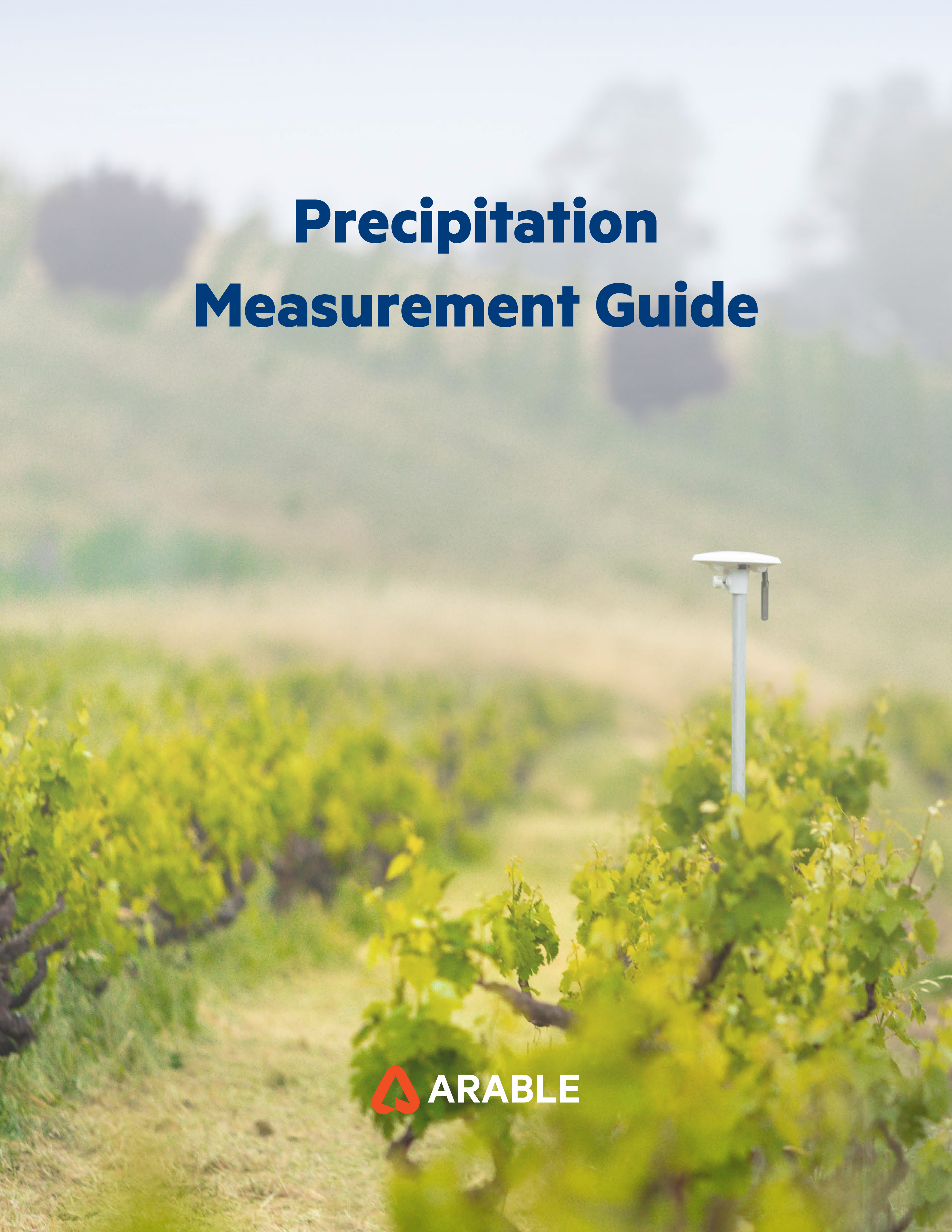
Precipitation Measurement Guide



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SUMMARY

Determining ground-truth precipitation amounts is a complex endeavor. Rainfall is extremely temporally and spatially variable, even across small distances and co-located gauges. While this can be in part due to natural variability, differences in precipitation measuring techniques and ensuing errors can add to differences observed. Conventional rain gauges are subject to a wide array of errors, which are often exacerbated by field conditions like high winds. They generally require specific configurations, plus regular cleaning, leveling, and calibration, and are prone to compounding errors if these specifications are not met and maintained.

A fickle, complicated, and labor-intensive measurement setup presents challenges to anyone seeking accurate data to inform irrigation decisions, and a streamlined operation to carry them out. Arable's simple Mark 2 device, dynamic data, and unique machine learning platform introduce a novel approach to rainfall with proven accuracy against gold-standard sensing. Let's explore the state of precipitation measurement today, and see how Arable works to improve it.

- Rainfall is complex, variable, and highly subject to subtle shifts in microclimate.
- Most rain gauge accuracy claims are validated in a controlled laboratory setting.
- Field weather conditions play a significant role in rain gauge measurement errors.
- Most rain gauges require regular maintenance and calibration to maintain accuracy.
- Rain measurement with fewer moving parts and machine learning models reduce errors significantly.

Rainfall is generally the most variable hydrologic element over any space, and its characterization is one of the most commonly needed and difficult to rectify. Rainfall has multiple modes for non-stationarity—the small-scale variability induced by processes like cloud formation, droplet formation, and wind; and larger scale variability induced by the movement of rainfronts, local and regional geography, and, in some cases, plant canopies.

Comparing very localized data, such as what you receive from the Arable Mark 2, to either a forecast or a distant weather station may show some of this variability. Forecasts are usually looking at the likely conditions over a large area—individual points may see substantially more or less rainfall. The same is true for the nearest weather station; many weather stations in the US are at airports with conditions that may be quite different from the ones you see in your fields. The spatial variability can be remarkable, as research has demonstrated:

- Up to 100% variability between rain gauges within 500 meters of each other (Jensen and Pedersen 2005)
- Up to 26% (or more) variability between gauges within 250 meters of each other (Pedersen et al. 2010)
- Variability is strongly influenced by the type of rainfall that is occurring (Emmanuel et. al. 2012)

You may also witness some spatial variability when comparing the rainfall among your devices if you have them in many fields. The ultimate value of a network of devices is that you get the truest picture of your weather conditions.

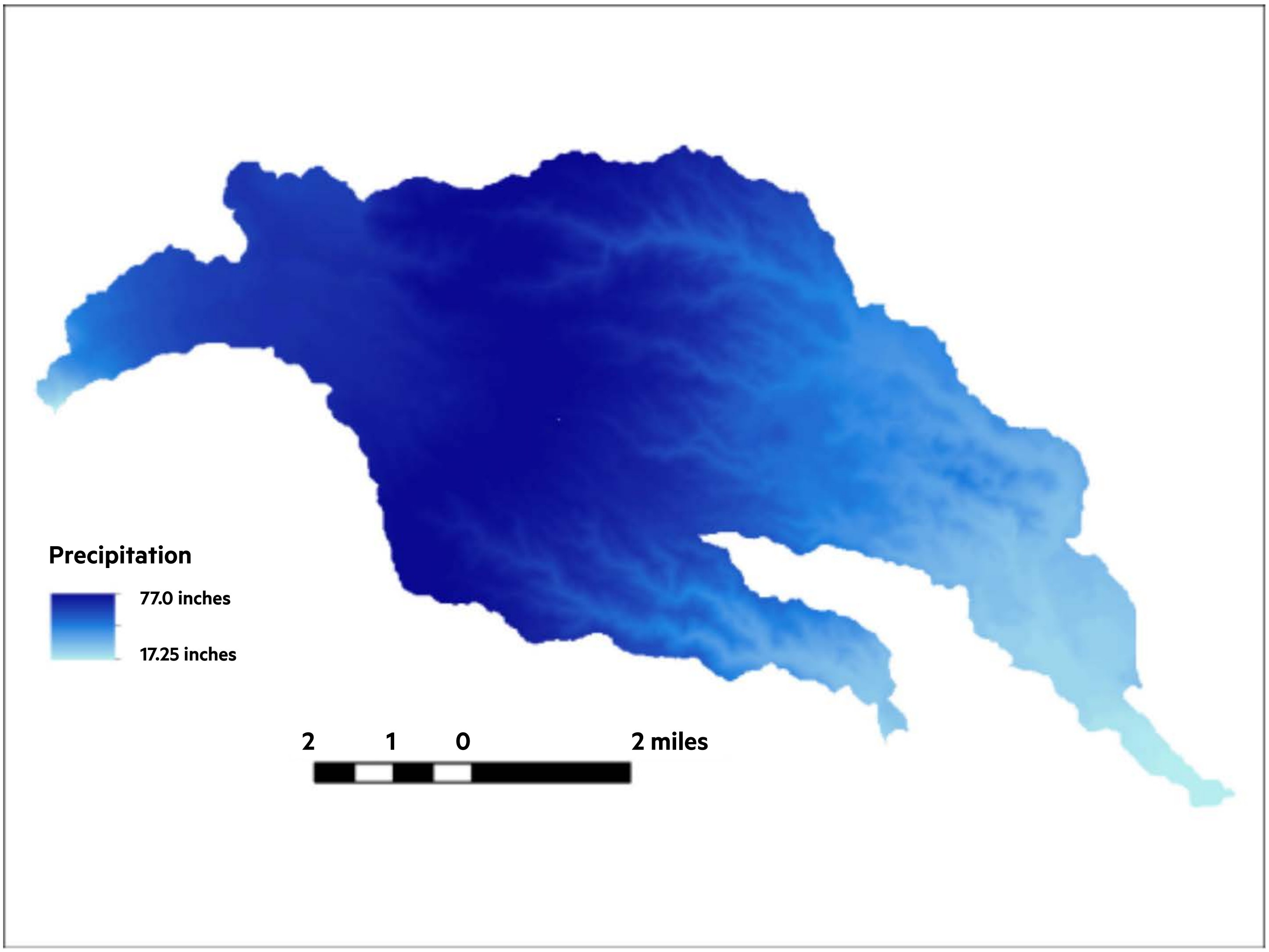

Figure 1. There is significant spatial variability in rainfall even across small distances (Mokondoko et. al. 2018).

This demonstrates that it is common to see rainfall variability among rain gauges that have some spatial spread to them. But what about rain gauges that are right next to each other (we refer to this as “co-located”)? It has been found that rain gauge measurements taken by identical gauges located a few feet apart have experienced differences as much as 20% (Curtis & Burnash 1996). This somewhat baffling result is due to the natural variability of rainfall.

A two-year study conducted by the World Meteorological Organization (WMO) in Italy (E. Vuerich et. al. 2009) rigorously tested 25 well-known and high-quality rain gauges, including tipping buckets and weighing gauges, as well as optical and impact disdrometers. This was a controlled experiment where all instruments were placed at the same height in an open field without any obstructions.

Figure 2. The field test site in Vigna di Valle, Italy (E. Vuerich et. al. 2009).

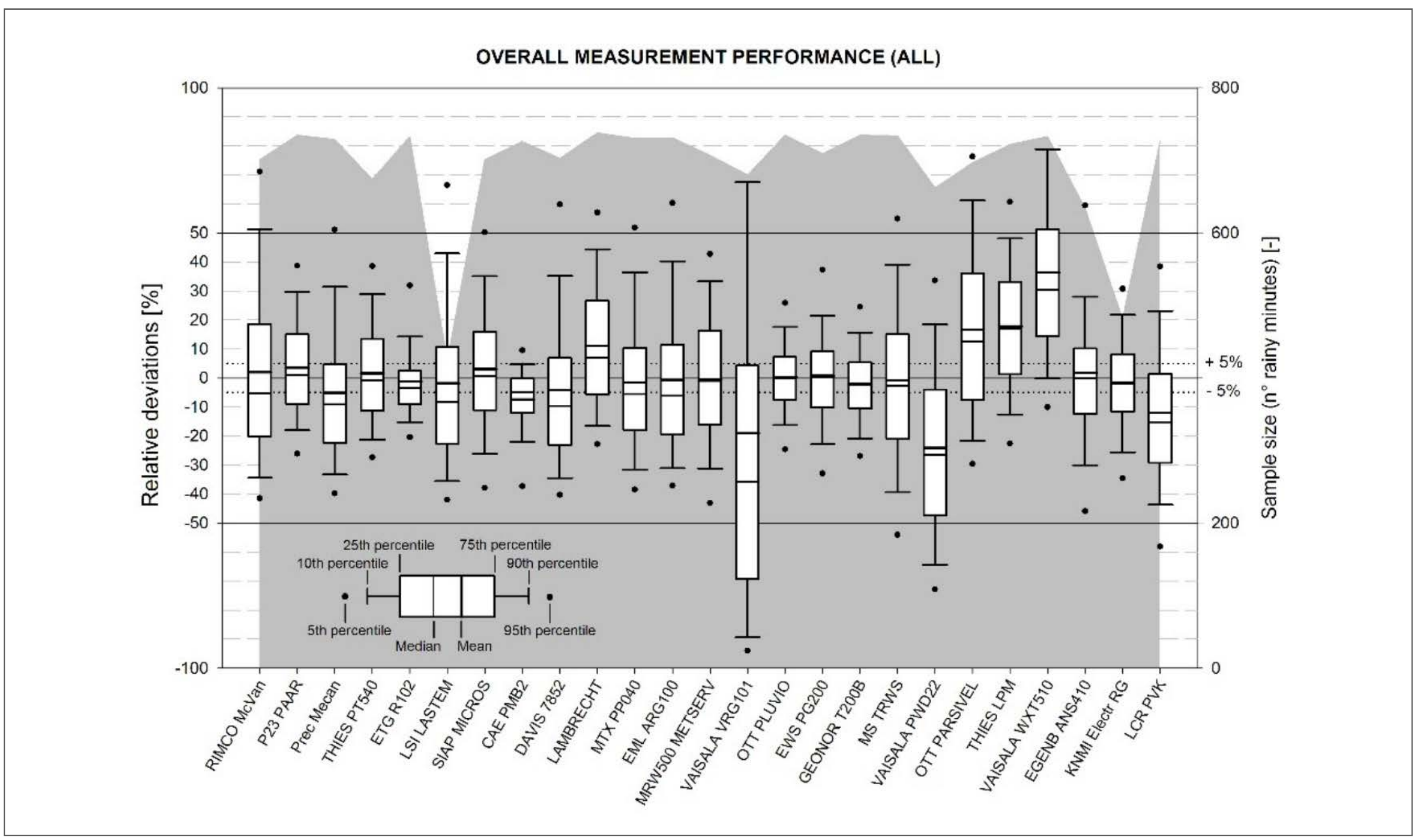

Figure 3. Average relative errors over the whole measurement range of all instruments analyzed (E. Vuerich et. al. 2009).

The study found significant rainfall variability among the rain gauges, with the worst instruments presenting average errors that underestimated by more than 20% and overestimated by more than 30% (keep in mind that these were average errors; there were 5th- and 95th-percentile outliers that underestimated by more than 90% and overestimated by more than 70%). Even among the best instruments, there was still considerable variability, with more than half their measurements presenting errors greater than 5%. These results are consistent with other findings in that they show variability, even among co-located rain gauges of the highest quality that were calibrated and well-maintained.

This might seem contradictory to the general understanding of rain gauge accuracies, as most product specifications often quote rainfall accuracy at around 5% or less. But these metrics are often derived from laboratory testing conditions and thus do not take into account important factors like wind or varying rainfall types and intensities typical of field conditions. These weather conditions play a significant role in precipitation errors, and so the true accuracies of rain gauges are often much larger when deployed in the field.

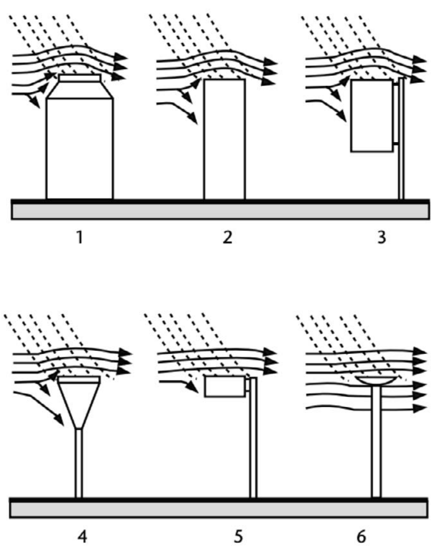

Figure 4. Different shapes of standard precipitation gauges. The solid lines show streamlines and the dashed lines show the trajectories of precipitation particles. The first gauge shows the largest wind field deformation above the gauge orifice, and the last gauge the smallest. Consequently, the wind-induced error for the first gauge is larger than for the last gauge (World Meteorological Organization 2018).

The WMO published an extensive guide covering the measurement of meteorological variables, including precipitation. According to the WMO, rain gauges are subject to many different sources of error, yielding amounts less than the actual precipitation reaching the ground by up to 30% or more (World Meteorological Organization 2018). The magnitude of these errors are highly dependent on weather conditions, especially wind speed and precipitation type and intensity, and can be caused by:

1. Systematic wind field deformation above the gauge orifice (2-50%) —see Figure 4
2. Wetting loss on the internal walls of the collector as well as wetting loss in the container when it is emptied (1-15%)
3. Evaporation from the container (0-4%)
4. In- and out-splashing of water (1-2%)
5. Systematic mechanical and sampling errors, and dynamic effects errors (5-15%)
6. Random observational and instrumental error

Instrument placement and site geography are important factors that can potentially exacerbate the inconsistencies among co-located rain gauges. For example, differing gauge heights or variable protection relative to different wind directions (e.g., nearby vegetation that effectively blocks wind from certain directions) yield different wind speeds. This, in turn, will impact the magnitude of errors due to aerodynamics around the gauge orifice, as shown in Figure 4. This effect has dramatic consequences for precipitation measurement accuracy; one study showed that wind-induced undercatch is on the order of 1% for each mile per hour of wind at the gauge orifice (Larson & Peck 1974). The support documentation for commonly available tipping bucket rain gauges recommends a 2-foot mounting height within a clear field of view (Davis Instruments 2009), while other commercial sources warn that "siting the gauge at any significant height will expose the gauge to wind effects and hence typically cause significant under-recording of rainfall" and "even residual objects in the vicinity of the gauge will potentially have some impact on recorded rainfall" (Prodata Associates Ltd 2020).

In addition to being subject to the sources of error listed above, many rain gauges are sensitive to leveling errors and require regular cleaning and calibration intervals. If the recommended specifications are not met, this can further reduce the efficacy of the system and compound on errors already present. For example, gauge manufacturers warn that "accuracy degrades significantly if the unit is not level" (Davis Instruments 2009) and "cleaning as often as necessary is vital for rainfall accuracy" (Prodata Associates Ltd 2020). In addition, the system may require recalibration, as many rain gauges often do. The necessary dynamic calibrations are often not performed for years after they are due, and so errors induced by fouling and drift in the tipping mechanisms (often induced by the expansion of water) are compounded. The drift from calibration can be as much as 3-8% within the first year in the field, although sensors vary in their resistance to drift (United Kingdom Environment Agency 2004).

Arable co-founder Adam Wolf summarized conventional rain gauges succinctly: "The main problem with these is they fill up with schmutz, they lose their calibration, they lose water from too little rain (evaporation), too much rain (tipper can't keep up) and wind, which blows rain out due to the aerodynamics." Hence, one of the design goals of the Arable Mark 2 was to avoid the pitfalls of tipping buckets and other gauges —bulky, moving parts; accumulation of debris; insensitivity to small rain events; wind-sensitivity; etc.

Arable's solution to measuring precipitation is a novel approach that uses a patented acoustic disdrometer to capture the sound of rainfall (Wolf et al. 2018). The disdrometer effectively "listens" for raindrops to hit the top dome. As audio data is collected, it is analyzed to determine whether the source of sound is rainfall and filters anything else out. The rainfall sounds are transformed to energy bins, which are then mapped to individual rain droplet sizes. The accumulation and size characterization of each droplet is what ultimately generates an overall rainfall rate and accumulated rain measure.

An integral part of this process is the application of both classification and regression machine learning (ML) models that enhance the rainfall estimates. These models are built and trained on data collected by the Arable Calibration & Validation (Cal/Val) network, which includes 36 (and counting) field sites around the world and generates millions of data points every month. These field sites are equipped with gold-standard, research-grade instrumentation like the second-generation OTT Parsivel2 laser disdrometer (Nemeth and Beck 2011). We not only use this data to train our models, but also to rigorously test their performance across variable field conditions and climate zones. In Figure 5 below, we see a full year of data where a Mark 2 is deployed next to an OTT Parsivel2. The Mark 2 tracks closely over the entire year, with an accumulated percent difference of only 1.5%.

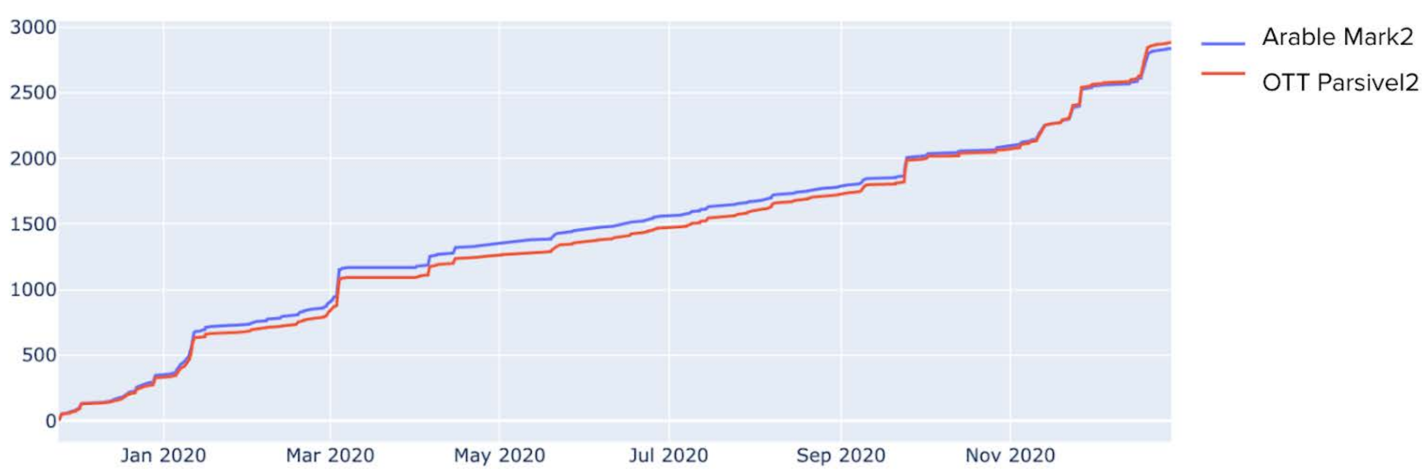

Figure 5. Accumulated precipitation from a co-located Arable Mark 2 and OTT Parsivel2 at one of our Cal/Val field sites.

This global calibration and validation strategy has achieved excellent results, often outperforming commercial-grade weather stations (see the Mark 2 Product Sheet for a more complete list of measurements and their corresponding accuracy ratings). Furthermore, this strategy provides continuous improvement of the ML models over time as additional training data is collected through the Cal/Val network. Our regular software releases contain automated ML model updates that increase our measurement accuracies and maximize performance across all of our feature offerings—without needing to replace the units with new hardware. It is a genuinely flexible and sustainable way of developing and building technologies, and allows us to do it at a more affordable price. Our technologies will continue to evolve and further improve over time by leveraging Arable's dynamic data and ML platform.

For best results, we recommend that customers who are evaluating Arable rainfall data against other gauges to consider the distance between sensors, differences in wind exposure, and the time since any in-house rain gauges were cleaned, leveled, and calibrated. Even then, as we have shown, the spatial variability of rainfall across small distances and even within co-located setups can be remarkable, and common precipitation measurement errors may never be entirely removed. If you would like to read more about the common pitfalls that can occur when attempting to compare two different rainfall sources and related errors, please see this paper and this resource.

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