Author's response to interactive comments by Referee #1

Post-processing is essential to the automated accumulating precipitation gauges, although it is just a filtering technique. This study proposed an improved post-processing technique to tackle the noise caused by diurnal oscillations and drift from the evaporation of the bucket contents. Comparing with other techniques, the major advantage of the suggested one is its fully automated processing with a 24-hour latency.

Generally, this study is well written and presented. I am happy to see this paper published in the Atmospheric Measurement Techniques. But the following issues should be addressed properly before the paper can be considered for publication.

1. For users, people would like to know what are the performances of the filter for all-weather precipitation. Compared to a much smaller amount of solid precipitation in the cold season, testing the filter might be more important in the warm season. First of all, the drift from evaporation in the warm season can be much more serious in most cold regions, and the evaporation rate can be much larger. Secondly, the noise features can be quite different between warm and cold seasons. Thus, to make the conclusion more solid for both rainfall and solid precipitation, I would like to see the performance for the warm season.

AC: The reviewer makes a good point. It is important that users know the performance of the filter for each season. For this analysis, however, we chose winter for several reasons:

1)The data set that we had available to us was a mainly cold season precipitation data set originating from the WMO-SPICE (or post-SPICE) project. We chose this data set because it had a known quality. This data came with relatively meticulous metadata such as service logs and field notes so that we were confident in our ability to quality control this data to allow for a level playing field for each filter. The quantity and quality of the warm season data from SPICE is reduced and much of this wasn't readily available at the time that this analysis was undertaken.

2)The signal to noise ratio is always lower in the winter due to lower (generally) precipitation rates. In our opinion, this makes filtering of winter data substantially more difficult than filtering of summer data, where small absolute errors are less likely to be large relative errors.

3)We know that the evaporation signal in the SPICE data is significant during the shoulder seasons (Fig. 5c as an example), perhaps even more significant relative to total precipitation than evaporation during the summer months. We felt that this cold (shoulder) season evaporation would be a considerable challenge to the filters.

To help answer the question about warm season performance, we ran a separate control experiment on the warm season and added 11 available unprocessed warm season time series to the analysis.

The results of the warm season control analysis suggested that in general, the performance of NAF remained consistent, NAF-S improved, O15 became even more unstable, and the performance of NAF-SEG dropped somewhat, apparently because of a lower recovery rate for evaporation (Table 4). However, NAF-SEG continued to outperform NAF and O15 in nearly every metric.

Although we don't have nearly as much summer data as winter data due to the focus of SPICE, we filtered 11 available warm season time series of known data quality for comparison with winter results. All filters showed a slight reduction in performance for the warm season with an increase in RMSD vs. the cold season (Table 5). The biggest increase in RMSD was in the O15 filter (increase of nearly 0.03 mm).

Action: We have clarified our justification in the methods section for focussing on the filtering of cold season data but since we agree that assessing the performance during the warm season is also important, we have added the warm season control exercise and the addition of the 11 warm season time series to the methods sections and summarized the results from these experiments in the appropriate sections, including an update of Tables 2-5 and the addition of Table A2. A substantial addition to the Discussion section was made to discuss the results of both the pre-processed and unprocessed warm-season testing.

2. Compared to the robustness of NAF-S, the validity of NAF-SEG is closely related to the setting of the minimum threshold P* = 0.001 mm. Although the authors assert it is somewhat arbitrary within the tested conditions of solid precipitation measurements, it might be challenging for the noise features in the warm season. Considering the more variability of precipitation and stronger evaporation in the warm season, further exploration in the point is necessary. In addition, there is no validation for the raw precipitation data when using the filters. Therefore, validation using independent measurements from the tipping bucket would be very helpful for the filtered measurements from the accumulating gauges.

AC: Analysis not shown in the manuscript tests the sensitivity of NAF-SEG to P* and found little to no sensitivity (which was actually somewhat surprising), but the reviewer would be correct in assuming that the tests were only performed on winter data. This can be tested relatively easily using the same data used to address comment 1. As for using tipping bucket rain gauge (TBRG) data as a reference (during warm season tests), the authors feel that TBRG data has it's own inherent problems and would be not be conducive for use as a reference or even as an independent validation due to known issues with splash, siphoning delays, unknown maintenance issues, calibration, etc. We think that the greatest potential for future improvements could be the incorporation of present weather detectors or disdrometers into the filtering process for identifying light and false events.

Action: Using the same observed warm season time series data discussed above, the NAF-SEG filter was tested using different P* values ranging from 0.0001 mm to 0.5 mm. This is a very similar test to that run using cold season data. Results were similar to the cold season in that the response in the metrics was subtle up to 0.05, only dropping off substantially at 0.5. This was added to the discussion section. Also, in response to the reviewers question about independent validation, we added a paragraph to the discussion section suggesting that the use of present weather detectors or optical disdrometers could be explored to validate or improve filtering techniques. The use of a TBRG or other precipitation detectors is out of the scope of this current analysis.

3. As we know the performances of the filters are slightly related to the climate of the observed sites. Further discussion of the relationships between the biases for the 44 raw time series would help understand the validity of the filters in different environments.

AC: The reviewer makes a good point. However, it’s not the filter that is impacted by climate but rather the behaviour of the precipitation gauge. Although climate is a factor (e.g. wind vibration, temperature signals, evaporation), there are many non-climate related factors that also have a significant impact on gauge performance, such as electrical interference, service interval, or even the actual installation of the gauge and infrastructure. These are very difficult to isolate from the impacts of climate. Examining the impact of these factors, including climate conditions, on the signal behaviour of the gauge was discussed in the SPICE final report and was recommended for further analysis, but understanding these impacts are out of scope for this analysis.

Action: In the discussion section, we suggest that filtering techniques (whether this filter or others) could be improved by better understanding the cause of signal noise and filtering made easier by reducing signal noise during measurement.

Minor comments:

(1) P1-L5: If my understanding is correction, this study is talking about the weight-based precipitation gauge. It is quite confusing when using ’automatic precipitation gauge’, ‘automated accumulating precipitation gauge’ and ‘automated accumulating (weighting) precipitation gauge’.

AC: These gauges are in fact accumulating automated weighing precipitation gauges.

Action: We will define this better and make the nomenclature consistent to “automated weighing gauge”

(2) P12-L406: ‘his’ to ‘this’

Action: done

Author's response to interactive comments by Referee #2

Throughout the paper

In the introduction, you do name three post-processing challenges: mechanical and electrical interference, diurnal oscillations, and evaporation of the bucket contents. While you treat mechanical and electrical interferences and evaporation explicit with your filtering method, possible diurnal variations as the temperature dependency of the measurement device are treated more implicit with the introduction of a 24h measurement window, where you can assume similar temperatures at the end and beginning of the cycle without explaining this part of the algorithm. However, synoptic changes can make this assumption not valid and thus some of the detected precipitation or evaporation can be due to temperature changes independent of a diurnal cycle. I don't think that this is problematic for your results, but I suggest to discuss this issue throughout your paper.

AC: True, a non-diurnal temperature fluctuation may have an impact on signal noise and therefore impact the NAF-SEG filtering. It might be worthwhile looking at strong non-diurnal gradients to determine if that could explain when and why the filters have a reduced performance.

Action: The following sentences were added to the discussion: "There may also be a decrease in the performance of NAF-SEG when signal noise is due to non-cyclical temperature fluctuations, such as those that occur during strong synoptic events. Although this wasn't explicitly assessed, it may be a situation that a user should be aware of."

Section 2.4 Segmented Neutral Aggregating Filter, page 6, algorithm description and Figure 1 in Appendix (flowchart): Please clarify that the measurement interval in your case is actually a minute or has to be a much shorter interval than the 24 hour segments. I think it may also help if you punctuate (in addition to the use of indices) when you are treating the 24 hour segment as one: i.e. all individual measurements from one interval is assigned the same flag "precipitating", "evaporating" or "neither E nor P", and when you are treating minute by minute (each single measurement can get its individual P(i) or E(i), and from step 4 you evaluating minute values).

Action: added the following paragraph to Section 2.4:

"The measurement interval used in this analysis to evaluate NAF, NAF-S, and NAF-SEG is 1-min. This interval is used here because it was chosen as the preferred interval for archiving of the SPICE data, and was therefore available for this analysis. NAF has been shown to work on data of larger intervals (i.e. 30 min in Pan et al.,2016) and there is no reason why NAF-SEG could not be used with larger intervals as well, provided that the intervals are considerably shorter than the 24-hour window (i.e. 30 minutes or less)."

Please reword 6c. While the flowchart indicates clearly that if answers on both questions 6a and 6b are no, precipitation and evaporation are set to zero. That includes also (and especially) those cases where not all three overlapping windows do agree. After repeated reading of sentence "6c" and a look on the flowchart, I actually understood that 6c could be understand this way. However, I do suggest to rewrite and clarify the point that you are also looking for disagreement between the three flags here and not only for those cases where all three flags indicate (in agreement) no precipitation nor evaporation (the latter is how I understood the sentence when reading it the first time).

AC: Agreed

Action: The sentence now reads “a. For intervals which are not precipitating (a) or evaporating (b), i.e. when the flag from all three overlapping windows indicates the absence of both precipitation and evaporation, or when the three flags do not agree with each other, P(i) and E(i) are set to zero.

Section 3.1. Testing with pre-procesed (control) precipitation data

The description of the creation of the synthetic signal is very informative. I was searching after a figure illustrating the level of noise visual. Maybe you can hint other readers that figure 3 in the appendix actually have that kind of visualization. Also, in contrast to figure 2, where the difference between the three noise levels is not visible due to the higher overall changes.

Action: we indicated near the end of Section 3.1 that the various noise levels in the synthetic data can be visualized in Figure 3.

Section 3.2 Testing with raw precipitation data

From your description, it becomes clear, that you actually include a double filtering. The QC process used for the WMO-SPICE analysis is already cleaning and smoothing the data series before you apply the described filters of this study. That is off course no problem, but I do think it is important enough that it should be mentioned earlier in the paper and also be taken up again in the discussion of the results.

AC: agreed. This is already noted in Section 3.2

Action: A brief discussion of the impacts of the Gaussian filter is included in the discussion section.

I am wondering especially about:

Have you tried to apply your filtering algorithm without this additional SPICE-filtering and QC?

AC: We have in more recent work but not in this work. Preliminary results suggest that the Gaussian filter has little impact on the performance of NAF-SEG but it may help O15. Unfortunately, it was built into the SPICE data QC, some of which was completed before we received the data, so it was maintained for consistency.

In the operational use of your O15 filter, you calculate a 5-minute mean prior to filtering. Do you assume that the 5-minute average calculation would do about the same as the 4-minute Gaussian filter of the SPICE-algorithm?

AC: I think that the 5-minute mean would be more aggressive than the Gaussian filter. This is considered part of the O15 filter, not a pre-filter process. This is what is implemented on the operational data loggers.

In case of your study, did you still use the 5-minute averaging step of the O15 filter after applying the 4 minute Gaussian filter of the SPICE-algorithm?

AC: Yes, the 5-min mean was applied after the Gaussian smoothing, which probably gave the O15 filter more of an advantage with this test data than it would get in real-time on the data logger. This should be pointed out in the discussion.

Action: added the following sentences to the discussion section: "It should also be noted that the unprocessed data in these tests were pre-filtered with a Gaussian filter with a 4-min window, which was integrated into the SPICE quality control process, prior to testing the algorithms. This likely resulted in the O15 filter performing better than it would have in the operational setting, but this was not confirmed."

Do you think a quality control of the time series is necessary before applying the filter?

AC: Yes, some quality control of the time series is necessary before applying the filter. We can speculate that the Gaussian filter has a negligible impact on performance, but artifacts such as those caused by gauge servicing (as an example) need to be removed. Generally, these don't appear in the operational data due to servicing protocols (i.e. the data is suspended during servicing) but simple range checks and jump filters would prevent other artifacts from impacting the data.

Action: we added the recommendation for a post-processing enhanced quality control procedure, along with the archiving and re-processing of the 1-min operational data in non-real-time, to the final sentence in the conclusions section.

Especially when thinking of the O15 filter, but also for the other filters, it may be more usual to apply the complete or parts of the quality control on the filtered (with your algorithm) data - what are the advantages/disadvantages of either way?

AC: The advantage, and perhaps the only advantage, of the O15 filter is that it can be deployed operationally (i.e. on the data logger) to work in real-time. This means that only rudimentary quality control measures are available. The O15 filter definitely benefits from pre-filtering data quality control, as do the other filters. Testing the impacts of QC procedures was out of scope for this analysis (which is why we used the pre-tested SPICE process), but we can certainly see the benefit of testing and implementing enhanced QC processes in operational data management systems as a first step to an integrated precipitation post-processing technique. I don't see any disadvantages, other than keeping processes separate may make revisions, documentation, and implementation less complex.

Action: see above

Chapter 5 – Discussion, lines 364-372:

I think the necessity of antifreeze and oil, also when an algorithm is applied, is valuable information, which should also occur in the conclusions (in a slightly shorter form)

AC: agreed

Action: added “This, in combination with routine site servicing to pre-empt evaporation and other sources of noise, can result in improved operational precipitation data.” As the final statement in the conclusions section.

Use of Ott Pluvio2 data – throughout the paper

In the Introduction (lines 68-71), you describe that you are using somewhat processed values of the Ott Pluvio2 gauges. In Section 3.2 (lines 285ff.), however, you do not distinguish between data from Geonor or Pluvio2. Do you apply the SPICE-algorithm on the preprocessed or the raw bucket data from Ott Pluvio2? To my understanding, the SPICE algorithm is meant to be applied to the raw bucket data. Depending on what you actually did, Pluvio2 and Geonor data may have been treated significantly different and I wonder if that should be visible in your results. Do you see any effect of a possible different treatment of the data from the different gauges? I was surprised to see that evaporation was detected in a similar manner for Pluvio2 gauges as for Geonor gauges even if (after my understanding) evaporation for Pluvio2 gauges were already treated from the inbuilt algorithm and thus probably be “treated” twice.

AC: The description in the introduction describes what is available as output from the Pluvio2, but states that some users (including the authors) would like to bypass “further processing” and have the option to “complete their own post-processing of the data in its rawest form.” The output used for testing from the Pluvio2 was the real-time bucket weight output. This data, according to OTT, is pre-processed by the onboard algorithm in that it is a high frequency measurement which is internally corrected for temperature and vibration effects on the load cell. This output is NOT corrected for evaporation. This is the “rawest” output product available from this gauge and is as close as possible to the raw unprocessed data derived from the Geonor. The SPICE algorithm was designed to be applied to both the raw Geonor ouput and the Pluvio2 real-time bucket weight data in the same manner, with only parameter changes for range and jump thresholds. Having said that, the signal noise for the gauges have both similarities and differences, but are treated the same by all four filtering algorithms under test.

Action: clarified the output source of both the Geonor and Pluvio2 in paragraph 2 of Section 3.2

Appendix

Flowchart and figures 2 and 3 contain relevant information and I suggest moving them from the appendix into the main text.

AC: We apologize as this was a mistake in the order of the tables and figures. Only Table A1 is meant to be in the Appendix while the figures, including the flow chart, should be integrated into the manuscript during final publication.

Appendix, Figure 5

The lines are very thin and difficult to distinguish; the evaporation line seems to be almost constantly zero, due to the different orders of magnitude. You try to overcome some of these issues with the smaller inserts, but those makes the plots “untidy” and difficult to understand. Please consider to use several plots, shorter time intervals, or some other way to improve the quality of these figures.

AC: agreed. These will be improved when we re-submit the manuscript for final publication.

An improved post-processing technique for automatic precipitation gauge time series

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Abstract. The unconditioned data retrieved from accumulating automated ~~accumulating~~weighing precipitation gauges is inherently noisy due to the sensitivity of the instruments to mechanical and electrical interference. This noise, combined with diurnal oscillations and signal drift from evaporation of the bucket contents, can make accurate precipitation estimates challenging. Relative to rainfall, errors in the measurement of solid precipitation are exacerbated because the lower accumulation rates are more impacted by measurement noise. Precipitation gauge measurement post-processing techniques are used by Environment and Climate Change Canada in research and operational monitoring to filter cumulative precipitation time series derived from high-frequency, bucket-weight measurements. Four techniques are described and tested here: 1) the operational 15-minute filter (O15), 2) the Neutral Aggregating Filter (NAF), 3) the Supervised Neutral Aggregating Filter (NAF-S), and 4) the Segmented Neutral Aggregating Filter (NAF-SEG). Inherent biases and errors in the first two post-processing techniques have revealed the need for a robust automated method to derive an accurate noise-free precipitation time series from the raw bucket-weight measurements. The method must be capable of removing random noise, diurnal oscillations, and evaporative (negative) drift from the raw data. This evaluation primarily focuses on cold-season (October to April) accumulating automated~~-~~ weighing precipitation ~~-~~gauge data at 1-min resolution from two sources: a control (pre-processed time series) with added synthetic noise and drift; and raw (minimally-processed) data from several WMO Solid Precipitation Inter-Comparison Experiment (SPICE) sites. Evaluation against the control with synthetic noise shows the effectiveness of the NAF-SEG technique, recovering 99%, 100%, and 102% of the control total precipitation for low, medium, and high noise scenarios respectively for the cold-season (Oct-Apr) and 97% of the control total precipitation for all noise scenarios in the warm-season (May-Sep). Among the filters, the fully-automated NAF-SEG produced the highest correlation coefficients and lowest RMSE for all synthetic noise levels, with comparable performance to the supervised and manually-intensive NAF-S method. Compared to the operational O15 method in cold-season testing, NAF-SEG shows a lower bias in 37 of 44 real-world test cases, a similar bias in 5 cases, and a higher bias in 2 cases. In warm-season testing, the NAF-SEG bias was lower or similar in ~~8~~7 of 11 ~~time seri~~cases. The results indicate that the NAF-SEG post-processing technique provides substantial improvement over current automated techniques, reducing both uncertainty and bias in accumulating-gauge measurements of precipitation, with a 24-hour latency. Because it cannot be implemented in real time, we recommend that NAF-SEG be used in consort with a simple real-time filter, such as the operational O15 or similar filter.

1 Introduction

Accurate precipitation measurements are crucial for a variety of applications, including water resource forecasting, future water availability, and hydrological and climate analysis and modelling (Barnett et al., 2005; Bartlett et al., 2006; Wolff et al., 2015). Canada's Changing Climate Report led by Environment and Climate Change Canada (2019) highlights the importance of accurate precipitation measurements as fundamental climate quantities that play an important role in human and natural systems. Although the systematic bias due to the impact of wind on solid precipitation measurements is well documented (Goodison, 1978; Sevruk et al., 1991; Goodison et al., 1998;Yang et al 2005; Sevruk et al., 2009; Smith, 2009; Wolff et al., 2015; Kochendorfer et al., 2017a), errors related to the automatic recording of precipitation measurements have only relatively recently been identified as automated weighing gauges come into common use (Sevruk, 2005). The cumulative precipitation data output from automated weighing gauges is subject to noise, diurnal temperature oscillations, and negative drift from evaporation which can often mean that the precipitation signal over short sampling periods is influenced or hard to detect (Rasmussen et al., 2012). The nature of the noise and drift often varies substantially from site to site and between gauge configurations. High frequency noise can exceed ± 1 mm and evaporation from the bucket can be in excess of several mm between precipitation events. It is therefore necessary to filter the raw data to separate real precipitation events from signal noise and identify and remove periods with evaporation (keeping in mind that evaporation reduces the precipitation amount derived from the differential in bucket weight). Improper filtering can lead to the accumulation of errors and result in significant inaccuracies in total seasonal precipitation. Duchon (2008) suggests that errors due to the diurnal oscillation in Geonor T-200B gauges could be 1-10% of the precipitation total. Three post-processing challenges in the derivation of 'clean' precipitation time series are the focus of this study: mechanical and electrical interference, diurnal oscillations, and evaporation of the bucket contents.

This study incorporates two commonly-used accumulating automated weighing precipitation gauges (henceforth referred to as automated weighing gauges)~~ ~~: the Geonor T-200B and OTT Pluvio². The Geonor T-200B implements up to three vibrating wire transducers, which provide a frequency output that varies as a function of the fluid weight in the gauge bucket. The cumulative precipitation amount (bucket weight) is calculated from the frequency of each wire via calibration coefficients, with no onboard filtering (Geonor, 2019). The OTT Pluvio² ~~precipitation~~ automated weighing gauge uses a high-precision load cell to weigh the bucket contents and provides several outputs including intensity and precipitation accumulation (Nemeth, 2008; Nitu et al., 2018). The OTT Pluvio² output has been pre-processed using an onboard proprietary algorithm which adjusts the high frequency load cell measurements for temperature and vibration to derive a more accurate bucket weight. Further onboard processing removes the impact of unrealistic bucket weight changes and evaporation from the output, however,~~ some would prefer to bypass~~ this~~e~~ onboard algorithm was bypassed in this analysis to obtain~~and complete their own post-processing of~~ the data in its rawest form.

A number of post-processing techniques have been developed to derive a noise-free precipitation time series from high-frequency automated weighing gauge bucket weight measurements. Some examples are described here.

The Rolling Maximum filter was used by Harder and Pomeroy (2013) to remove the “jitter” from the accumulated precipitation datasets by retaining a cumulative precipitation observation if it is greater than the previous maximum cumulative precipitation. The previous maximum is assumed to be the cumulative precipitation in all other cases. This filter reportedly works well in preserving the cumulative change in precipitation but it may not always catch the precise start of precipitation events and will not always perform optimally in the presence of negative gauge drift (i.e. evaporation).

The World Meteorological Organization (WMO) Solid Precipitation Inter-Comparison Experiment (SPICE, 2013-2015) developed a uniform post-processing method for defining and quantifying precipitation events (Nitu et al., 2018). The process includes calculating a 30-minute bucket weight differential using thresholds and filters, effectively producing what was termed the Site Event Datasets (SEDS). For an event to be identified, the net precipitation duration needed to be sufficiently long (as measured by a precipitation-detector or disdrometer) and the total accumulation (as measured by the reference automated weighing gauge) needed to be equal to or greater than a defined threshold (set at 0.25 mm when a reliable precipitation-detector was available). This process was effective at creating a high confidence data set for developing and testing transfer functions (Kochendorfer et al., 2017b) but because of the rigorous filtering of shorter and smaller events, was not an effective means of filtering a time series.

The U.S. Climate Reference Network (USCRN) uses the redundancy of the Geonor T-200B three vibrating-wire load sensors in the determination of precipitation events (Leeper et al., 2015). Initially, a pairwise calculation was used which relies on pairwise agreement of bucket weight changes using the wire redundancy as a check on the measurement. This was determined to be sensitive to gauge evaporation and noise, leading to the development of a weighted average calculation using the change in bucket weight between successive sub-hourly periods for each transducer output. A weighted mean is then used to average the bucket weights, with greater weight given to less noisy measurements.

The Meteorological Service of Canada currently implements a real-time threshold filter in their data loggers to automatically determine the occurrence of precipitation events. The filter is based on the 15-min differential in the Geonor T-200B bucket weight (Mekis et al., 2018). Although this filter is unnamed, we call it the Operational 15 Minute (O15) automated processing technique. This technique is included in this analysis and is described below in more detail. The filter tends to fail when the noise threshold is exceeded, resulting in false precipitation reports, and when evaporation exceeds the acceptable limits.

Limitations in the O15 technique led to the development of the Neutral Aggregating Filter (NAF), previously known as ‘Brute Force’ (Pan et al., 2016). The NAF, described in greater detail by Smith et al. (2019), iteratively adds all negative and small positive changes to proximate positive changes until all changes exceed a user-specified threshold. Because the technique preserves the total change in bucket weight over the time series, it cannot account for the negative drift that results from evaporation. To overcome this deficiency, the Supervised Neutral Aggregating Filter

(NAF-S) was created to allow user intervention and minimize evaporation errors through interactive manual adjustment. Both NAF and NAF-S are explained in greater detail in the next section.

To overcome the limitations of the O15, NAF, and NAF-S techniques, we evaluated a moving-window modification of the NAF, implementing the NAF on 24-hour overlapping windows, which we will call the Segmented Neutral Aggregating Filter (NAF-SEG). The objective was to obtain a robust post-processing technique that is completely automated, easily implemented, and successfully eliminates varying levels of noise, diurnal oscillations and evaporation without significantly impacting the timing and amount of precipitation. This study introduces the NAF-SEG technique and examines its performance compared to the O15, NAF, and NAF-S methods.

2 Processing Techniques Under Test

2.1 MSC Operational O15 Minute

The O15 filtering technique is used operationally by the Meteorological Service of Canada (MSC) for Geonor T-200B measurements at the Reference Climate Stations (RCS). The O15 filter is implemented in real time at the measurement site data logger. The algorithm is intended to filter out noise and eliminate evaporation while minimizing the reports of false precipitation. For each 15-min period, a mean bucket weight is computed over the last 5 min (minutes 11 to 15) of the period. The mean bucket weight from the initial period is used to establish the baseline. For each successive 15-min period, the difference between the current mean bucket weight and the baseline is calculated. If the bucket weight difference is greater than or equal to 0.2 mm, the difference is attributed to precipitation and added to the cumulative precipitation total, and the baseline is reset upwards to the current mean. If the difference is less than or equal to -1.0 mm, the difference is attributed to evaporation and the baseline is adjusted downward to match the current mean. This process is performed separately on each of the three installed transducers in the RCS gauge although ultimately only one is used to determine reported precipitation.

The O15 technique is used operationally in real-time, and so must be simpler than other post-processing techniques. As a result, it has the potential to be problematic, including a sensitivity to the positive and negative thresholds used to identify precipitation and evaporation events. The 0.2 mm positive accumulating (noise) threshold can cause an overestimation of precipitation if the data are inherently noisy or have a high diurnal oscillation. Additionally, if the negative drift from evaporation lies just above the -1.0 mm threshold, the baseline will not be adjusted before the next precipitation event, resulting in an underestimation of the next event by up to 1.2 mm (evaporation threshold plus the noise threshold).

2.2 Neutral Aggregating Filter

The NAF method, developed by Environment and Climate Change Canada’s Climate Research Division, is an automated method that removes noise from cumulative precipitation time series (Pan et al., 2016; Smith et al., 2019). The processing is done iteratively, beginning with the minimum non-zero interval precipitation value. All non-zero changes in interval precipitation, with values below a user-defined threshold are transferred to neighboring periods with positive or larger changes. The results from the algorithm are “neutral” as the filter balances the positive and negative noise until all changes below the user-defined threshold are eliminated.

The technique removes random noise and accounts for diurnal oscillations in the bucket-weight signal but, because the total precipitation is forced to equal the total bucket weight increase at the end of the time series, it cannot account for negative drift. This means that it will not perform well if the time series has significant periods with evaporative losses from the automated weighing precipitation ~~accumulating~~ gauge bucket. The significance of the error could exceed 10% depending on the effectiveness of the servicing measures to reduce evaporation from the bucket contents. NAF serves as the framework for both the NAF-S and NAF-SEG techniques described below.

In this study, the NAF, NAF-S (2.3) and NAF-SEG (2.4) methods all use a minimum threshold P^* of 0.001 mm. P^* was somewhat arbitrarily set at 0.001 mm based on the minimum resolution of the gauge data. Testing (not shown here) suggests that the method is not overly sensitive to P^* and that a 5-fold increase in the magnitude of P^* had minimal impact on the performance in either the cold- or the warm-season.

2.3 Supervised Neutral Aggregating Filter

The NAF-S method is used to manually adjust the cumulative time series for evaporation and other spurious data, effectively reducing the NAF estimation error. The NAF-S method uses the NAF output as a first guess, and then allows for manual, interactive adjustment of the baseline to account for evaporation events and other data artifacts impacting the time series. The NAF-S creates an interactive plot, showing both raw (quality controlled) and NAF output data, which highlights periods with drift caused by evaporation. The user is then given the capability to identify and manually exclude each period with evaporation, using the cumulative precipitation value before each evaporation event as a new baseline. NAF-S successfully minimizes the impact of evaporation but requires user intervention (i.e. it cannot be automated) along with user subjectivity to identify the endpoints of evaporative and other spurious events (Smith et al., 2019).

2.4 Segmented Neutral Aggregating Filter

The NAF-SEG is a fully automated technique that implements the NAF to process multi-day precipitation time series in successive 24-hour segments using overlapping moving windows. The use of 24-hour windows automates the identification and removal of evaporation, minimizing the negative biases in total precipitation from evaporation without the need for user intervention. Additionally, the NAF-SEG method provides an estimate of evaporative losses on precipitation-free days for evaluating servicing procedures.

The NAF-SEG technique uses three overlapping moving windows per day, advanced in increments of 8 hours. The algorithm begins by filtering the first 24-hour segment using NAF. It then advances 8 hours and filters the next 24-

hour segment. This filtering process is repeated until the end of the data is reached. Each 8-hour data segment thus passes through the NAF three times. The processing steps are listed below and outlined in Fig. 1.

The measurement interval used in this analysis to evaluate NAF, NAF-S, and NAF-SEG is 1-min. This interval is used here because it was chosen as the preferred interval for archiving of the SPICE data. ~~, and therefore available for this analysis.~~ NAF has been shown to work on data of larger intervals (i.e. 30 min in Pan et al.,2016) and there is no reason why NAF-SEG could not be used with larger intervals as well, provided that the intervals are considerably shorter ~~longer~~ than the 24-hour window (i.e. ~~less than~~ 30 minutes or less).

We will denote the precipitation amount from one measurement interval (i) as P(i); cumulative precipitation as cumP(i); evaporation from one measurement interval as E(i) ; and cumulative evaporation as cumE(i). All units are in mm.

1. The time series is processed in successive 24-hour segments.
2. For each 24-hour segment, the change in bucket weight, which we will call Δ^{24h}, is computed as the difference between the final and initial observations.
3. Based on the value of Δ^{24h}, the 24-hour segment is assigned one of three states: 1) precipitating, 2) evaporating, or 3) neither. It is then processed accordingly:
   a. If $\Delta^{24h} \geq P^*$, the 24-hour segment is flagged and treated as a precipitation period with no evaporation. The 24-hour segment is passed through the NAF, resulting in values of *P(i)* that are either zero or greater than or equal to P^*.
   b. If $\Delta^{24h} \leq -P^*$, the 24-hour segment is flagged and treated as an evaporation period with no precipitation. The 24-hour segment is passed through the NAF but with the sign of the data reversed, resulting in values of *E(i)* that are either zero or less than or equal to $-P^*$.
   c. If $-P^* < \Delta^{24h} < P^*$, the 24-hour segment is flagged as free of both precipitation and evaporation, and all values of *P(i)* and *E(i)* are set to zero.
4. The NAF *P(i)* and *E(i)* outputs from step (3), as well as the flags that indicate the presence of precipitation or evaporation, are added to arrays with three columns corresponding to the three overlapping windows per day (i.e. as *P(i,j)*, *E(i,j)* and *flag(i,j)* where *j* denotes columns (windows) 1 to 3).
5. Steps (2) to (4) are repeated using moving windows on successive 24-hour segments, beginning 8 hours apart, until the entire time series has been processed.
6. The *P(i,j)* and *E(i,j)* arrays from steps (3) to (5), with three overlapping windows, are processed to create a single time series for *P(i)* and *E(i)*, based on the *flag*.
   a. For intervals when the *flag* from all three overlapping windows indicates the presence of precipitation, *E(i)* is set to zero and the three *P(i,j)* values are averaged to produce *P(i)*, otherwise *P(i)* is set to zero.
   b. For intervals when the *flag* from all three overlapping windows indicates the presence of evaporation, *P(i)* is set to zero and the three *E(i,j)* values are averaged across columns to produce *E(i)*, otherwise *E(i)* is set to zero.

c. For intervals which are not precipitating (6a) or evaporating (6b), i.e. when the *flag* from all three overlapping windows indicates the absence of both precipitation and evaporation, or when the three flags do not agree with each other, ~~does NOT indicate the presence of precipitation or evaporation,~~ *P(i)* and *E(i)* ~~is~~ are set to zero.

7. The *P(i)* and *E(i)* outputs from step (6) are summed to create the *cumP* and *cumE* time series. Lastly, *cumP* is passed through the NAF to ensure that all *P(i)* values are either zero or greater than or equal to *P**; *cumE* is passed through the NAF but with the sign of the data reversed to ensure that all *E(i)* values are either zero or less than or equal to -*P**. The evaporation estimate is taken as the absolute value of the cumulative total of *cumE*.

Two additional steps not shown in Fig. 1 are required. First, additional 24-hour segments need to be added to the start and end of the time series to ensure that all core intervals are covered by three overlapping windows. Since these time series begin at 0 mm at the start of the season, the 24-hour segment added to the start of each time series is set to all zero values. The 24-hour segment added to the end of the time series is set to the maximum of the cumulative time series. This step is only necessary if the user requires processed data from the first and last 24-hour period in the time series and does not impact the precipitation amounts.

A second step is required to ensure that the precipitation during data gaps is not omitted from the accumulated total. Note that when gaps occur in an automated weighing gauge time series, the total accumulation across the gap is preserved but the event timing is lost. In the NAF-SEG implementation, precipitation occurring over data gaps is preserved if all three windows capture the jump in the bucket weight over the gap. But this will not always be the case. We resolved the problem as follows. First, we identified data gaps that overlapped the start or end of each 24-hour segment, computed the difference in bucket weight across the gap, and flagged windows when the difference was greater than or equal to *P**. For those segments only, we added a processing step between steps (5) and (6), as follows. If any of the three overlapping windows captured the jump in the bucket weight across the gap, the window(s) in P(i,j) that did not capture the jump were excluded from the averaging, and all three windows were flagged to indicate the presence of precipitation. If none of the windows captured the jump in bucket weight across the gap, the difference across the gap was assigned to the final interval of the gap in P(i,j) for all three windows, with all windows flagged to indicate the presence of precipitation.

3 Filter Evaluation

Two data sources, both with 1-min resolution, were used to evaluate the O15, NAF, NAF-S and NAF-SEG precipitation filters: a control (pre-processed) precipitation time series which is free of noise and drift; and raw (minimally filtered) automated weighing ~~accumulating~~ gauge data collected at a number of international sites, which contain varying levels of noise, diurnal oscillations, and evaporative drift. The control~~clean~~, pre-processed time series were used to evaluate all four filters -- by adding synthetic noise, diurnal oscillations, and evaporative drift, then evaluating the ability of the filters to recover the original time series. The raw time series, following quality control procedures, were passed through each of the filters, and the supervised NAF-S output was used as the standard against which to evaluate the others.

Both data sources, raw data with real-world noise, and control~~clean~~ data with synthetic noise added, have advantages and disadvantages in assessing filter performance (Peters et al., 2014). Clean data with added noise provide a known 'true' control but add the risk that the added noise and drift may not adequately capture the characteristics of real-world measurements. Raw measurements preserve observed noise patterns and capture the variability in noise behavior across sites and instruments, but do not provide a control time series for filter evaluation. By using both complementary data sources, we exploit their respective strengths and thus better assess the relative effectiveness of each filter.

3.1 Testing with pre-processed (control) precipitation data

The pre-processed 1-minute cumulative time series was originally derived from an Alter-shielded Geonor T-200B precipitation gauge at Caribou Creek, Canada from October-2013 through September~~April~~-2014. It was broken into two seasons to better assess filter performance differences between the cold-season (Oct-Apr) and the warm-season (May-Sep).~~.~~ The raw gauge outputs were filtered using NAF-S, resulting in a cold-season precipitation total of 259 mm and a warm-season precipitation total of 282 mm. Historically, this particular gauge has performed well with minimal noise (< ± 0.25 mm) and evaporation issues; the time series was very clean even prior to filtering, and therefore the filtered output provides a suitable control.

To evaluate the four filters, we added synthetic noise and drift to the filtered (noise-free) control, then tested each filters ability to recover the original signal. The perturbations included synthetic evaporation, diurnal oscillations, and random noise, computed as follows:

1. Negative evaporative drift was added that totaled 25.9 mm and 28.2 mm in the cold and warm-seasons respectively, or 10% of the precipitation totals. The synthetic evaporation was partitioned among the 1-min intervals assuming that interval evaporation was proportional to the vapor pressure deficit (VPD). The fraction of evaporation for each interval was calculated by dividing the interval VPD by the VPD sum over the entire time series. Those fractions were then multiplied by the total (25.9 mm or 28.2 mm), and the resulting cumulative sum was subtracted from the control cumulative precipitation.
2. Temperature-dependent diurnal oscillations $\delta^T(i)$ were computed from observed air temperature at gauge height and added to the cumulative precipitation control. The diurnal oscillations were calculated as:

$$\delta^T(i) = fTs * (T(i) - mean(T)) / (0.5*range(T) \quad (1)$$

   where fTs is a coefficient that varies for the different noise scenarios (Table 1**)**. The temperature-oscillation time series δ^T was then subtracted from the cumulative time series from Step 1.
3. Normally-distributed random noise was generated for each 1-min interval, with a mean of zero and a specified standard deviation (Table 1). Because the synthetic noise time series is generated randomly, it does not necessarily sum to zero. To avoid adding bias, we forced the sum to zero by subtracting the mean. The result was then added to the cumulative time series from Step 2.

The artificially-noisy time series from Step 3 were~~as~~ adjusted to a value of zero at the start, and then filtered using the O15, NAF, NAF-S, and NAF-SEG techniques. The nature and magnitude of the various noise levels can be visualized in Fig. 3.

3.2 Testing with raw precipitation data

Automated weighing ~~Precipitation~~ gauge data were collected between 2013 and 2017 at seven WMO-SPICE (Nitu et al., 2018) sites including Bratt's Lake (XBK; Canada), Caribou Creek (CCR; Canada), Centre for Atmospheric Research and Experiments (CAR; Canada), Formigal (FMG; Spain), Haukeliseter (HKL; Norway), Sodankylä (SOD; Finland), and Weissfluhjoch (WFJ; Switzerland). These sites provided high-quality precipitation observations (with a focus on cold-season measurements) from several automated weighing~~precipitation~~ gauge (Geonor T-200B and OTT Pluvio^2) configurations at a temporal resolution of 1-minute. In addition, the sites utilized a number of wind-shield configurations including the WMO Double Fence Automated Reference (DFAR), and the single Alter-shield, as well as unshielded configurations. The combination of different climate regimes, gauge types, and wind-shield configurations, provides the opportunity to test processing algorithms on contrasting noise patterns. Although the SPICE intercomparison period (2013-2015) officially ended in 2015, many of these high-quality precipitation observations were continued beyond 2015 and made available by the site hosts for this evaluation.

In total, 44 cold-season~~winter time series~~ time series (from October through April over years 2013 to 2017) and 11 warm-season time series (May through September over years 2015 to 2017) ~~time series~~ were used in testing. The raw 1-minute data (raw frequency output converted to bucket weight from the Geonor T-200B and real-time bucket weight output from the OTT Pluvio^2) were first run through an automated quality control process to remove out-of-range outliers and data jumps, which included the removal of data jumps/drops related to gauge servicing (bucket emptying and/or charging) consistent with the quality control process used for the WMO-SPICE analysis (Nitu et al., 2018). Anything missed or flagged by the automated quality control process was examined and, as necessary, cleaned manually. The 1-minute precipitation bucket-weight data were then smoothed using a Gaussian filter with a 4-minute running window. This filter smoothed large spikes in the time series that may have resulted from mechanical or electrical noise. Since all of the Geonor T-200B gauges used in this analysis were equipped with three vibrating wire transducers, the bucket weights from each wire were averaged following the quality control process to derive a single time series. This has been shown to further reduce random noise (Duchon, 2008). Finally, the time series were zeroed at the start of the season and the cumulative time series was filtered using the O15, NAF, NAF-S, and NAF-SEG techniques.

Unlike the first data sources, the raw (minimally-filtered) observations do not provide a control. To overcome this limitation, we used the NAF-S output as the reference standard for the other three methods. This adds a potential bias because of NAF-S-user subjectivity, but we believe the bias to be small. Previous tests have shown NAF-S to achieve favorable results (Smith et al., 2019).

3.3 Analysis methods

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For analysis, the 1-minute filtered data were aggregated into 30-minute accumulation intervals. Three statistical tests were chosen to analyze the performance of the post-processing techniques: total bias (for each seasonal time series), root mean square error (RMSE; or more appropriately, root mean square deviation RMSD for the tests with unfiltered data), and Pearson's correlation coefficient (r). The total bias is a valuable metric that demonstrates the post-processing technique's overall ability to generate an accurate total. The RMSE (or RMSD) quantifies the variability of the filter outputs relative to the control or reference standard. Finally, Pearson's correlation coefficient determines the strength of the linear relationships between the filter outputs and the control or reference. RMSE (or RMSD) and r are based on the interval precipitation amounts and include the intervals with zero precipitation.

4 Results

4.1 Filter evaluation using pre-processed (control) data

The performance of the four filters was evaluated by adding synthetic noise and drift to ~~a~~ clean (control) cold-season and warm-season time series and then assessing each filter's skill in recovering the control. The cold-season results are shown in Fig. 2, and an in-depth look at the first simulated cold-season evaporation event is shown in Fig. 3**,** for each of the three noise scenarios. The warm-season results (~~are~~ not shown) ~~here but~~ are ~~they look~~ very similar to the cold-season results ~~shown~~ in Fig. 2 and Fig. 3. Tables 2 to 4 show the associated 30-minute total seasonal biases, correlation coefficients, and RMSE for all four filters, and the NAF-SEG evaporation estimates, broken down by season.~~.~~

Based on their success in eliminating the added synthetic noise and drift and recovering the original control time series, NAF-S and NAF-SEG outperformed NAF and O15. O15 performed well at low noise but was sensitive to higher noise levels, with biases in total precipitation of +1% (+8%), +13% (+21%) and +33% (+46%) for the cold-season (warm-season) low, medium and high noise scenarios respectively. NAF was insensitive to noise but failed to recover the added evaporative losses (10% of the precipitation total) at all noise levels. NAF-S and NAF-SEG performed well at all three noise levels, recovering the control precipitation to within 3~~2~~% of the total (regardless of season) and generating the highest correlation coefficients and lowest RMSE. NAF-SEG also produced an estimate of evaporation; its skill in detecting evaporative losses varied by both season and noise level. In the cold-season, NAF-SEG overestimated the synthetic evaporation by~~had , with a~~ 16% ~~overestimation of the synthetic total~~ at high noise and underestimated the synthetic evaporation by ~~a~~ 19% ~~underestimation~~ at low noise. In the warm-season, NAF-SEG underestimated the synthetic evaporation by ~~total from~~ 10% at ~~(~~high noise and ~~) to~~ 26% at ~~(~~low noise~~)~~. Given the inherent difficulty of ~~the~~ deconvolving the evaporation and precipitation signals, ~~task~~ and the high degree of temporal detail in the added evaporation time series, ~~and given that the fully automated NAF-SEG matched the skill of the manually supervised NAF-S,~~ the ability of the NAF-SEG filter to detect and eliminate ~~negative~~ evaporative drift was encouraging. Indeed, the fully automated NAF-SEG was able to match the skill of the manually supervised NAF-S.

4.2 Filter evaluation using unprocessed data

This intercomparison examines the relative performance of the O15, NAF and NAF-SEG filters on raw (minimally-processed) weighing-gauge time series, using the NAF-S output as the reference standard. Individual results from the 44 cold-season and 11 warm-season test time series are shown in Tables A1 and A2 respectively. Overall, the NAF-SEG technique gave the lowest mean bias, highest mean correlation coefficient r, and lowest mean RMSD value (Table 5) in both seasons. In cold-season testing, t~~T~~he absolute bias from NAF-SEG was lower than the O15 bias in 37 of 44 cases (84%), similar in 5 cases (11%) and higher in 2 cases (5%). In warm-season testing, NAF-SEG showed a lower or similar absolute bias in ~~8~~7 of the 11 cases (~~73~~64%). NAF-SEG also produced the lowest variability in r, RMSD and seasonal total (Fig. 4, showing cold-season only), suggesting the greatest consistency in processing performance across sites, configurations and years.

The relative performance of NAF-SEG, NAF, and O15 varied across the 55~~44~~ test time series, related to the nature and magnitude of the~~ added~~ noise and negative drift due to evaporation from the bucket (Table A1 and A2). Figure 5 shows four cold-season examples, comparing raw and processed time series. The y-axis is scaled to the precipitation total to provide perspective on the relative errors in the processing techniques. The inset graphs in Fig. 5, which zoom in on particular events, highlight the magnitude of noise and drift in the raw data and show how the filters respond.

Figure 5a shows a time series for Caribou Creek (CCR), Canada, where the raw data exhibit~~s~~ very little noise or evaporation. For that reason, all processing techniques are within a few percent of the NAF-S reference, and it is difficult to see the differences during much of the time series. Fig. 5b, from Haukeliseter (HKL), Norway, exhibits higher noise, resulting in an O15 precipitation overestimate of +9% due to false precipitation detection. A moderate amount of evaporation is seen in the growing difference between NAF and NAF-S, with NAF-SEG nearly replicating NAF-S. Fig. 5c and 5d, from Bratt's Lake (XBK), Canada, show cases with high evaporation (5c) and high noise (5d). In Fig. 5c, evaporation causes a low bias in NAF, which recovers only 87% of the NAF-S precipitation total; O15 shows two compensating errors – an underestimation in precipitation due to evaporation and an increase in false precipitation detections due to noise, resulting in a recovery of 94% of total precipitation relative to NAF-S; and NAF-SEG closely replicates NAF-S, with slight deviations in Nov. and Dec. Fig 5d shows the impact of high noise with little evaporation; O15 overestimates precipitation by 4%, whereas NAF-SEG is consistent with NAF-S throughout the time series.

5 Discussion

This study evaluated four filters for processing the outputs of accumulating automated ~~(~~weighing~~)~~ precipitation gauges, three that were fully automated (O15, NAF and NAF-SEG) and one that required manual supervision (NAF-S). Overall, NAF-S and NAF-SEG outperformed O15 and NAF; both NAF-S and NAF-SEG showed similar skill in compensating for evaporative losses and eliminating false detections caused by random noise and diurnal oscillations. O15 performed well in low noise cases with minimal evaporation, but generated false precipitation detections when the data were noisy, and often underestimated evaporative losses. NAF performed well in cases with minimal evaporation regardless of the noise level but did not correct for evaporative losses. NAF-SEG performed consistently well and provided a fully-automated alternative that matched the skill of the manual NAF-S method. Moreover, NAF-SEG added a direct estimate of evaporation, without the user intervention required by NAF-S or the 1-mm threshold required by O15. Similar evaporation estimates are not directly available from the other techniques.

Although NAF-SEG did not perfectly recover the synthetic evaporation that was added to the control time series (the recovery rates were 81% to 116% depending on the noise level), it performed as well as the manually-supervised NAF-S technique. Both NAF-S and NAF-SEG failed to disentangle precipitation and evaporation when they occurred on the same day. The challenge to do so may be insurmountable. The imperfect recovery of synthetic evaporation, coupled with the sensitivity of the recovered evaporation to noise, highlights the need to implement measurement protocols that minimize evaporative losses. We recommend the use of NAF-SEG as a screening technique to identify gauges and locations that have significant evaporative losses, and then to implement adequate measures to minimize those losses, such as modifications to the oil and antifreeze mixture used to prevent freezing and evaporation.

Overestimation of precipitation by the O15 method occurs when the noise exceeds the filter's prescribed threshold of 0.2 mm. This value for the threshold has been set based on experience as a necessary and calculated balance between eliminating real precipitation events and detecting false events. When the noise level is low, as in the low noise scenario of the control data, the O15 technique works successfully. However, noise patterns vary substantially from site to site and among gauges, as illustrated by Nitu et al. (2018), and often exceed the filtering capabilities of O15. It should also be noted that the unprocessed data in our ~~these~~ tests were pre-filtered using ~~with~~ a Gaussian filter with a 4-min window, which was integrated into the SPICE quality control process~~,~~ prior to testing the algorithms. This likely resulted in the O15 filter performing better than it would have in the operational setting, but this was not confirmed.

The NAF technique is fundamentally effective at filtering noise and diurnal oscillations, but underestimates precipitation when evaporative losses occur, because the algorithm forces the precipitation total to match the final raw bucket weight in the time series, with evaporation assumed to be zero. The NAF-SEG technique, which implements NAF over 24-hour windows, maintains all the strengths of NAF with the added functionality of automating the detection and removal of bucket evaporation. Neither NAF-S ~~or~~nor NAF-SEG remove evaporation perfectly, particularly when it occurs in consort with precipitation, but both represent a major step forward compared to other processing methods. We attribute the effectiveness of NAF-SEG to two characteristics ~~properties~~ of precipitation events, first that evaporation is relatively small during periods with precipitation, and second that both precipitation and evaporation are persistent over time scales of days. In the development of NAF-SEG, a 24-hour moving window was chosen to minimize the impact of temperature-related diurnal oscillations, but fortuitously the 24-hour window also ~~serves~~ served to separate days with precipitation and little evaporation from days with evaporation and little or no precipitation. The ~~re may also be a decrease in the~~ performance of NAF-SEG may decline when signal noise is due to non-cyclical temperature fluctuations, such as those that occur during strong synoptic events. Although this possibility was no~~'~~t ~~explicitly~~ assessed, it ~~may be a situation~~ is one that ~~a~~ users should be aware of.

As mentioned in the introduction to NAF-SEG, a sensitivity analysis was performed for a range of P* values ranging from 0.0001 to 0.5 mm using the pre-processed high-noise time series for both warm and cold-seasons. ~~Although the results are not discussed in greater detail, t~~The analysis ~~experiment~~ showed negligible sensitivity as P* ranged from 0.0001 through 0.05~~,~~ and higher sensitivity as ~~although the metrics changed substantially at~~ P* further increased to ~~the~~ 0.5 mm, ~~setting~~ for both seasons. Given the relative insensitivity of NAF-SEG to P* < 0.5 mm, the use of 0.001 mm seems to be an appropriate baseline value for both seasons; ~~, but~~ users may want to further experiment with the parameter as their own data requires.

NAF-SEG provides an attractive alternative to NAF when negative evaporative drift is present in the raw data, but it is not designed to handle all contingencies. For instance, unexplained positive then negative excursions in bucket weight are sometimes observed. If the positive and negative excursions are separated by more than 24 hours (the size of the window), the NAF-SEG filter will errantly attribute the positive excursion to precipitation and the negative excursion to evaporation.

The results of the testing on unprocessed time series from different sites, seasons, and gauge configurations showed that NAF-SEG generally outperformed O15 on both cold- and warm-season test cases. Of the 44 cold-season ~~raw-data~~ test cases ~~from different sites, seasons, and gauge configurations~~, O15 outperformed NAF-SEG in only two cases: the DFAR and unshielded Pluvio^2 gauges at WFJ, 2016-2017. However, ~~These~~ these gauges may not have been serviced adequately; note the extreme evaporation rates as evidenced in the high biases between NAF and NAF-S in Table A1. This ~~may~~ diminishes their usefulness ~~value of these time series~~ for this evaluation; they were among the most challenging to process, with the greatest ~~adding~~ uncertainty in ~~to~~ the supervised NAF-S output ~~which~~ that served as the reference standard.

Filter evaluation was more limited in the warm season because the raw site data were obtained from the SPICE project, which focused on the measurement of solid precipitation. Still, we were able to assemble 11 warm-season cases. The warm-season data were expected to differ from the cold-season data in two respects: higher evaporative losses and different noise characteristics. Each of the filters generated a higher RMSD in the warm season than the cold season; the greatest increase was found for O15, consistent with the pre-processed control experiments. In general, NAF-SEG outperformed both NAF and O15 in the warm season.~~-~~ NAF-SEG outperformed O15 in all warm season cases for r and RMSD, and resulted in a lower or similar seasonal bias in 7 of the 11 cases. The NAF-SEG totals consistently underestimated warm-season precipitation but the biases ~~was~~were small, averaging 1.7% compared with 1.0% for the cold season. ~~Although RMSD increased for each of the filters for the warm-season, the increase in O15 was the largest, and consistent with the pre-processed control experiments.~~ ~~Fewer warm-season test cases were examined, largely due to data availability, since the unprocessed data used in this analysis were obtained from the SPICE project that had a focus on cold-season precipitation intercomparisons. It was expected that warm-~~

~~season bucket evaporation would be higher relative to the cold-season and that the warm-season noise could exhibit different characteristics and therefore have a negative impact on the performance of the filters. Of the 11 warm-season test cases, O15 only outperformed NAF-SEG in three of those cases (all from XBK). The reason for these three cases cannot be easily explained. Although all of the NAF-SEG warm-season biases were negative (under-estimating), and on average slightly higher than for the cold-season (1.7% and 1.0% for the warm- and cold-season respectively), the differences were not substantial. Although RMSD increased for each of the filters for the warm-season, the increase in O15 was the largest, and consistent with the pre-processed control experiments. However, with~~~~Given the smaller warm-season sample size, it iwas not possible to difficult to determine if the performance differences are significant. Filter performance for warm-season processing should be explored further.~~ Regardless of the sample size, the performance metrics all show that NAF-SEG outperformed both NAF and O15 in the warm-season as well as the cold-season.

~~The~~ The evaluation of filter ~~analysis of the~~ performance ~~metrics of the filters~~ based on ~~the~~ raw site ~~unprocessed~~ data ~~is observation~~ begs the question: how reliable are the NAF-S outputs as reference standards, given that they rely on the operator's subjective judgment during the interactive elimination of negative drift and other spurious bucket weight changes? We acknowledge that operator bias is possible but are confident that its impact in this study is minimal. A single, skilled operator processed all of the data and made every attempt to apply the NAF-S method consistently. Adding further confidence to the NAF-S outputs are the tests with control data, which independently demonstrated the efficacy of the NAF-S to eliminate noise and evaporative drift.

~~The precipitation time series used in his study were collected during October to April as part of an intercomparison of solid-precipitation measurement techniques. Although the data include liquid, mixed, and solid precipitation events at many of the sites, the precipitation is predominately snowfall. We recommend a complementary follow-up study on the processing of warm-season precipitation measurements from accumulating gauges. The issues faced may vary by season. Compared to other seasons, cold-season evaporation rates are low, as was confirmed for most cases in this study (Table A1). The identification and elimination of evaporative losses may be more challenging in the warm season when evaporation rates are higher. On the other hand, precipitation rates are generally lower for solid precipitation than rainfall, which reduces the signal to noise ratio, therefore adding difficulty to the processing of solid precipitation data.~~

One suggestion to ~~for~~ improv~~ing~~e the ~~the~~ quality of data from accumulating precipitation gauges is ~~NAF-SEG filter, or any of the tested filters for that matter, would be~~ to add~~incorporate~~ ~~the use of present weather detectors or~~ disdrometers, which detect the current weather conditions, ~~in~~to the site measurements, then incorporate their outputs ~~configurations for use during~~ into the quality control and filtering process. These augmented observations could be used to refine the noise filtering by automating the high temporal resolution (e.g. 1-min) detection of light precipitation events and assist in removing false precipitation ~~report~~detections. These ancillary data ~~measurements~~ were used in this way during SPICE (Nitu et al., 2018) and ~~they~~ should be further explored for enhancing operational filtering.

6 Conclusions

This study reports the development and implementation of a robust, fully-automated technique for post-processing data from automated ~~accumulating (~~weighing~~)~~ precipitation gauges. The NAF-SEG technique is designed to eliminate varying levels of random noise and diurnal oscillations, as well as correcting for negative drift from bucket evaporation. An intercomparison of four filtering techniques shows that the operational O15 filter, although simple and deployable in real-time, fails when noise levels exceed the filter's threshold, and may undercompensate for bucket evaporation. NAF, although highly effective in eliminating noise, does not correct for evaporative losses. NAF-S, which adds manual supervision to NAF, is effective in removing noise, eliminating spurious data, and correcting for negative drift from evaporation. However, it is labour intensive and best suited to complete seasonal time series.

Our results show that NAF-SEG is equally effective to NAF-S in eliminating noise and evaporative drift from automated weighing ~~accumulating~~ gauge precipitation measurements. When tested against a control data set with added synthetic noise and evaporation, NAF-SEG was able to recover the original control to within ± 3~~2~~% of the total, with a lower RMSE than the other techniques. When evaluated on 55~~44~~ raw time series from various sites, years and gauge configurations, NAF-SEG outperformed O15 and NAF and gave the highest mean correlation coefficient and lowest mean RMSD.

One limitation of NAF-SEG is that it requires 24-hour data segments; consequently, it cannot be deployed for real-time processing of automated weighing ~~-~~gauge precipitation measurements. Until other alternatives are found, we recommend the use of a simple threshold filter like O15 for real-time applications, but with the archiving of the raw 1-min time series for subsequent enhanced quality control, reprocessing using NAF-SEG, and the archiving of the NAF-SEG outputs. This, in combination with routine site servicing to minimize ~~pre-empt~~ evaporation and other sources of noise, can result in improved operational precipitation data.

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Data and code availability

The code for NAF-SEG and the precipitation time series intercomparison data used in this evaluation will be made available in a suitable online repository.

Author contribution

A.R. is the lead author and was responsible for the processing and analysis of these data. A.R. also completed much of the coding required to implement the data processing. C.S. oversaw the development of this project and provided guidance in the analysis and the development of this manuscript. A.B. designed and coded the NAF filters and provided guidance in the analysis and in the writing of this manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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Table 1: Diurnal and random noise parameters in the simulated precipitation time series

Noise Level	High	Medium	Low
Diurnal coefficient (fTs) (mm)	2	1.5	1
Random noise (std dev) (mm)	0.1	0.01	0.001

~~**Table 2: Total seasonal bias in mm and percent of total for NAF, NAF-S, O15, and NAF-SEG post-processing techniques at different simulated noise levels.**~~

Noise Level	NAF (mm)	NAF (%)	NAF-S (mm)	NAF-S (%)	O15 (mm)	O15 (%)	NAF-SEG (mm)	NAF-SEG (%)
Low	-26.1	-10.1%	-6.4	-2.5%	1.5	+0.6%	-2.8	-1.1%
Med	-26.2	-10.1%	-3.4	-1.3%	33.5	+12.9%	1.0	+0.4%
High	-26.3	-10.2%	-2.7	-1.0%	86.0	+33.2%	5.0	+1.9%

Table 2: Total seasonal bias in mm and percent of total for NAF, NAF-S, O15, and NAF-SEG post-processing techniques at different simulated noise levels for the cold (C) and warm (W) seasons.

Noise Level	NAF (mm)	NAF (%)	NAF-S (mm)	NAF-S (%)	O15 (mm)	O15 (%)	NAF-SEG (mm)	NAF-SEG (%)
Low-C	-26.1	-10.1%	-6.4	-2.5%	1.5	+0.6%	-2.8	-1.1%
Low-W	-27.7	-9.8%	-3.3	-1.2%	22.8	+8.1%	-8.2	-2.9%
Med-C	-26.2	-10.1%	-3.4	-1.3%	33.5	+12.9%	1.0	+0.4%
Med-W	-27.6	-9.8%	1.9	+0.7%	58.3	+20.7%	-7.4	-2.6%
High-C	-26.3	-10.2%	-2.7	-1.0%	86.0	+33.2%	5.0	+1.9%
High-W	-27.7	-9.8%	2.1	+0.7~~8~~%	130.0	+46.1~~2~~%	-9.2	-3.3%

~~**Table 3: Correlation coefficient (r) and RMSE for NAF-SEG, NAF-S, NAF, and O15 post-processing techniques at different simulated noise levels.**~~

Noise Level	r NAF	r NAF-S	R O15	r NAF-SEG	RMSE NAF (mm)	RMSE NAF-S (mm)	RMSE O15 (mm)	RMSE NAF-SEG (mm)
Low	0.97	0.99	0.94	0.99	0.029	0.020	0.044	0.019
Med	0.97	0.98	0.92	0.98	0.032	0.025	0.053	0.024
High	0.95	0.96	0.87	0.96	0.041	0.038	0.069	0.037

Table 3: Correlation coefficient (r) and RMSE for NAF-SEG, NAF-S, NAF, and O15 post-processing techniques at different simulated noise levels for the cold (C) and warm (W) seasons.

Noise Level	r NAF	r NAF-S	r O15	r NAF-SEG	RMSE NAF (mm)	RMSE NAF-S (mm)	RMSE O15 (mm)	RMSE NAF-SEG (mm)
Low-C	0.97	0.99	0.94	0.99	0.029	0.020	0.044	0.019
Low-W	0.98	1.00	0.98	1.00	0.045	0.020	0.054	0.021
Med-C	0.97	0.98	0.92	0.98	0.032	0.025	0.053	0.024
Med-W	0.98	0.99	0.97	0.99	0.049	0.027	0.061	0.027
High-C	0.95	0.96	0.87	0.96	0.041	0.038	0.069	0.037
High-W	0.97	0.99	0.95	0.99~~7~~	0.057	0.041	0.084	0.041

~~**Table 4: NAF-SEG evaporation estimates for different simulated noise levels with actual evaporation constant at 25.9 mm in the control.**~~

~~Noise Level~~	~~Recovered Evaporation (mm)~~	~~% of Actual~~
~~Low~~	~~21.0~~	~~81%~~
~~Med~~	~~25.1~~	~~97%~~
~~High~~	~~30.1~~	~~116%~~

Table 4: NAF-SEG evaporation estimates for different simulated noise levels with actual evaporation constant at 25.9 mm in the cold-season (C) and 28.2 mm in the warm-season (W) control.

Noise Level	Recovered Evaporation (mm)	% of Actual
Low-C	21.0	81%
Low-W	20.8	74%
Med-C	25.1	97%
Med-W	22.7	81%
High-C	30.1	116%
High-W	25.5	90%

Table 5: Mean correlation coefficients (r) and RMSD along with standard deviations (SD) for all observed real-world precipitation time series using NAF-S as the reference (warm-season, May through September, in parenthesis).

~~Post-Processing Technique~~	~~Mean r~~	~~SD r~~	~~Mean RMSD (mm)~~	~~SD RMSD (mm)~~
~~NAF-SEG~~	~~0.99~~	~~0.006~~	~~0.017~~	~~0.006~~
~~NAF~~	~~0.98~~	~~0.040~~	~~0.020~~	~~0.025~~
~~O15~~	~~0.95~~	~~0.032~~	~~0.041~~	~~0.024~~
Post-Processing Technique	Mean r	SD r	Mean RMSD (mm)	SD RMSD (mm)
NAF-SEG	0.991 (0.999)	0.006 (0.001)	0.017 (0.020)	0.006 (0.008)
NAF	0.983 (0.998)	0.040 (0.003)	0.020 (0.027)	0.025 (0.013)
O15	0.952 (0.989)	0.032 (0.010)	0.041 (0.068)	0.024 (0.015)

Appendix A: Raw time series used in precipitation filter evaluation, with evaporation estimates and total precipitation bias.

Table A1: Seasonal total precipitation (unfiltered, NAF-S and NAF-SEG filtered), filter biases (NAF, O15 and NAF-SEG) and derived bucket evaporation (NAF-SEG) from 44 WMO-SPICE precipitation time series. Biases (mm) are calculated using NAF-S as the reference filtering technique. Filtered time series that do not show an improvement with the NAF-SEG method when compared to O15 are indicated by an asterisk (*).

Site/Shield/Gauge/Year	Unfiltered Total (mm)	NAF-S Total (mm)	NAF-SEG Total (mm)	Bias NAF (mm)	Bias O15 (mm)	Bias NAF-SEG (mm)	Evaporation NAF-SEG Estimate (mm)
CAR-R2P-2016-2017	441.6	468.8	455.2	-27.2	-15.0	-13.6	9.6
CAR-R3AG-2016-2017	400.4	407.0	406.0	-6.6	-5.7	-1.0	4.7
CAR-R3AP-2016-2017	365.1	394.0	380.2	-28.9	-17.7	-13.8	12.0
CAR-R3UP-2016-2017	313.5	345.8	330.1	-32.3	-19.1	-15.7	11.6
CCR-ABG-2013-2014	256.5	259.0	258.0	-2.5	-2.2	-1.0	2.1
CCR-ABG-2014-2015	168.6	172.7	171.7	-4.1	-3.7	-0.9	3.5
CCR-ABG-2015-2016	171.5	174.3	174.8	-2.8	-1.1	0.4	3.8
CCR-ABP-2014-2015	166.1	174.8	172.7	-8.8	-5.4	-2.2	6.2
CCR-ABP-2015-2016	171.1	177.1	177.0	-6.0	-2.1	-0.1	5.9
CCR-R2G-2014-2015	105.7	106.3	108.1	-0.6	8.1	1.8	3.4
CCR-R2G-2015-2016	186.5	189.3	188.3	-2.8	-2.0	-1.1	2.3
CCR-R2G-2013-2014*	275.5	279.6	276.5	-4.0	0.4	-3.1	3.0
CCR-R3AG-2013-2014	222.9	224.1	224.6	-1.2	-1.0	0.4	2.5
CCR-R3AG-2014-2015*	85.8	86.8	88.1	-1.1	-0.4	1.3	2.6
CCR-R3UG-2013-2014	183.4	185.2	184.4	-1.9	-1.3	-0.8	2.5
CCR-R3UG-2014-2015*	72.3	73.9	75.6	-1.6	-0.7	1.7	3.0
FMG-R2P-2015-2016	1036.7	1053.8	1042.1	-17.1	-13.0	-11.7	3.4
FMG-R3AP-2015-2016*	828.1	849.1	832.6	-21.0	-15.6	-16.5	2.6
HKL-R2G-2016-2017*	748.5	755.0	754.0	-6.5	-0.5	-1.0	5.1
HKL-R3AG-2016-2017	423.9	437.5	438.0	-13.6	39.4	0.5	11.1
HKL-R3AP-2016-2017	385.4	403.0	399.5	-17.6	-3.7	-3.5	10.3
HKL-R3UG-2016-2017	320.5	328.3	329.2	-7.8	-2.2	0.9	7.8
SOD-R2P-2016-2017	215.0	238.4	234.7	-23.4	-7.4	-3.7	15.7
SOD-R3AP-2016-2017	187.7	212.9	207.8	-25.2	-8.9	-5.1	16.7
SOD-R3UP-2016-2017	180.9	194.1	192.0	-13.2	-4.1	-2.2	9.4
WFJ-R2P-2016-2017*	595.4	715.1	706.6	-119.7	-1.5	-8.5	102.4

WFJ-R3AP-2016-2017	375.4	605.7	598.0	-230.3	13.2	-7.7	208.6
WFJ-R3UP-2016-2017*	246.6	434.6	423.6	-188.0	0.4	-11.0	167.0
XBK-AP-2013-2014	83.8	91.9	90.7	-8.1	-4.2	-1.2	4.9
XBK-AP-2014-2015	49.5	59.5	58.1	-10.0	-6.6	-1.4	7.1
XBK-AP-2015-2016	61.1	74.9	71.8	-13.7	-9.4	-3.1	8.2
XBK-DAG-2013-2014	131.4	136.0	134.2	-4.6	-3.9	-1.8	3.3
XBK-DAG-2014-2015	104.3	111.0	108.5	-6.7	-3.4	-2.4	5.6
XBK-DAG-2015-2016	90.2	97.1	95.5	-7.0	-5.5	-1.6	5.2
XBK-R2G-2013-2014	167.2	170.2	170.4	-3.0	-2.8	0.2	2.3
XBK-R2G-2015-2016	71.1	75.5	75.7	-4.4	-4.1	0.3	3.8
XBK-R2P-2014-2015	110.3	119.2	114.9	-8.8	-7.6	-4.2	3.7
XBK-R2P-2015-2016	80.4	92.6	91.2	-12.2	-5.6	-1.3	9.4
XBK-R3AG-2013-2014	97.7	100.7	101.4	-3.0	-2.9	0.7	3.7
XBK-R3AG-2014-2015	73.0	78.3	76.9	-5.3	-2.8	-1.4	4.7
XBK-R3AG-2015-2016	72.7	78.2	77.8	-5.5	-5.0	-0.4	5.2
XBK-R3UG-2013-2014	83.1	89.6	90.2	-6.5	3.8	0.6	7.3
XBK-R3UG-2014-2015	56.4	63.8	62.3	-7.5	-3.0	-1.6	7.2
XBK-R3UG-2015-2016	69.5	76.2	75.2	-6.7	-4.2	-1.0	5.7

Table A2: Warm-seasonal total precipitation (unfiltered, NAF-S and NAF-SEG filtered), filter biases (NAF, O15 and NAF-SEG) and derived bucket evaporation (NAF-SEG) from ~~6~~11 WMO-SPICE precipitation time series. Biases (mm) are calculated using NAF-S as the reference filtering technique. Filtered time series that do not show an improvement with the NAF-SEG method when compared to O15 are indicated by an asterisk (*).

Site/Shield/Gauge/Year	Unfiltered Total (mm)	NAF-S Total (mm)	NAF-SEG Total (mm)	Bias NAF (mm)	Bias O15 (mm)	Bias NAF-SEG (mm)	Evaporation NAF-SEG Estimate (mm)
CCR-ABP-2015	344.8	353.5	350.9	-8.7	-4.4	-2.6	5.7
CCR-R2G-2015	349.3	354.0	353.3	-4.7	-3.1	-0.7	3.4
XBK-R2P-2015*	222.8	242.0	232.2	-19.2~~1~~	-4.7	-9.8	5.7
XBK-R2P-2016*	261.5	282.6	271.6	-21.1	-6.4	-11.0	7.6
XBK-R3UG-2015*	253.5	260.3	258.3	-6.8	-0.9	-2.0	5.3
XBK-R3UG-2016	287.6	293.7	290.4	-6.1	7.0	-3.3	4.9
CAR-R3AG-2016	294.8	307.0	305.1	-12.2	-7.8	-1.9	9.0
CAR-R3AG-2017	386.3	389.6	389.2	-3.3	-3.4	-0.4	3.1
CAR-R3UP-2017	346.7	369.3	361.3	-22.6	-8.1	-8.0	10.1
CAR-R2P-2017*	358.1	383.5	372.2	-25.4	-8.9	-11.3	10.6
CAR-R3AP-2017*	345.1	368.8	361.2	-23.7	-4.1	-7.6	12.2

Table A3~~2~~: A description of the different shield/gauge configurations used in tables A1 and A2.

Code	*Description*
R2	DFAR Reference (SPICE)
R3	Alter or Unshielded Reference (SPICE)
A	Single Alter shield
U	Unshielded
DA	Double Alter shield
B	Bush shield
P	Pluvio gauge
G	Geonor gauge

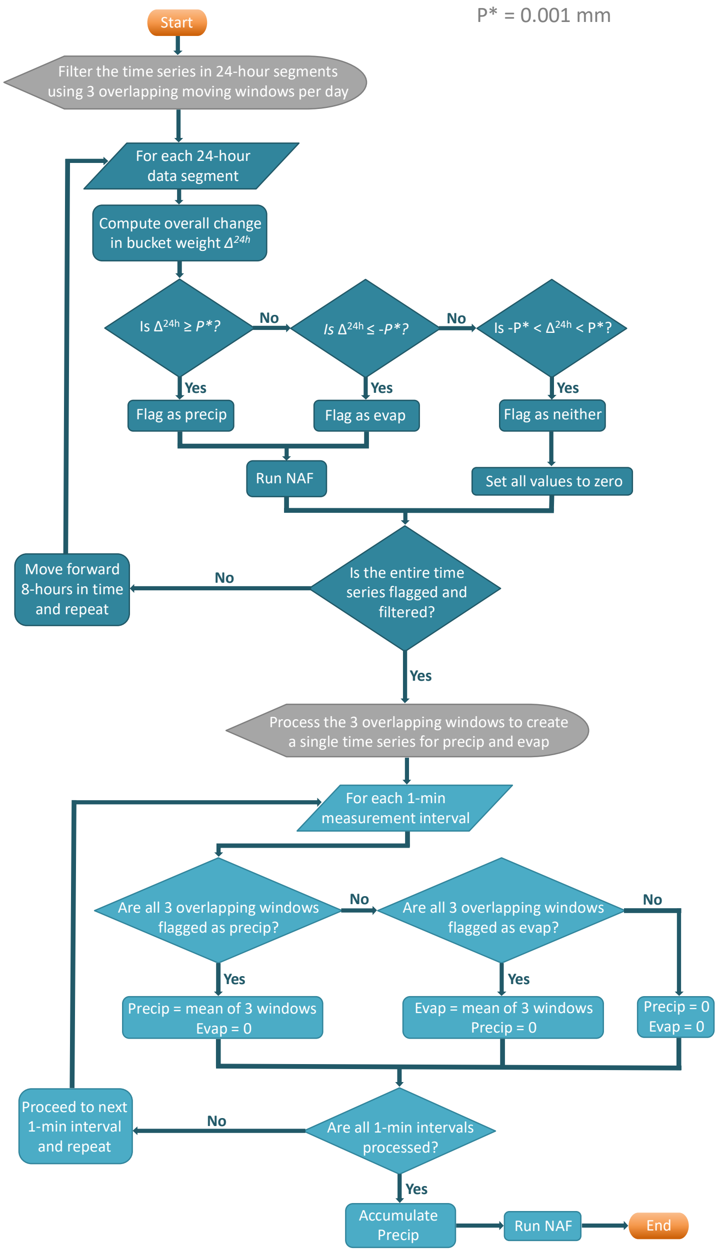


Figure 1: NAF-SEG data flowchart

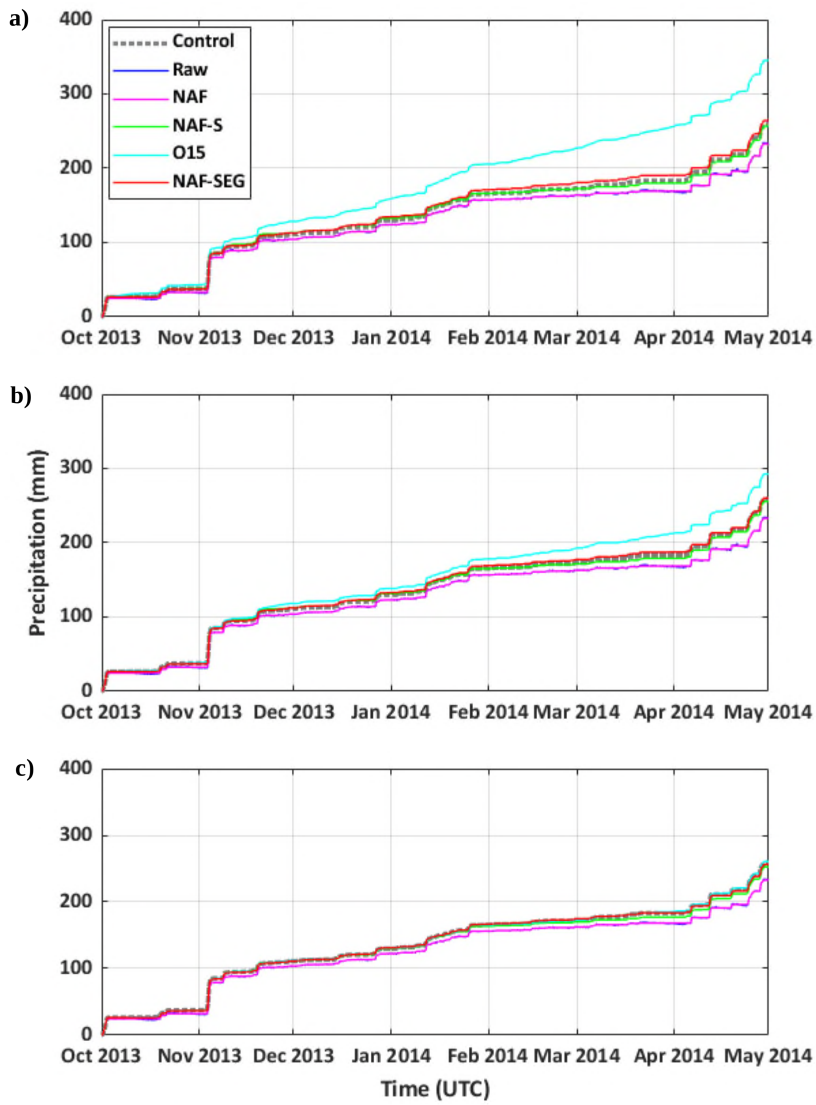


Figure 2: Time series of simulated cold-season precipitation gauge bucket weight with synthetic evaporation and varying levels of synthetic noise and diurnal oscillations (A - high noise; B - med noise; C - low noise).

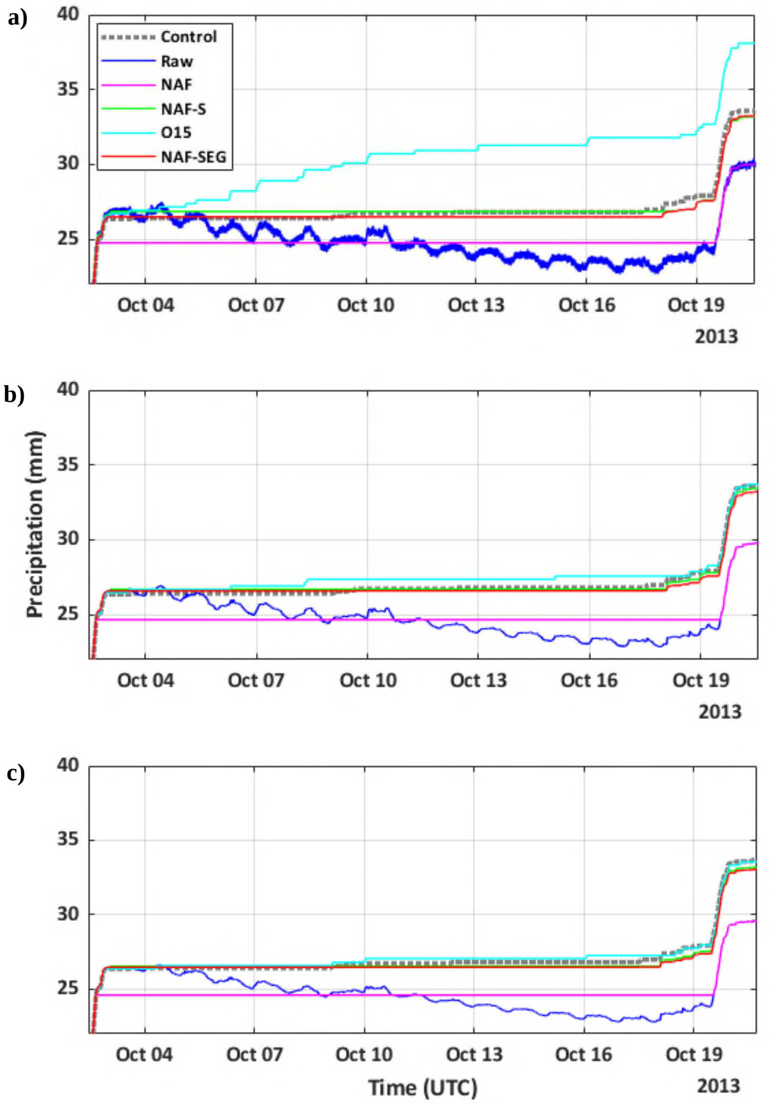


Figure 3: Time series of simulated cold-season precipitation gauge bucket weight (zoomed into the first evaporation event) with synthetic evaporation and varying levels of synthetic noise and diurnal oscillations (A - high noise; B - med noise; C - low noise).

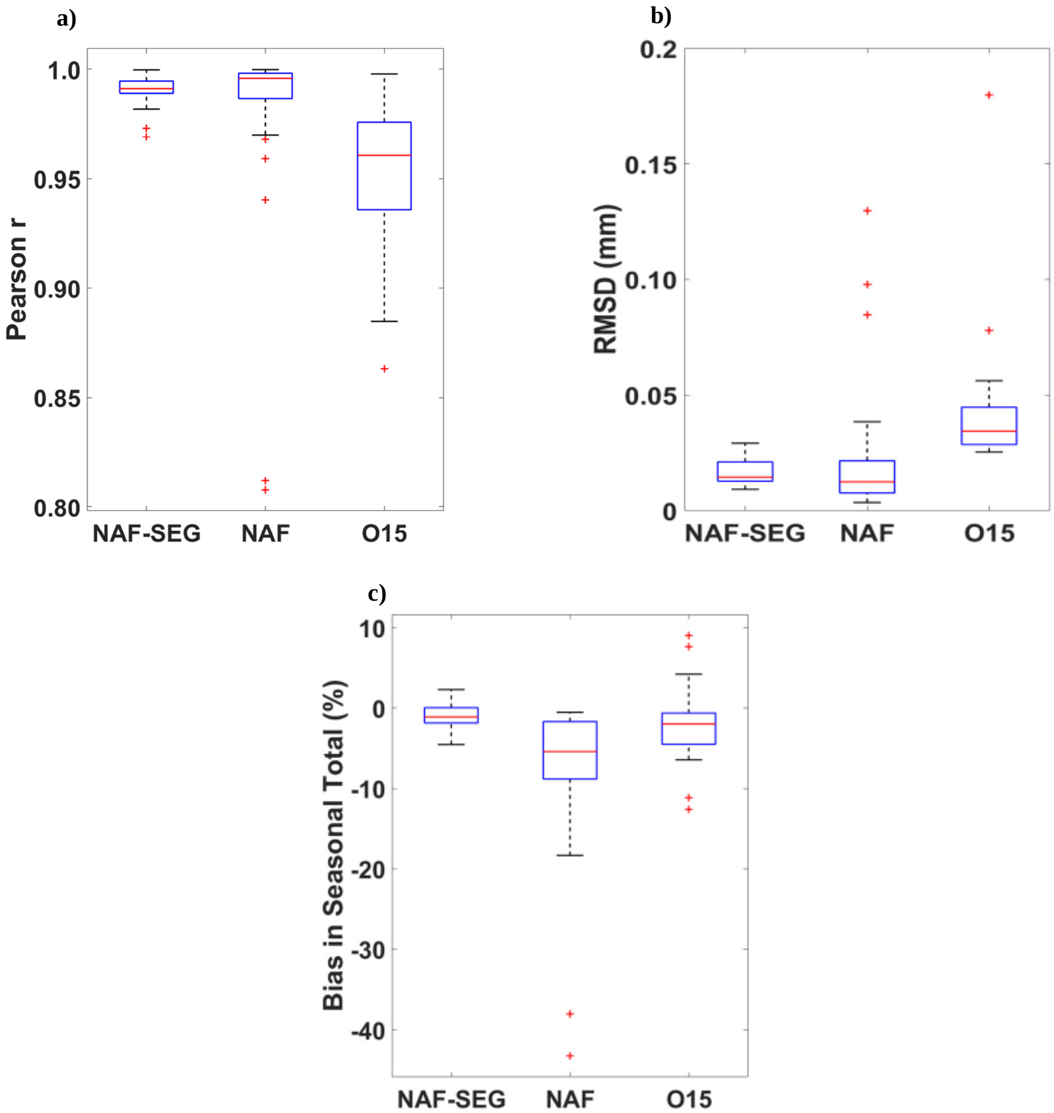
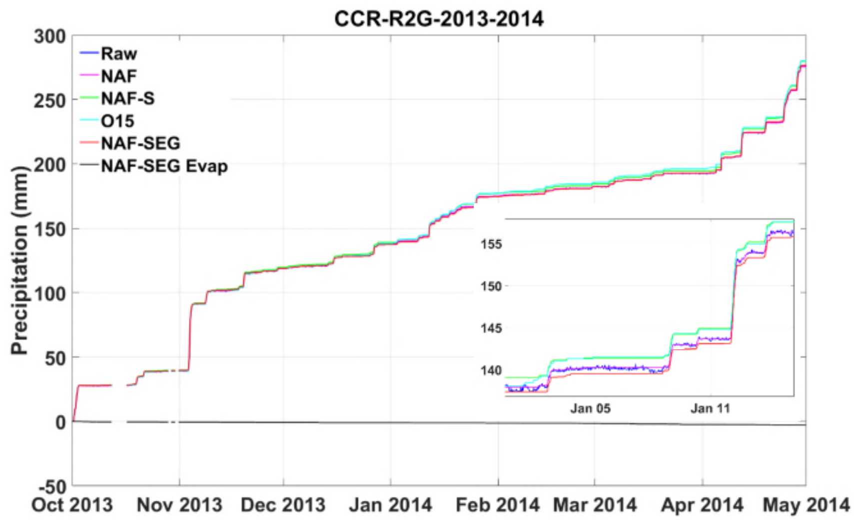
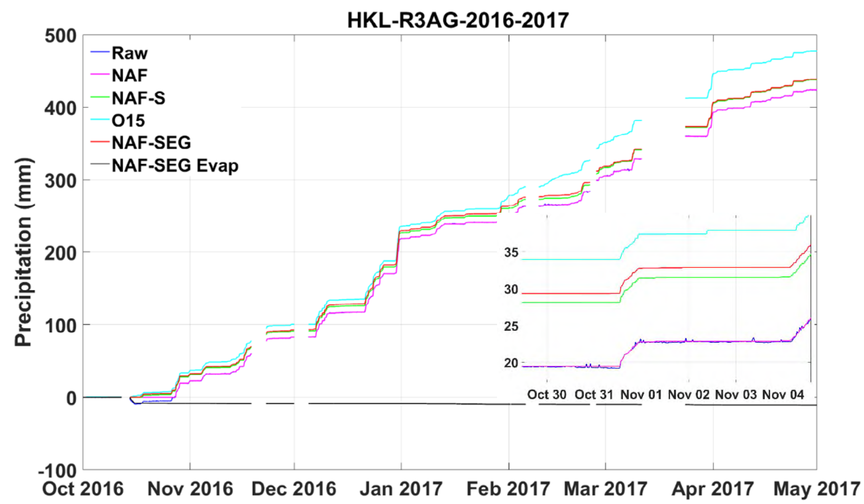


Figure 4: Box and whisker plots of (a) Pearson r, (b) RMSD and (c) bias in ~~seasonal~~ cold-season total precipitation relative to the reference for each of the evaluated filtering techniques (NAF-SEG, NAF, and O15) as compared to the reference technique (NAF-S) for the 44 unprocessed time series.

a)


CCR-R2G-2013-2014
Raw
NAF
NAF-S
O15
NAF-SEG
NAF-SEG Evap
Precipitation (mm)
300
250
200
150
100
50
0
-50
155
150
145
140
Jan 05
Jan 11
Oct 2013
Nov 2013
Dec 2013
Jan 2014
Feb 2014
Mar 2014
Apr 2014
May 2014

b)


HKL-R3AG-2016-2017
Raw
NAF
NAF-S
O15
NAF-SEG
NAF-SEG Evap
Precipitation (mm)
500
400
300
200
100
0
-100
35
30
25
20
Oct 30
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Nov 02
Nov 03
Nov 04
Oct 2016
Nov 2016
Dec 2016
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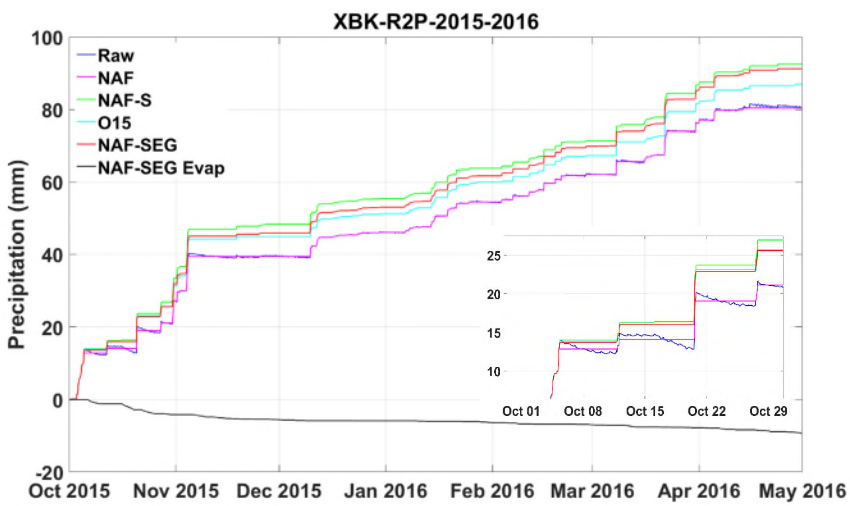
Feb 2017
Mar 2017
Apr 2017
May 2017

c)



d)

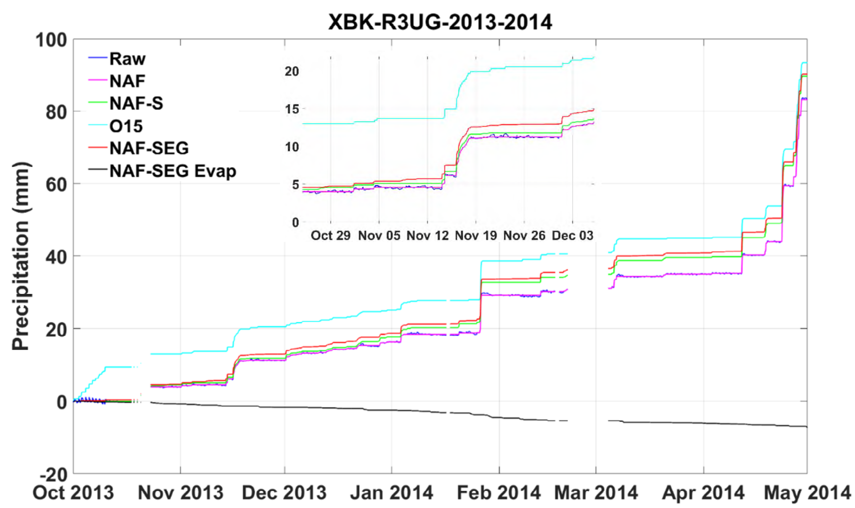


Figure 5: Time series of observed cold-season precipitation gauge bucket weight processing (NAF, NAF-S, O15, and NAF-SEG) along with the NAF-SEG evaporation estimate for a) Caribou Creek R2G 2013-2014, b) Haukeliseter R3AG 2016-2017, c) Bratt's Lake R2P 2015-2016, and d) Bratt's Lake R3UG 2013-2014. Insets show a zoomed example with consistent vertical scaling to illustrate the issues and filter performance relative to each time series.