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Research Article

Identifying Individual Rain Events with a Dense Disdrometer Network

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The use of point detectors to measure properties of rainfall is ubiquitous in the hydrological sciences. An early step in most rainfall analysis includes the partitioning of the data record into "rain events." This work utilizes data from a dense network of optical disdrometers to explore the effects of instrument sampling on this partitioning. It is shown that sampling variability may result in event identifications that can statistically magnify the differences between two similar data records. The data presented here suggest that these magnification effects are not equally impactful for all common definitions of a rain event.

1. Introduction

The term "rain event" seems—on its surface—rather unambiguous. At some physical location of interest, rain starts to accumulate; some time later, it stops. This process constitutes a rain event.

However, rain is made out of discrete drops. Though even small detectors are exposed to raindrop arrivals many times each second during an event, the rain is not strictly continuous in time. There is a finite (and, for detectors with sufficient temporal resolution, a measurable) time interval between the arrivals of individual drops in any measurement area. This fact is problematic for the definition of "rain event" proposed above; there is little utility in defining each separate raindrop as a separate "rain event," but—if we formally apply the proposed definition—each raindrop making up a data record *would* constitute a separate rain event.

The reader might argue that this observation is rather pedantic. After all, the use of the word "storm" seems to have clear enough meaning in many contexts, and certainly the term seems unambiguous in nonscientific settings. The most common way of solidifying the proposed definition above is to argue that a rain event is defined by its boundaries. As stated in [1], "Rain events are commonly delimited by nominating the required length of rainless intervals that precede and follow a rain event." There is a sizeable amount of literature on the topic, which is reviewed very well in [1, 2].

A wide variety of investigators have interest in dividing precipitation records into rain events, and—depending on the context of the study and the nature of the investigation—a number of different definitions of rainfall may be appropriate. Different definitions for rain events are used for studies associated with erosion or runoff (e.g., [3–5]), studies characterizing the long time-scale climatological or meteorological behavior in a region (e.g., [6–8]), higher resolution studies characterizing rainfall over more modest time intervals (e.g., [9, 10]), or studies where even individual drop arrivals may be of physical significance (e.g., [11]). Trying to force investigators to choose a common definition for all of these applications would be impractical, given the varying temporal resolution of equipment used in other studies (see, e.g., [12]).

Because different definitions are used for "rain event" in different communities, it naturally follows that the exact same data record could consequently be partitioned into a different number of rain events for different studies. These issues, however, have already been discussed fairly extensively in the literature and a recommendation has been put forth that investigators should clearly state the definition of "rain event" used in each study to keep the situation as unambiguous as possible [2].

There is another potential source of ambiguity that has not yet been addressed. Point detectors are imperfect; they are subject to sampling fluctuations due to their finite temporal resolution and sampling area. Due to these limitations, it seems reasonable to ask whether a single point detector really gives an accurate, unambiguous account of the true number of rain events.

The use of the term "true" number of rain events above merits some clarification. Much like everyone has a general understanding of what a "rain event" is, most precipitation scientists certainly feel like the idea of a raindrop size distribution is well established. Yet, when the question was carefully explored [13], it was found that the idea of a raindrop size distribution is intricately linked to the spatiotemporal scale used to conduct the measurement. There is a subtle distinction that needs to be considered between what is the "true" raindrop size distribution and how it relates to the raindrop size distribution *as it is measured*. Ultimately, the message of this previous work requires careful interpretation; the authors concluded "[a raindrop size distribution] is just what you measure, but these are statistical distributions of mean concentrations that should be interpreted in a statistically appropriate manner, not as steady distributions having intrinsic, deterministic meanings independent of the measurement process." This paper involves a similar investigation within the realm of the definition of a rain event; once a definition is chosen, how much does the measurement process influence the number of rain events reported?

This question is not of mere academic interest. Rain event start and stop times are needed to estimate the most commonly reported statistics associated with a study, especially mean rain rate. One long event with a modest mean rain rate will typically be treated distinctly from two shorter events with disparate rain rates but resulting in the same total accumulation as the longer event.

A natural way to investigate the degree to which the measurement process (and associated measurement error) influences the number and properties of detected rain rates is to utilize several identical instruments to measure the same rain. By exploring an ensemble of detectors, the effects (if any) of sampling fluctuation should be evident. The idea of studying a detector array was mentioned in passing within [2] but not explicitly addressed elsewhere in the literature; most previous studies involved a single point detector. The few studies that involved an ensemble of point detectors had spatial separations between detectors large enough that a different number of reported events between detectors could have been physically justified.

As discussed above, the definition of a rain event may be context dependent. Under many conditions, however, it seems desirable to set parameters defining a rain event in such a way to ensure detectors less than 100 meters apart identify the same number of rain events. A recent study [14] revealed that raindrop size distribution spatial variability over modest scales can be substantial and even exceed interepisode variability; this suggests that it may be reasonable to question whether small-scale spatial variability is substantial enough to influence event identification using standard methods. To explore this possibility, this study uses data from a very dense array of optical disdrometers to explore the combined influence that instrumental sampling variability and natural small-scale spatial variability may have in rain event identification.

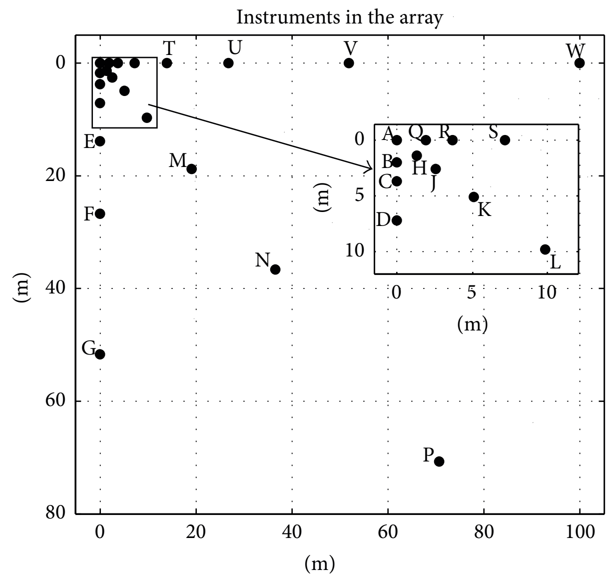


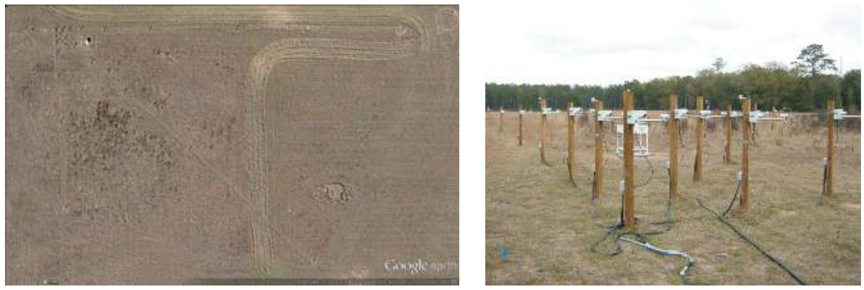
Figure 1: A schematic of the layout of the disdrometer array used for this study. Detectors near the "origin" of the array are shown in the figure inset. The one-minute summary data telegrams from each detector are transmitted via serial cable to a computer located approximately 80 meters west of detector A where they are stored for later processing and analysis.

2. Materials and Methods

2.1. Instrument Network and Data Utilized. The data used in this study come from an array of 21 Thies Laser Precipitation Monitors (hereafter LPMs). These LPMs are optical disdrometers that measure drops via occlusion of an infrared laser beam. The sampling area of each LPM is nominally 4560 mm^2. Each drop detected by the LPM is assigned into one of 22 nonoverlapping size bins (ranging from 0.125 mm diameter to 8+ mm diameter in nonuniform steps) and one of 20 nonoverlapping velocity bins (ranging from 0 m/s to 10+ m/s in nonuniform steps). Once per minute, each LPM transmits a data telegram indicating the number of drops detected in each of the 440 (22×20) different classifications possible. (A more thorough characterization of these instruments can be found in [15].)

These 21 LPMs have been distributed in a very dense network as shown in Figure 1. The design of the network is optimized to study small-scale spatial variability of raindrop size distributions. (e.g., see [16]. Note that other similar, but less dense, disdrometer networks have recently been constructed and utilized for the study of precipitation variability on small scales; see [12, 14, 17].)

The 3 "arms" of the array have logarithmically spaced instruments. The pairs of detectors with the smallest separation (e.g., A-B, A–H, and A–Q) are separated by a distance of only 1.93 meters. The largest distance between any two detectors in the whole array (e.g., G–W) is 112.62 meters.



(a) (b)

Figure 2: Pictures of the disdrometer array. (a) shows an overhead view of the site (as of March 1, 2014). The shadows of the LPMs can be identified by looking closely. The picture is aligned to replicate the general geometrical alignment shown in Figure 1; detector "A" is in the upper-left. The white object in the center of the box formed by detectors K, L, S, and T is a 2-dimensional video disdrometer (not used in this study). (b) displays part of the array from ground level. The first detector in the foreground is detector "A," with the 2-dimensional video disdrometer visible in the background. All detectors are mounted nominally 1.75 meters off of the ground.

Consequently, the array used here is well suited for this study due to the very small distance between detectors, especially near the "origin" of the array.

The LPM array was constructed between May and November 2013, and came online in late December 2013. All of the data were acquired with a single acquisition computer in a remote site near Hollywood, SC. The array is located at 32° 44′ 26″ N, 80° 10′ 36″ W. An overhead view of the array (as of March 2014) and a photograph at ground level (as of December 2013) are shown in Figure 2.

Data acquisition was sporadic during the array installation and testing phase. Due to some power outages, computer failures, and the periodic accumulation of frozen precipitation in January of 2014 (which is poorly characterized by LPMs), the data set here is limited to all data taken by detectors A, B, C, E, F, G, H, J, S, and W between February 23, 2014, 16:04 UTC and April 19, 2014, 12:43 UTC (when all observed precipitation is believed to be in liquid form). These 10 detectors measured total accumulations of between 0.17 and 0.22 meters for the time period studied. The detectors used in this study are shown in Figure 3.

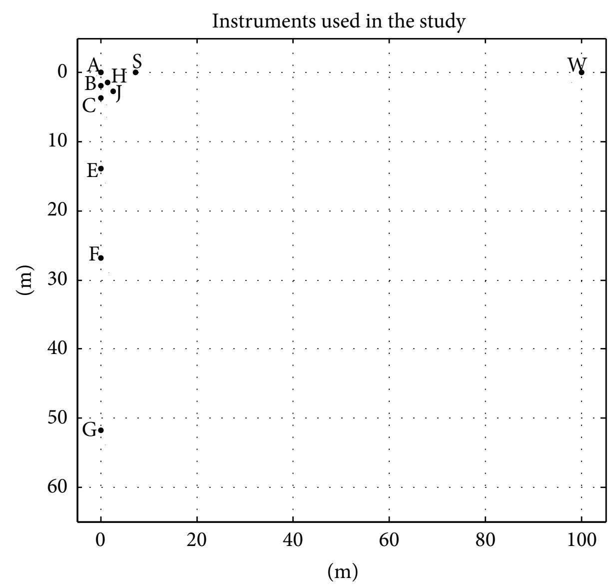


Figure 3: A schematic of only the equipment utilized in the study.

2.2. Definitions of Rain Event. As implied by the definition given in the introduction, the most common way of defining a rain event is through the so-called "minimum interevent time method" (see, e.g., [1]). According to this classification method, a rain event is identified by a continuous time interval of detected rain during which there are no rainless gaps of a duration exceeding the minimum interevent time (hereafter MIT). Sometimes—depending on the study—this basic method is augmented with the additional criterion that any rain event must have a specified minimum total accumulation. (This latter criterion is often dependent on the instrumentation utilized in the study; see [1].)

The MIT method of identifying rain events is widely used in a variety of different subdisciplines; most of the sources cited in the introduction that explicitly counted rain events used this method. Depending on the particular scientific subfield, the values of the MIT and minimum accumulations utilized can vary greatly. An excellent literature review including many parameters chosen in other fields is presented in [1, 2]; values reported for the MIT ranged from 3 minutes [18] to 24 hours [19, 20] and values for the minimum total accumulation range from small fractions of a millimeter [9] to over a centimeter [21].

More recently, there has also been some attention given to the question of defining a rain event in the scale-invariant/self-organized criticality literature (see, e.g., [22–25]). The perspective in this literature changes a bit from the MIT method. Rather than characterize events by the gaps that separate them, this community often opts to define a rain event through the "adjacent wet interval" (AWI) method. Though this involves a shift in perspective, the method was argued to be essentially equivalent to the MIT method in [11]; thus the focus in this manuscript will be on characterizing rain events via the MIT method.

3. Results

3.1. Analysis of Coarsened Data. Since most rain event studies cited earlier involved analysis of tipping-bucket disdrometers and/or pluviographs, the network disdrometer data was computationally coarsened to represent data that would have been obtained if 10 tipping-bucket rain gauges with 0.1 mm accumulation per tip had been utilized instead of each of the 10 disdrometers. To do this, each one-minute disdrometer record was inspected to infer the total volume of accumulation. (Each drop was assumed to have a volume equal to a spherical drop with a diameter equal to the minimum size of its associated bin.) The accumulated volume was continuously aggregated from minute to minute and a "tip" was identified every time the total accumulated volume exceeded an integer multiple of 0.456 mL (which would be the accumulation volume needed to tip a 0.1 mm tipping-bucket gauge with surface area 4560 mm^2). In 60-second intervals where more than one tip of the tipping-bucket would have occurred, the total number of tips occurring over that time interval was recorded.

At this point, each of the 10 equal-duration data sets (one from each detector) was used to count the number of detected rain events. Following the standard MIT method, a rain event was defined as an interval of time that met the following criteria.

(1) The interval contains at least $\mathscr{L}$ "rainy minutes." A minute is considered rainy if at least 1 tip is tallied by the detector.

(2) Preceding and following the interval in question, there was a gap devoid of any tips of duration exceeding the MIT.

Although most studies rely on fixed values of MIT and $\mathscr{L}$, a few other studies explicitly focus on studying the effects of varying these parameters (e.g., [8, 22]). In this study, MIT values ranging from 1 minute to 12 hours were used and $\mathscr{L}$ was allowed to vary from 1 to 30 rainy minutes. Some of the results from this analysis are shown in Figures 4 and 5.

Figure 4 shows how the number of detected events strongly depends on the values of MIT and $\mathscr{L}$ utilized. The results are only shown for detector A, but the other detectors show qualitatively similar behavior. Since the number of detected events seems to remain constant for values of MIT longer than about 4 hours and values of $\mathscr{L} \geq 10$, this may suggest that the concept of a rain event may not be overly sensitive to instrumental sampling issues when accumulations total at least 1 mm and at least half hour of dry period (rainlessness) precedes and follows each rain event. However, Figure 5 reveals that this line of reasoning may not always be accurate.

Figure 5 shows that detectors mere meters apart and running reliably can differ on the number of detected rain events, even when values of MIT exceed an hour. It is true that agreement between detectors improves for larger MIT and $\mathscr{L}$, but there is still no array-wide agreement on the number of rain events for $\mathscr{L} = 30$ (indicating at least 3 mm of accumulation) and MIT equal to four hours (despite the fact that the data set explored was less than two months long).

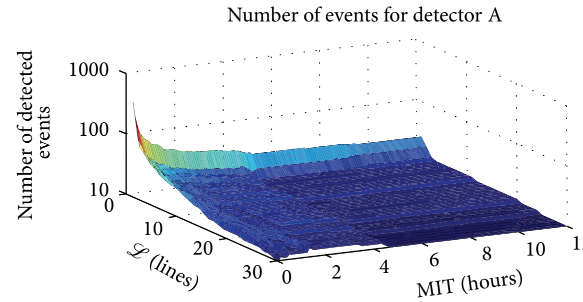


Figure 4: A plot showing the number of events as a function of MIT and $\mathscr{L}$ for detector A for data taken between February 23, 2014, 16:04 UTC and April 19, 2014 12:43 UTC. Clearly, increasing either MIT or $\mathscr{L}$ can substantially decrease the number of identified rain events. Note that the decrease in event count is not strictly monotonic with increasing MIT; even though merging "possible events" may decrease the total number of events, it is also possible that an increase in MIT will keep a potential event "alive" long enough to obtain the minimum number of minute observations with tips $\mathscr{L}$. Increasing $\mathscr{L}$ while holding MIT fixed does monotonically decrease the number of observed events.

Some insight into how this can occur can be developed by examining Figure 6. This figure explores a subset of the data lasting about 15 hours. In this subset, a rather intense period of rain is followed by a very light drizzle. After this light drizzle, a light rain began and persisted for a few more hours. As noted on the figure, 3 of the 10 detectors reported this as a single event (using a minimum interevent time of 1 hour and requiring 15 minutes with recorded tips to define an event); the remaining 7 detectors went through at least an hour of no detected rainfall and categorized this same subinterval into 2 different events.

With less than two months of data during the drier part of the South Carolina year, it is hard to estimate what fraction of the time sampling fluctuations can influence event identification in lengthier data sets. However, the fact that events like this can be found in such a short data record suggests that further study may be warranted.

3.2. Analysis of Raw Disdrometer Data. The above section relied on using data from disdrometers in coarsened form to simulate typical rain gauge data records. However, the one-minute drop spectra for each of these detectors are available. Here, we explore the possibility of using the full available data record to search for a definition of rain event that may not be as susceptible to disagreements between detectors similar to the scenario outlined in Figure 6.

The MIT method could be extended to disdrometer data in a number of ways. Perhaps the most straightforward method would be to apply the exact same principles used for tipping-bucket gauges to the disdrometer data—though the specific definition of a rainy minute could be modified to be based on the drop spectrum observed. Using disdrometer data instead of rain gauge data does give the added advantage of removing some of the uncertainty associated with the initiation time of a weak event (see, e.g., [26]). Since no consensus among different subfields regarding an appropriate

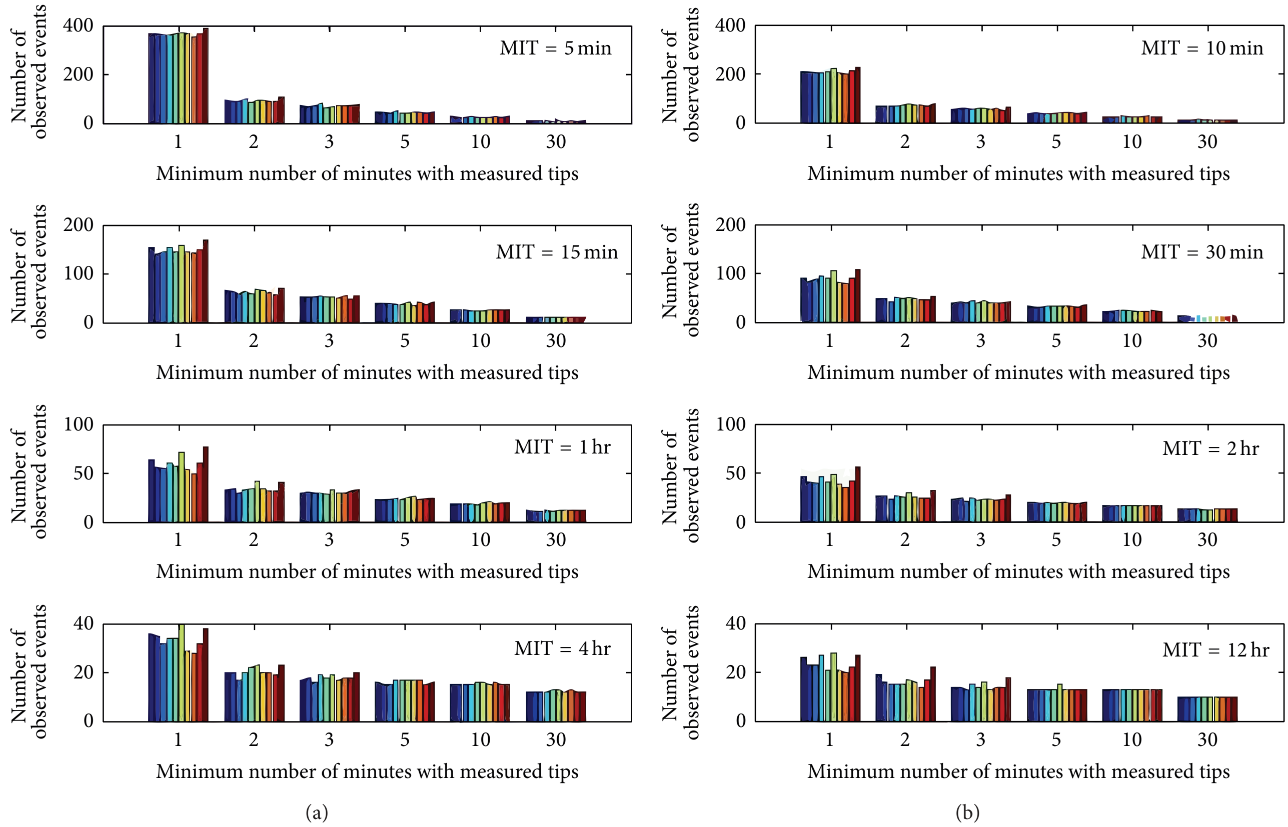


Figure 5: Some subsets of the rain event parameter space. Each panel uses a different value for MIT duration. For each panel, 6 different values are displayed for $\mathscr{L}$. Each of the ten detectors is displayed in a different color. The reader should take care to note the different scales on the y-axes from panel to panel. Although there is approximate agreement between the detectors, there is nonnegligible variability in the total number of events detected for most combinations of MIT and $\mathscr{L}$. Note also the very large number of $\mathscr{L} = 1$ events that do not qualify as events once $\mathscr{L} = 2+$; these brief events are particularly numerous for brief MIT.

MIT value has been reached for tipping-bucket data, it seems reasonable that the same types of challenges may still exist when expanding the notion of an MIT-defined-event to disdrometric data. Nevertheless, the added information associated with disdrometer data may be beneficial to investigators in disparate subdisciplines; thus, an extension of the MIT method to disdrometer data may be useful.

Consider the following extension of the MIT method for a rain disdrometer; for disdrometer data, a rain event is defined as an interval of time that meets the following criteria.

(1) The interval contains at least $\mathscr{L}$ "rainy minutes." A minute in the data record is considered rainy if at least $\mathscr{N}$ drops are detected in the reported drop spectrum in size bins meeting or exceeding diameter $\mathscr{D}$.

(2) Preceding and following the interval in question, there is a gap devoid of any one-minute spectra that meet the criteria to be considered a "rainy minute" as defined above; this gap with no "rainy minutes" must last for a duration exceeding the MIT.

Thus, the parameter space has expanded with the addition of $\mathscr{N}$ and $\mathscr{D}$. (Note that this definition is consistent with the perspective put forth in [22] when setting $\mathscr{L} = 1$, MIT equal to the minimum instrument resolving time, $\mathscr{N} = 1$, and $\mathscr{D}$ equal to the minimum resolvable drop size; see also [11]. This choice of parameters was not the only one explored in this study, but it is an interesting case; it is the only parameter set that ensures that every detected raindrop is part of some rain event.)

Reporting the results of the exploration of this parameter space is challenging; since this particular definition of a rain event is new, there is an unconstrained four-dimensional parameter space to compare among the ten detectors utilized.

Figure 7 explores just a very small part of the parameter space that was investigated for this study. A more comprehensive overview focusing on points in the parameter space where all instruments agree on the number of rain events is presented in the Appendix Section.

It is interesting to utilize the modified definition of a rain event to reexplore the time interval analyzed earlier in Figure 6. Figure 8 clearly demonstrates that raw data acquired by detectors A and B is extremely similar. (This is not surprising; the detectors are spatially separated by less than 2 meters. Any disagreement in the observed drop size distribution is likely due to sampling variability.)

Figure 9 displays the number of identified events in the subset examined in Figure 6 for detectors A and B. These two

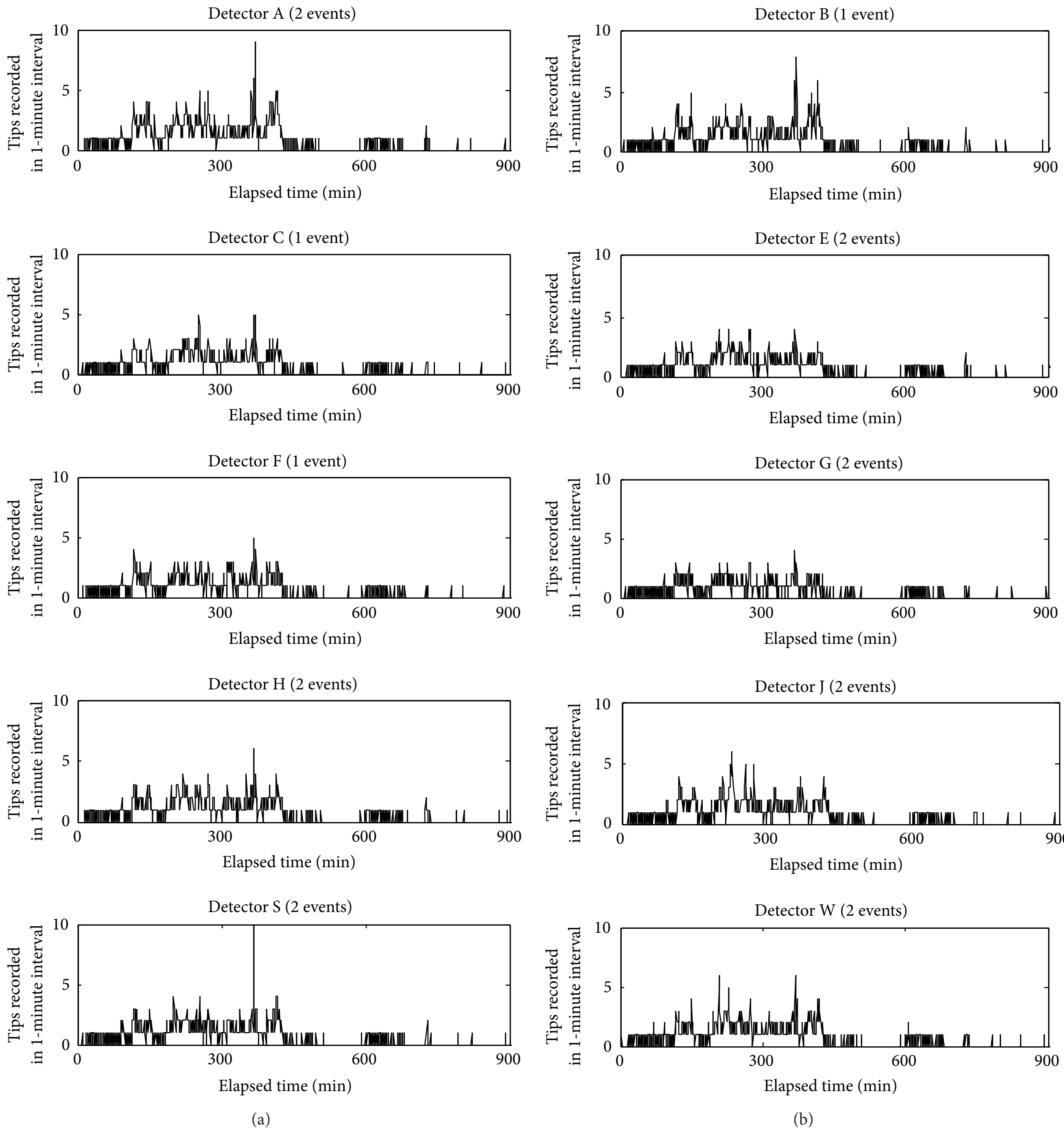


Figure 6: An illustration showing how extremely similar data records can sometimes be partitioned into events differently. Here, an intense rain event trails off to a drizzle. However, this slight drizzle is just enough to finish a single tip (over a one-hour period) in detectors B, C, and F. Other detectors less than 5 meters away did not accumulate exactly the same amount of rainfall and thus did not have this tip occurring during the mostly quiescent period. Consequently, 3 of the 10 detectors see one long (but highly variable) event while the other 7 detectors see 2 separate events—even though realistic values for MIT (1 hour) and $\mathscr{L}$ (15 minutes with detection) are used.

detectors saw different numbers of events when simulating a tipping-bucket gauge, but here the graphs of the number of detected events as a function of MIT and $\mathscr{L}$ (using the modified definition of $\mathscr{L}$ proposed above) are remarkably similar.

3.3. Examining the Utility of the MIT Method. The principle goal of this paper is to examine data from an array of identical detectors in close proximity to each other in order to determine whether common schemes for determining rain events do so reliably and unambiguously. Since a very wide

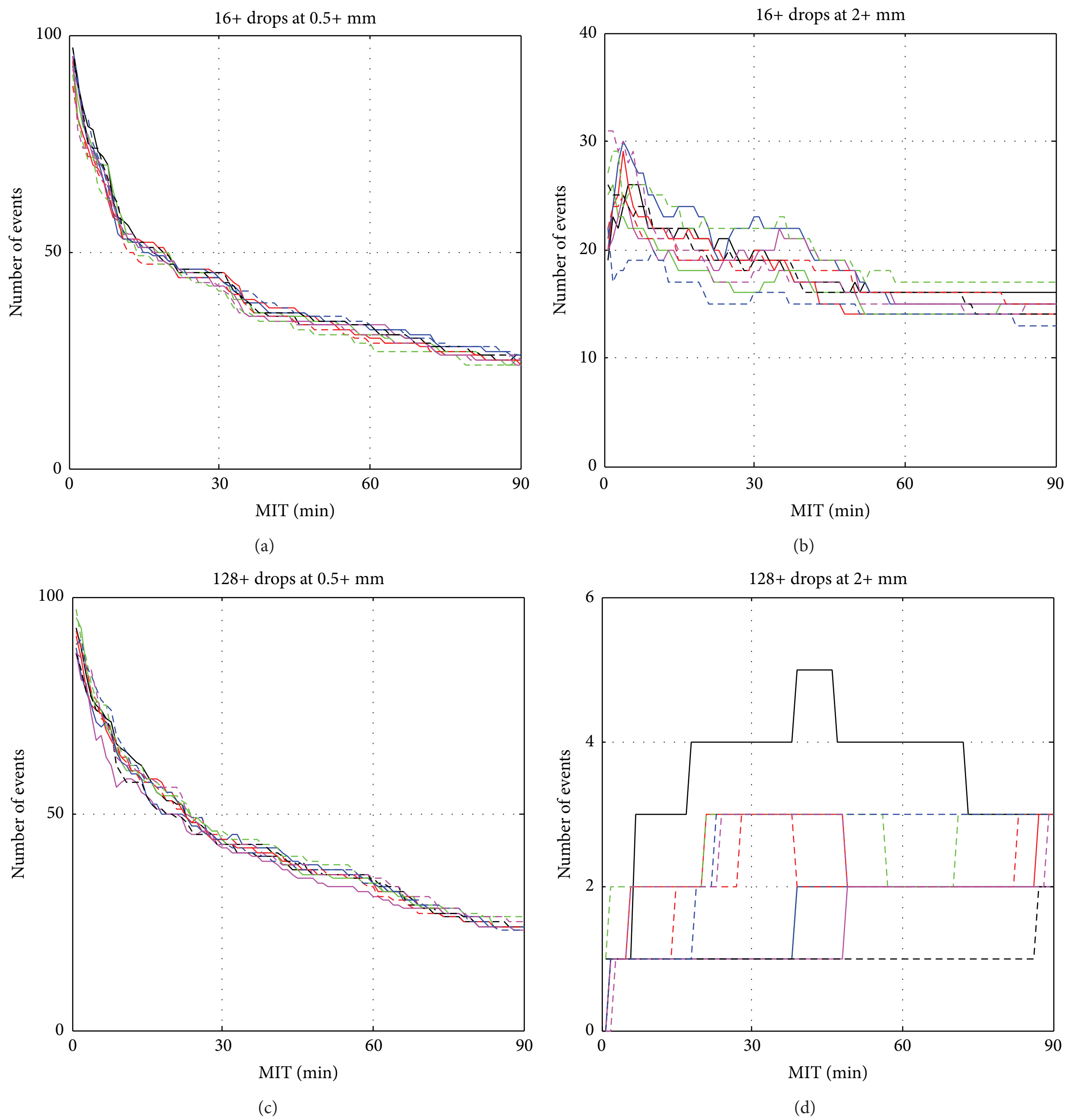


FIGURE 7: Part of the parameter space explored in the search for combinations of MIT, $\mathscr{L}$, $\mathscr{N}$, and $\mathscr{D}$ that report the same number of events across the whole array. For these figures, $\mathscr{L}$ (the minimum number of rainy minutes required to constitute an event) is constrained to be 10. The x-axis on all plots shows different possible values for MIT (in minutes). There are 10 curves in each plot indicating the 10 detectors. The values of $\mathscr{N}$ and $\mathscr{D}$ are specified in the title for each panel. It appears that none of the values shown on this figure give completely unambiguous definitions for the number of events that hold for all detectors in the array.

range of MIT values are found in the literature, the parameter space tested was reasonably expansive. Data were analyzed in the two separate formats described above: (1) coarsened (tipping-bucket-like) and (2) raw disdrometer returns. For each detector in each format, an ensemble of vectors in parameter space was explored. For the coarsened data, this included exploring two parameters: MIT and $\mathscr{L}$. For the raw disdrometer data, parameters MIT, $\mathscr{L}$, $\mathscr{N}$, and $\mathscr{D}$ were explored.

To adhere to the published literature, values of MIT from 1 minute to 12 hours were explored. (MIT values between 1 minute and 90 minutes were explored in 1-minute increments; the values between 90 minutes and 12 hours were explored in 5-minute increments). Values of $\mathscr{L}$ between 1

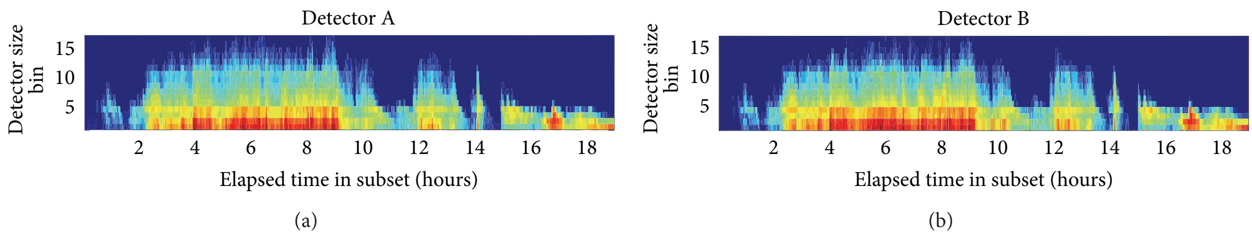


FIGURE 8: One-minute drop spectra for the interval discussed in Figure 6. The x-axis displays elapsed time through the subinterval in hours; the y-axis indicates the size bin of the associated drops. Color indicates the number of drops measured in the associated time interval (red corresponds to high concentrations; blue corresponds to low). The spectra for detectors A and B are shown, which—when analyzed in Figure 6—saw different numbers of events. Given the striking similarity of the underlying data, it seems reasonable to conclude that the spurious "tip" in detector B that prevented two separate events from being identified as one event was likely due to chance.

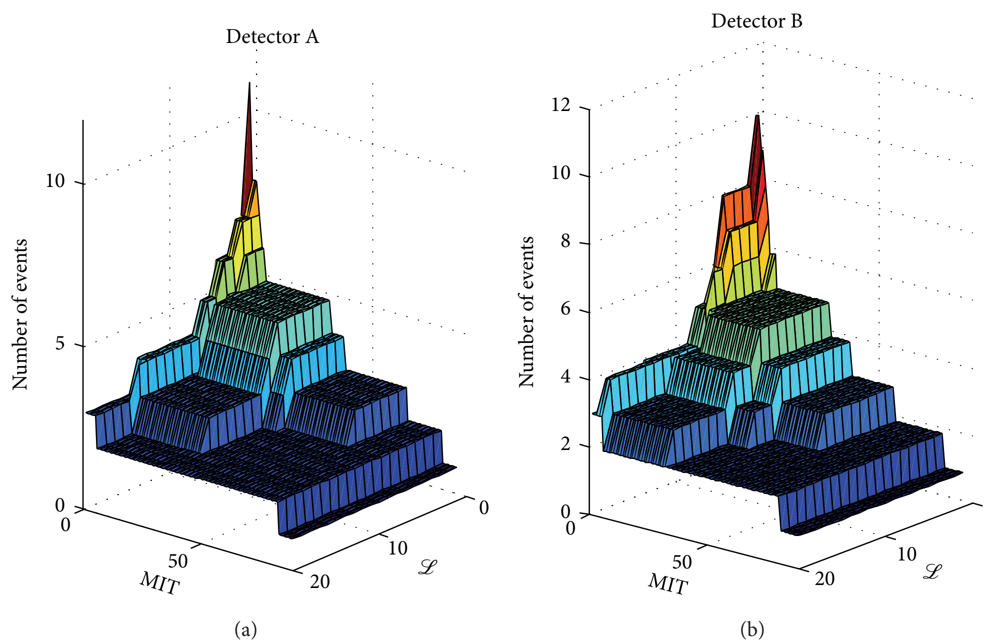


FIGURE 9: The figure shows the number of events as a function of MIT and $\mathscr{L}$ for A and B and associated with the data in the subset depicted in Figure 6. For simplicity, this plot defines a rainy minute as any one-minute spectra that contained at least 128 drops of at least 1 mm diameter. Note that despite the fact that these detectors disagreed on the number of events in this interval when simulating a tipping-bucket (see Figure 5), there is great agreement in this parameter space. (The agreement between the two detector event identification is especially striking when MIT and $\mathscr{L}$ are not close to the instrument's resolution).

rainy minute and 30 rainy minutes were used (in increments of 1 rainy minute). For the disdrometer data, values of $\mathscr{D}$ corresponding to the smallest 11 bins of the disdrometer were used. (These correspond to minimum drop diameters of 0.125 mm, 0.25 mm, 0.375 mm, 0.500 mm, 0.750 mm, 1.000 mm, 1.250 mm, 1.500 mm, 1.750 mm, 2.000 mm, and 2.500 mm. Only these 11 size bins were used due to the fact that $\mathscr{D}$ specifies the *minimum* size drop that is included in establishing the existence of a rainy line. Drops larger than 2.5 mm are rare in winter storms in South Carolina). The values of $\mathscr{N}$ explored were 2^n with $n \in [0, 12]$. Consequently, the coarsened data was explored in a parameter space including 216 (different MIT values) × 30 (different $\mathscr{L}$ values) = 6480 distinct different possible definitions of rain event. The disdrometer data was similarly explored in a parameter space including $216 \times 30 \times 11 \times 13 = 926 \sim 640$ distinct combinations of parameters that correspond to potential event definitions.

The results from such an undertaking can be rather overwhelming to interpret. To ease analysis, each point in parameter space was evaluated based on only one parameter—did all 10 detectors agree on the total number of events for the data presented? If all 10 detectors agreed on the number of events seen, the associated spot in parameter space was marked as "plausible." (Note that it is possible for detectors to all report the same number of total events observed but to assign those events to vastly different start and stop times. Though this is possible, this was neglected in the present study due to the computational cost of investigating it).

Table 1: Summary data associated with exploring the rain event definition parameter space. Values shown indicate percentage of parameters characterized as "plausible," as described in the text. MIT range 1 is associated with MIT values starting at 1 minute, incrementing by 1 minute, and ending at 90 minutes. MIT range 2 is associated with MIT values starting at 5 minutes, incrementing by 5 minutes, and ending at 12 hours.

Data set	All data	MIT range 1	MIT range 2
Coarsened	17.8%	0.3%	29.0%
Disdrometer	5.7%	0.5%	9.0%

Bulk statistical information is likely of limited utility given the brief duration of the data set, but some summary data is presented in Table 1.

An examination of the parameter space revealed the following general trends.

(i) For tipping-bucket-like data:

(a) no plausible values were found for $\mathscr{L} < 7$ minutes,

(b) plausible values are very rare for MIT <2 hours,

(c) for MIT >6 hours and $\mathscr{L} > 7$ minutes, a nonnegligible fraction of the parameter space remains plausible. (It merits mentioning, however, that with MIT >6 hours and $\mathscr{L} > 7$ minutes, the data set in question had only around 3 events. Therefore—if fluctuations are expected to scale with event number —this study may erroneously imply greater reliability for large MIT and $\mathscr{L}$ values than future investigations may reveal.)

(ii) For disdrometer data:

(a) generally, more plausible values are found when $\mathscr{L}$ and MIT are large,

(b) low (<30 minute) MIT values are seldom classified as plausible,

(c) for large values of MIT, intermediate values of $\mathscr{N}$ and $\mathscr{D}$ are more likely to be plausible.

Other than these broad observations, it has proven difficult to obtain any definitive trends from the data available. It is expected that once a longer data record has been accumulated, more comprehensive analysis can be communicated. Recall this data set only included a total of about 20 cm of accumulation and many of the results presented here could potentially be limited to regional or seasonal utility. In particular, the relative lack of large detected drops (typical for winter South Carolina storms) could substantially influence these basic observations. The basic figures that led to the general observations above are presented in the Appendix Section.

3.4. Influence of Event Identification on Data Interpretation. From the results above, it should be clear that—at least for some values of MIT used in the literature—the partitioning of rain into events may have been more ambiguous than the record from the single point detector may suggest. But why does this matter? Perhaps an example from the data presented in Figure 6 could help in illustration.

When reporting statistics for a rain event, the most common variable reported is the mean rain rate. For the interval shown in Figure 6 (and using MIT = 30 minutes and $\mathscr{L}$ = 15 minutes), detector A sees two events: an event that accumulates 68.3 mm rainfall in 8.3 hours for a mean rain rate of 8.23 mm/hr and—a bit over an hour later—a second event that accumulates 4.5 mm rainfall in 5.03 hours for a mean rain rate of 0.89 mm/hr. Categorizing an extremely similar looking data set (see Figure 8) into a single event, however, detector B reports a total of 67.5 mm of rainfall in 14.96 hours for a mean rain rate of 4.51 mm/hr. These are substantially different accounts of similar data records, and this change in categorization is created completely by a single tip of a tipping-bucket rain gauge. (The "offending" tip can be seen clearly in Figure 6 by looking for the isolated tip about 60% of the way through the time-series shown for detector B).

The studies cited in [1, 2] utilized a single point-instrument to identify rain events. If the results seen in the data record presented here are representative, this suggests that event identification in other studies may be less definitive than expected. (It should be emphasized that it is still an open question as to whether the results seen in the data record presented here are representative or not; further study at this site and elsewhere could help determine this definitively.)

All time-averaged statistical properties of a storm clearly depend on the inferred start and stop time of a rain event. It has been observed [1] that these start and stop times depend on rain event definition and available instrumentation. This study finds that the start and stop times can also depend on sampling fluctuations which can be difficult to characterize.

4. Conclusions

Rain event identification is of central importance in the hydrological sciences and related fields. Despite being a central concept in rain measurement, few studies have been conducted investigating the degree to which instrument finite sampling effects may influence rain event identification. Here, a dense array of optical disdrometers was used to demonstrate that there may be more ambiguity in the definition of a rain event when evaluated from a single point detector than previously anticipated.

Using the minimum interevent time (MIT) model, it was demonstrated that even considerable MIT values run the risk of categorizing rain events inconsistently between adjacent tipping-bucket rain gauges. A single tip of a rain gauge can lead to a completely different account of the detected rain, with substantial differences in mean rain rate and event duration.

The MIT method can be simply modified for application to rain disdrometer data. However, the data set examined suggests that despite the increase in quantity and quality of

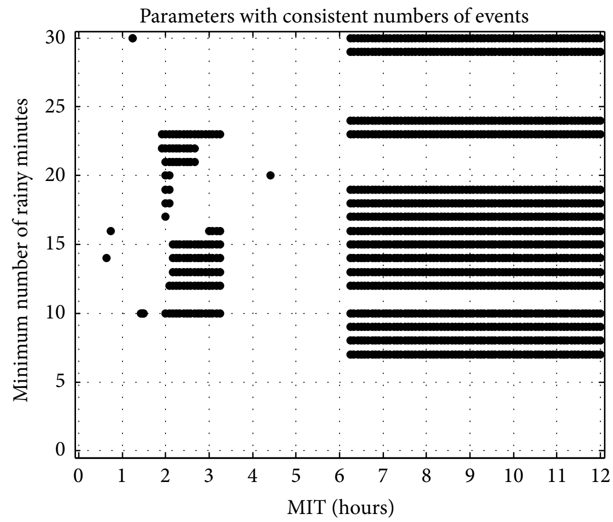


FIGURE 10: A plot of points in the MIT and $\mathscr{L}$ parameter space where all ten tipping-bucket detectors register the same number of observed events over the approximately 2-month long interval of investigation. Marks indicate plausible points.

data acquired from this instrument, there is no less ambiguity in rain event characterization. The analysis presented here is the result of a study conducted over a fraction of a single season; the results should be verified and extended in other studies of longer duration, different location, and different instrumentation. Once a more comprehensive data record is compiled, more general conclusions and recommendations regarding protocols of rain event definition can be established.

Appendix

Investigation of the Rain Event Parameter Space

A comprehensive investigation of the different ways the data record could be parsed was outlined in Section 3.3. This investigation involved the exploration of a parameter space (containing 2 parameters for coarsened data and 4 parameters for raw disdrometer data). All detector data records that identified the same number of rain events for a particular point in parameter space have been classified as "plausible" sets of parameters for unambiguous rain event definition.

To justify the general conclusions drawn in Section 3.3, plots of the locations of plausible points within parameter space have been constructed.

Figure 10 shows the 2-dimensional parameter space used for examining the coarsened "tipping-bucket" data. As noted in the main text, the large concentration of plausible points for MIT >6 hours and $\mathscr{L} > 7$ minutes may be partially due to the brevity of the analyzed data set. While these points in parameter space did have agreement among all 10 detectors, this often meant agreeing on the presence of only a few events. Note that most previous studies use the equivalent of $\mathscr{L} = 1$ minute or $\mathscr{L} = 2$ minutes to define an event (minimum 0.1 mm-0.2 mm accumulations); there are no plausible points in the presented parameter space with $\mathscr{L} < 7$.

Figure 11 shows some summary data from the 4-dimensional parameter space associated with the disdrometer data. Since this parameter space is 4-dimensional and has 926640 elements, traditional visualization methods are impractical. Rather, the plot attempts to convey a general sense of the density of plausible points within the parameter space. Selection of a particular x and y coordinate on a plot identifies a unique 2-dimensional subspace of parameters. This subspace looks like that seen in Figure 10. The color at that coordinate is related to p, where

$$p = \frac{N_{\text{plausible}}}{N_{\text{subspace}}}, \tag{A.1}$$

where $N_{\text{plausible}}$ is the number of points in the subspace classified as plausible and N_{subspace} is the number of points in the relevant parameter subspace. For example, let $\mathscr{L} = 4$ minutes and $\mathscr{N} = 8$ raindrops. There are 144 (MIT values) × 11 ($\mathscr{D}$ values) = 1584 points in the associated parameter subspace. Since there were 64 plausible points in this subspace, the value of p at this point is equal to $64/1584 \sim 0.04$. Thus, a random selection from all allowable values of $\mathscr{D}$ and MIT has about a 4% chance of being a plausible point.

As can be seen from the figure, few trends are obvious. It is hoped that any underlying trends will become evident if a longer data set is analyzed.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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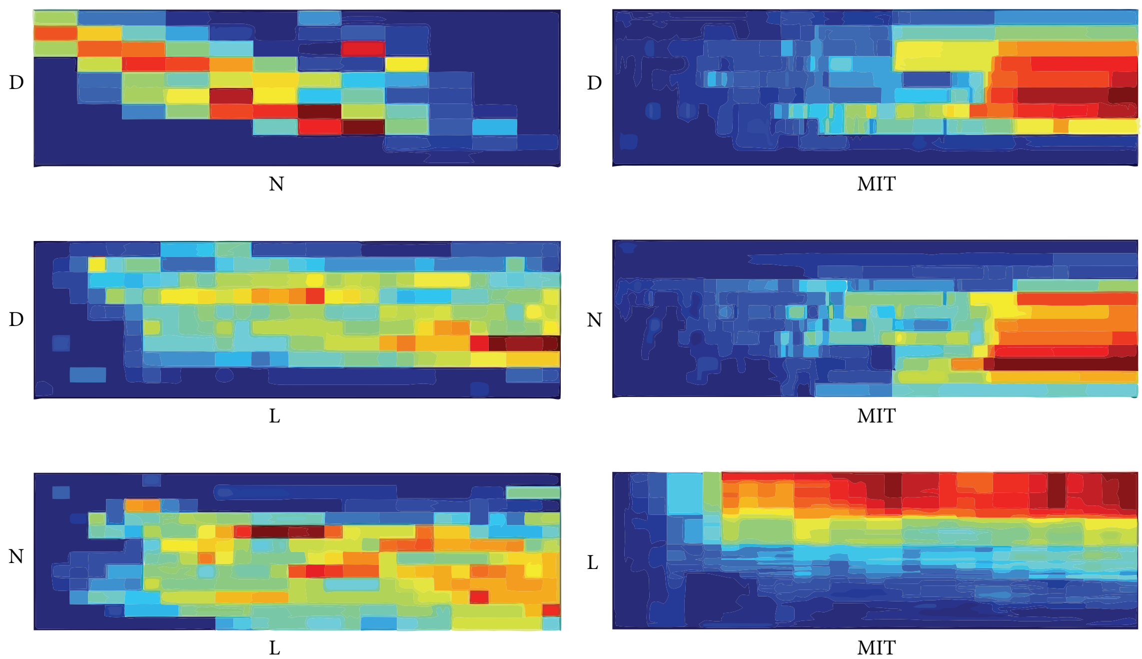

(a) (b)

Figure 11: A method to attempt to visualize elements of the 4-dimensional parameter space. For each panel, two of the four parameters are varied over their entire domain. The color associated with a particular point in the plane represents the probability that an arbitrary set of the other two parameters will result in a plausible designation. Red corresponds to higher probabilities (around 0.25) whereas blue corresponds to lower probabilities (near 0).

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