rain gauge network which, in the Amsterdam metropolitan area,

only measures rainfall at one location outside of the city (at Schiphol airport).

From comparisons between Netatmo rainfall time series in an experimental set-up that reduces the errors due to faulty installation to a minimum, the measurements closely resemble those from the high resolution electronic rain gauge. Larger differences are found with radar rainfall, likely due to differences in representativeness between pixels and point measurements. Although the sensor performance of this largest contributor of data in the PWS-network considered in this research looks promising, there is a significant loss in accuracy due to transfer of data to the online platform. **In our analysis, this leads to attribution of rainfall at later time-intervals, which Wundermap.** In this study, the daily cumulative rainfall values as obtained from Wundermap are rewritten as the difference in rainfall as compared to the previous time step. Wundermap cumulative daily rainfall can only become non-zero when at least 0.3 mm rainfall has been collected, and later increases are only registered if they amount to at least 0.2 mm. Especially in case of light rain, rainfall could occur for a longer period than the interval length in which the daily cumulative rainfall increases. The rainfall is then attributed to a single interval instead of all previous intervals in which it may have been raining as well. This causes significant errors at small timescales. **This becomes evident from comparisons between the PWS Amsterdam dataset with gauge-adjusted radar data. The scatter density plots show large variation between datasets, especially at short time intervals. Nevertheless, the scatter density plots show more correspondence for larger** These errors result in inter-station correlations that were considerably poorer than those found in literature, especially in winter and at short accumulation intervals. **Moreover, the cumulative rainfall graphs**

The median rainfall of the Amsterdam PWS-dataset shows less systematic bias in PWS than the real-time available radar product. Averaging PWS time series further improves correlation, standard deviation and coefficient of variation with the averaged gauge-adjusted radar rainfall in a certain region ($\sim 20 \text{ km}^2$). Provided that the degree and likelihood of overestimation of rainfall by PWSs is similar to the degree and likelihood of rainfall underestimation, as was the case in our Amsterdam city center dataset, a dense subset of PWSs can provide a good rainfall estimation over a small area, even for intervals of 5 min and without applying a quality filter.

Correlogram analyses of the PWS-dataset results in far smaller nugget-parameters than in similar research, suggesting small-scale measurement variability not related to rainfall. Correlation fits yield especially unlikely fitted spatial correlation parameters in winter, which in the Netherlands is characterized by frequent light homogeneous rainfall events. During winter and at short intervals, the correlations between non-Netatmo type stations resembles those in literature slightly better than Netatmo-pairs, although they are quite similar to one another for larger intervals and in summer.

The largest obstacles for the use of crowdsourced PWS datasets are the errors resulting from data-transfer, errors due to poor maintenance and faulty installations (i.e. at shielded locations). The rounding of cumulative daily rainfall measurements occurring in the Wundermap platform and the time stamp uncertainty of measurements obtained from the Netatmo platform with API platforms with faulty API's lead to considerable errors in the time series, which are only reduced at large accumulation intervals. For the purpose of a high-quality rainfall measurement network with PWS-data, these issues need to

be addressed first. As the experimental set-up provided promising results regarding the sensor quality of the largest contributor to the total PWS-dataset, there is a lot to be gained from reorganizing the data transfer so that this accuracy is maintained. The resulting PWS-platform provides global rainfall measurements Processing errors can be avoided by obtaining raw data from the Netatmo Weathermap platform, though the station density is slightly lower than that of the network linked to the Wundermap.

- 5 When the processing of data is no longer interfering with the quality of the datasets, the potential of PWS-platforms becomes significant. It provides rainfall measurements from all over the world that are easy to collect, located in rural areas as well as in cities, with station densities and coverage exceeding those from national weather services, and growing towards the a level matching the described reported resolutions that are required for urban hydrological applications.

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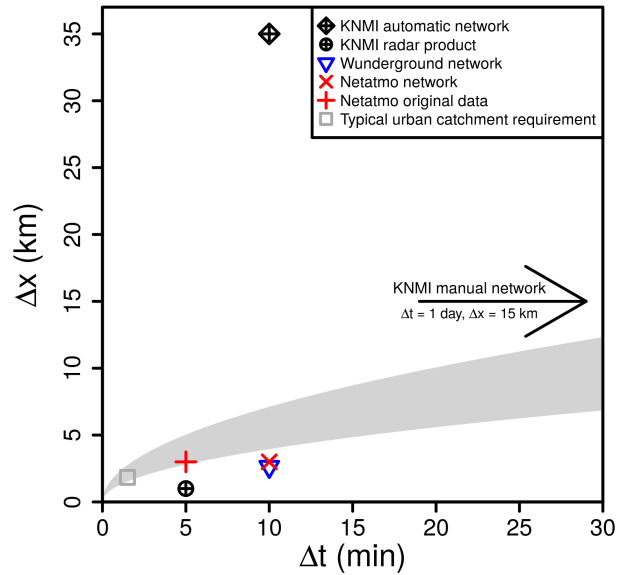


Figure 1. Temporal and spatial resolution of unfiltered rainfall measurements in the Netherlands with PWS network obtained via Netatmo API, Wundermap API and the potential availability of Netatmo measurements, **with as well as** the resolution of KNMI's automatic and **handheld manual** rainfall measurement network **and radar product**. The curve represents a relation between the temporal and the spatial resolution of rainfall measurement required for urban hydrology as determined by Berne et al. (2004) for Mediterranean climate, where the square represents the value for an urban catchment with surface area of 0.1 km^2 .

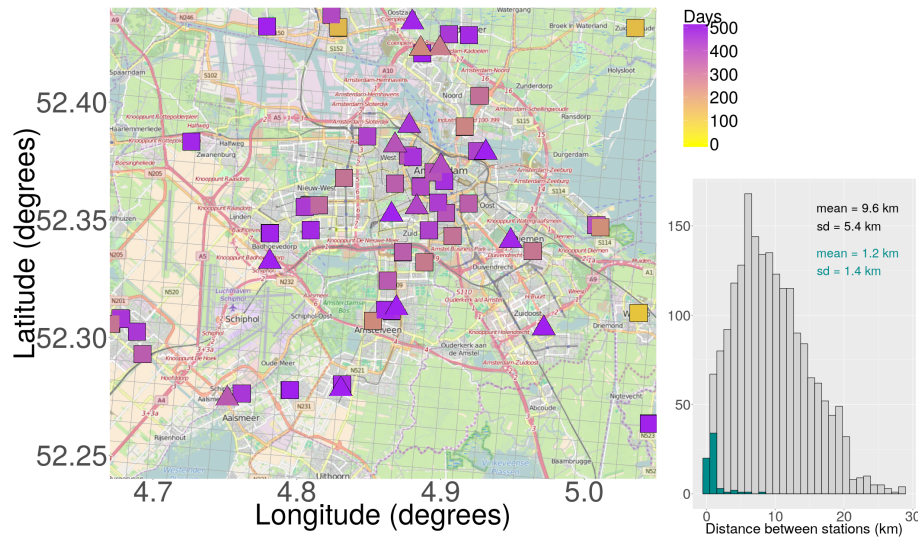


Figure 2. Locations and operational days (i.e. days with measurements) of Netatmo (squares) and other types (triangles) of PWSs, with the radar pixel grid in the Amsterdam metropolitan area. Inter-station distances are represented in the histogram, colored green for nearest neighbor distances.

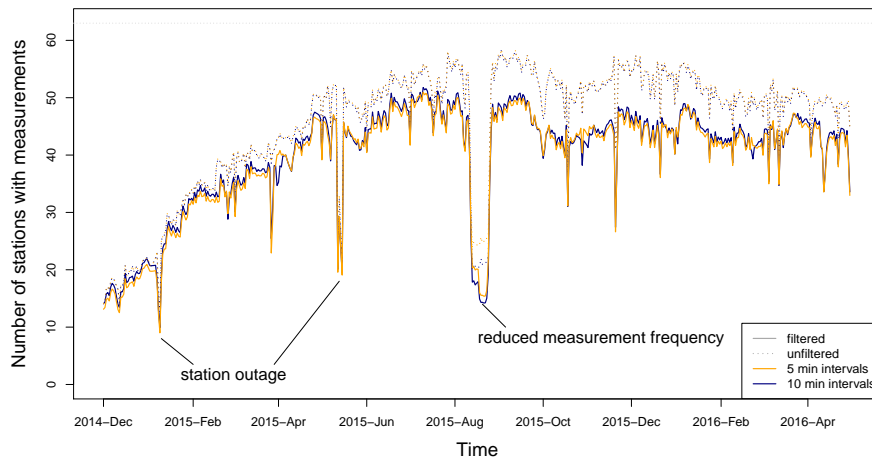


Figure 3. Number of stations with rainfall data from the PWS dataset, before and after applying filter, for every 5 and 10 minute interval over the entire period, smoothed per day. The two indicated dips corresponds correspond to complete outage of stations, the third with a longer period of fewer measurements in all stations.

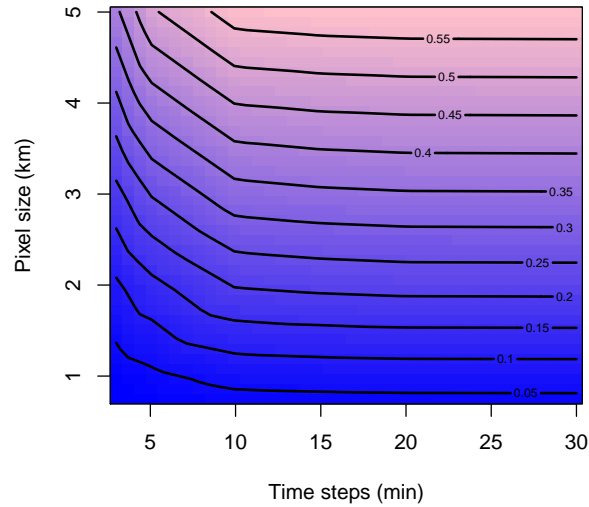


Figure 4. Fraction Indicated with curves as well as colors are the fractions of pixels containing at least one measurement (after filter is applied) of the unfiltered dataset for various combinations of time steps step length and pixel grid size (represented with cross) over the Amsterdam area between December 2014 and April 2016.

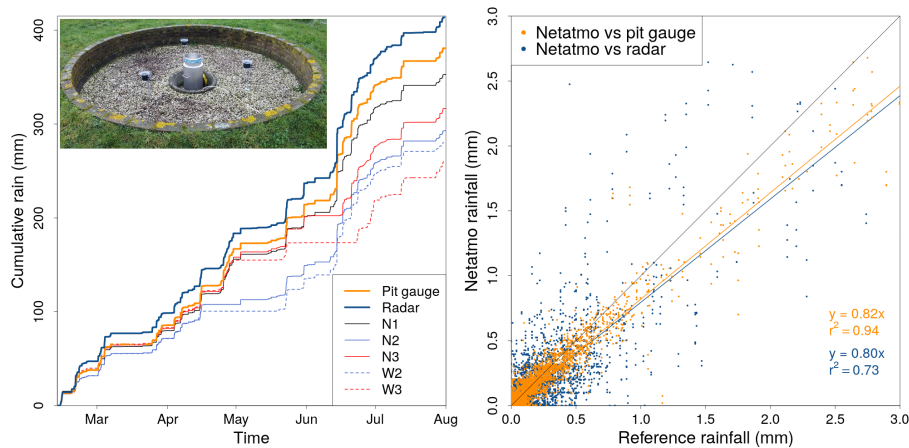


Figure 5. Left panel: Cumulative rainfall according to reference pit gauge, gauge-adjusted radar, Netatmo stations (N1, N2 and N3) and Netatmo stations obtained via Wundermap (W2 and W3). N2 (and consequently as a consequence W2) was offline between April 20th and May 1th. Photo shows the experimental set-up of the rain gauges in the pit gauge configuration. Right panel: scatter plots of 10 minute rainfall and linear fits of rainfall according to N1, N2 and N3 as compared to reference pit gauge (orange) and gauge-adjusted radar (blue).

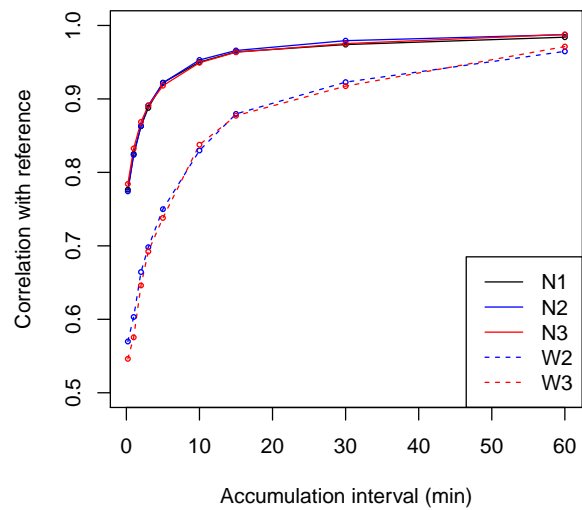


Figure 6. Correlation between rainfall measurements by Netatmo stations as obtained via personal dashboard (N1, N2 and N3), also obtained via Wundermap (W2 and W3), and the pit gauge reference for various accumulation time steps.

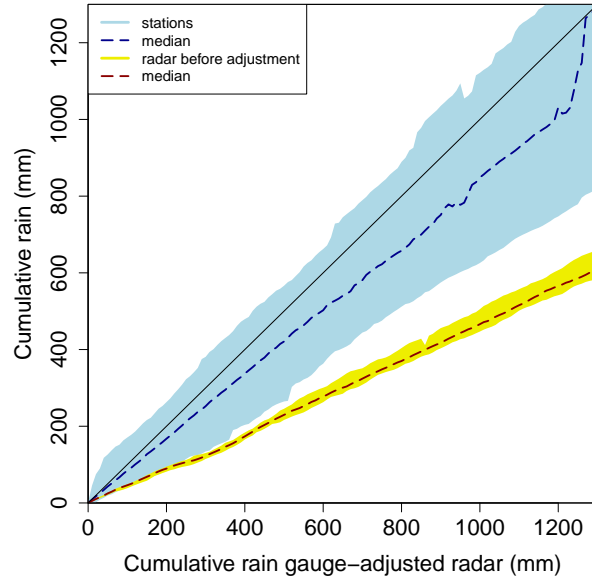


Figure 7. Double mass plots of station filtered rainfall measurements and real-time available radar data with gauge-adjusted radar rainfall at the corresponding location in the period between December 2014 and March 2016. Only intervals where both radar and station contain measurements are taken into account. Colored regions indicate the range between double mass plot of stations with minimum and maximum of the graphs steepness and dashed lines represent the median of the combined datasets.

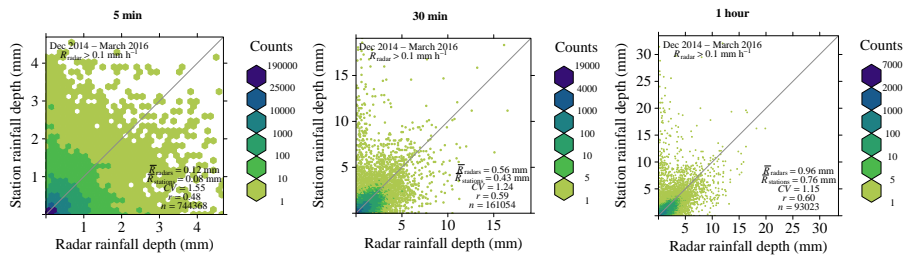


Figure 8. Scatter density plots of all station rainfall measurements against the gauge-adjusted radar rainfall data in the corresponding radar pixel when radar reported non-zero rainfall (> 0.1 mm). The \bar{R}_{radars} , $\bar{R}_{\text{stations}}$, CV , r and n values in the panels represent the average rainfall according to the gauge-adjusted radar data, the average rainfall according to the stations, the coefficient of variation of the residuals, the correlation and the number of intervals, respectively. Graphs are made for 5 min, 30 min and hourly accumulation intervals.

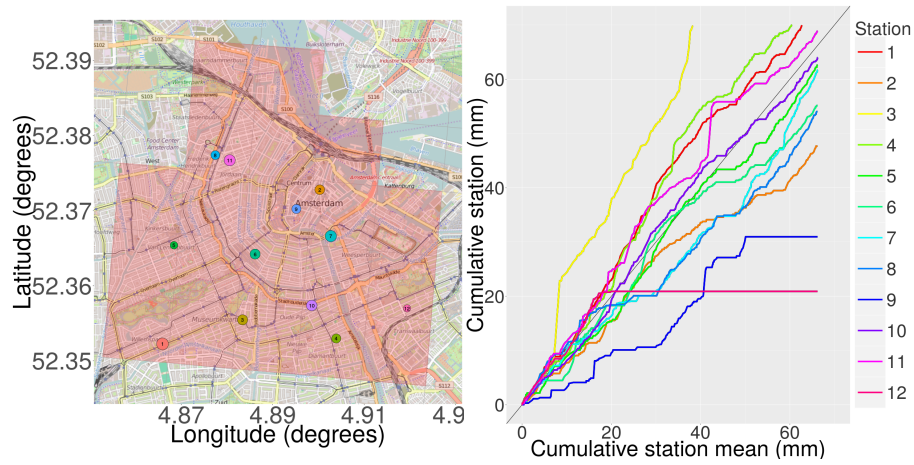


Figure 9. Left panel: Locations of 12 stations and 20 radar pixels in the city center of Amsterdam, where symbol size represents the number of unique days with measurements by the station (range 371-514 days). Right panel: Double mass plots of the station measurements as compared to the mean of all 12 stations over the intervals where all stations contain measurements.

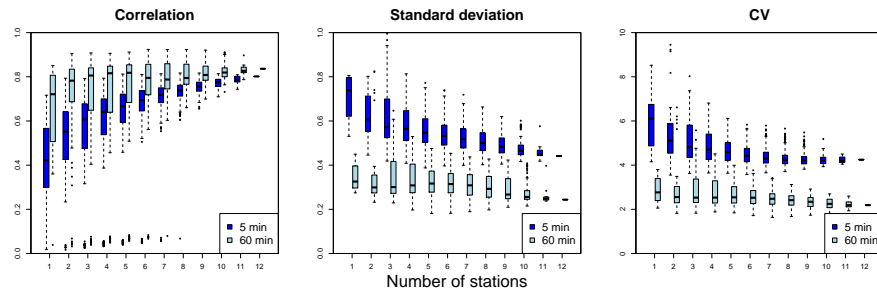


Figure 10. Boxplots of correlation, standard deviation and coefficient of variation of residuals ($CVCV$) of averaged rainfall intensity time series. The boxplots contain the outcomes for all subset means possible subsets within the 12 stations in Amsterdam city center, as compared to the gauge adjusted radar rainfall intensity 20 pixel mean for interpolated 5 minute and hourly time series.

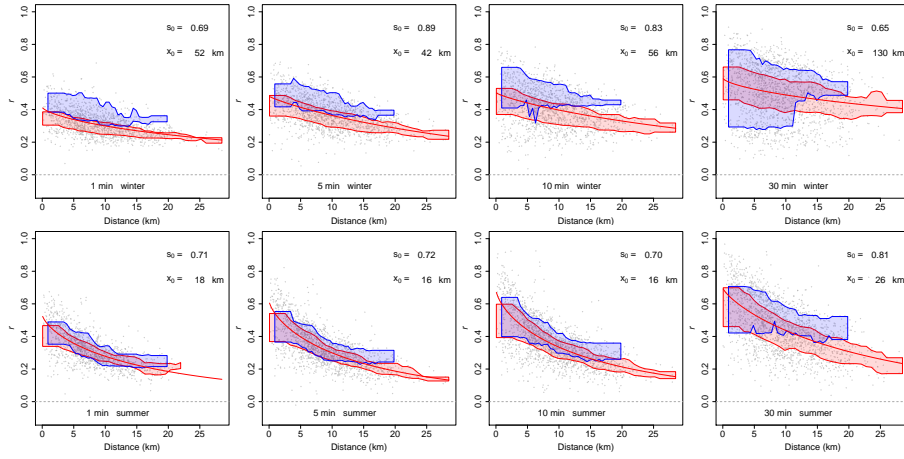


Figure 11. Correlograms of all stations after filtering at various accumulation values intervals for winter (top panels) and summer (bottom panels). The red and blue areas represent the interquartile range of the Netatmo stations and non-Netatmo stations, respectively. The areas are constructed with a moving window of width 5 km. The scatter plots are fitted with the exponential relation stated in of Eq. (2), which fitting parameters of which are given in the panels.

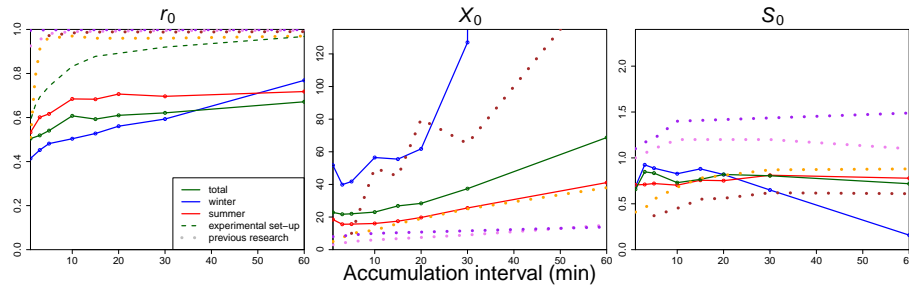


Figure 12. Timescale Time scale dependency of nugget (left panel), correlation (middle panel) and shape (right panel) parameters from fit described in Eq. (2), for total PWS dataset, as well as winter and summer only. Dotted lines represent values found in previous research by Peleg et al. (2013) (violet), Villarini et al. (2008) (orange), Tokay and Öztürk (2012) (brown) and Ciach and Krajewski (2006) (purple), where the dashed line in the first panel shows the timescale dependency of the Netatmo station nugget found in the experimental set-up as previously shown in Fig. 6.

