

Tipping Bucket Rain Gauges

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Tipping bucket rain gauges (TBRs) continue to be one of the most widely used pieces of equipment for rainfall monitoring; they are frequently used for the calibration, validation, and downscaling of radar and remote sensing data, due to their major advantages—low cost, simplicity and low-energy consumption.

Keywords: precipitation monitoring ; rainfall measurement biases ; rain gauge

1. Introduction

Rainfall is a phenomenon that has attracted the interest of human beings since ancient times; researchers have tried to measure it and to understand all the processes linked to it. The earliest reference to a rain gauge was in India, by Kautilya, in the fourth century B.C.; however, references regarding its use in Europe started in the 17th century in Italy, where Benedetto Castelli developed isolated experiments with a non-recording rain gauge in around 1639 and Sir Christopher Wren developed the earliest recording instrument ^[1]. Since then, this interest has grown, and nowadays, rainfall monitoring, research, and forecasting (calibration/validation) are of general interest to better understand the hydrological cycle and subjects that depend on water and precipitation, such as irrigation, hydrological research, water resource management, flood risk, flood alert, flood and weather forecast, hydraulic structure design, urban planning, industry, and a large number of human interest activities ^{[2][3][4][5][6][7][8][9][10]}. Human interest in precipitation monitoring has grown with technological development and the increase in human population, which demands increasingly more resources, generating stress on natural hydrological systems. Thus, hydrological research is gaining interest not only in the scientific community, but also in governmental institutions, with unprecedented support ^[11]. However, hydrologic systems are complex and to better address hydrological research, modeling, and forecasting, accurate data, and if possible, data obtained with a high space–time frequency are needed to understand and explain the nature of dynamical hydrologic systems and to help with decision making aimed at mitigating flood risk, among other branches of hydrological research ^{[11][12][13][14][15][16]}.

Moreover, the goals of the current International Hydrologic Scientific Decade 2013–2022 highlight these challenges, and call for the development of new and innovative monitoring techniques to improve hydrologic monitoring platforms, networks, and databases in order to obtain more reliable data ^{[12][15]}.

Among the different hydrological variables, rainfall monitoring is one of the most important factors in hydrological research and flood risk management ^{[11][17]}. Monitoring rainfall in time and space, together with the availability of accurate rainfall data, is a key issue for managing water resources and forecasting, such as water budget studies, flood frequency analysis, sewer drainage design, surface water hydrology, and flood risk ^{[16][18]}.

Accurate rainfall data are needed to understand the complexity of hydrological systems for water management and rainfall flood forecast, and to better understand extreme events, which can cause severe damage; these are scarcely documented and lead to difficulties in flood modeling ^{[19][20]}. Since precipitation (depth and intensity) is usually estimated by means of temporal averages and spatial interpolations that often do not represent their variability, accurate and reliable results can be achieved if good-quality hydrologic data are provided from a well-designed and well-implemented data collection program ^{[11][21]}.

Measuring rainfall is not only about instrument accuracy; it is also about the capacity of the data to represent the reality of the hydrological system. Since the rainfall phenomenon is characterized as being dynamic, not only in time but also in space, a proper frequency of data measurement and its spatial representativeness must be considered to achieve better results. As ^[22] commented, the starting point in gaining a good hydrological understanding is accurate rainfall measurement and forecasting with useful lead times. Nonetheless, instrument accuracy is a main factor to be considered, since most of the instruments used to measure rainfall are subject to measurement biases that can be reduced with proper equipment management ^[2].

2. Tipping Bucket Rain Gauges and Their Measurement Uncertainties

Among all the different rainfall measurement sensors, TBRs are the most widely used worldwide due to their simple manufacturing structure, which is based on an electric pulse, a magnetic reed switch mechanism, and a counter [2]. TBRs include a receiver (a funnel) that collects rainwater into a bucket, which is one-half of a two-bucket receptacle, pivoted on a cylindrical axis, that tips once the upper bucket fills up to a specified water amount (tipping volume, V_t) and raises the lower bucket into a position under the waterfall line, where it will begin to fill at the same time as the other bucket empties. In this movement, a magnet located in the tipping bucket mechanism generates an output signal through a magnetic reed switch to a recorder, and each pulse is set as a nominal amount of rainfall according to a fixed V_t , which can be set by two calibration stop screws (one for each bucket; **Figure 1**) [2][23][24].

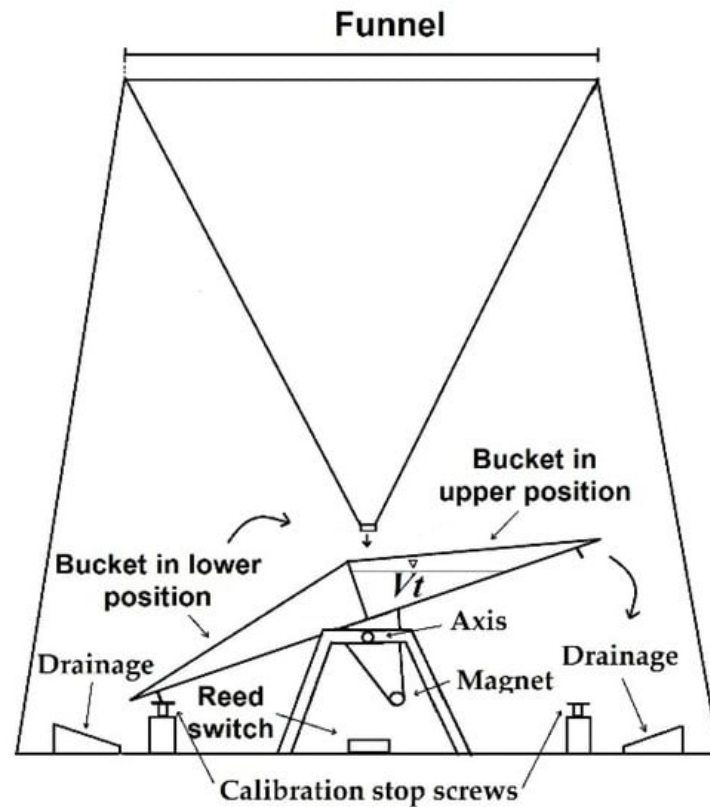


Figure 1. Tipping bucket rain gauge.

TBRs have become one of the most extensive rain gauges, due to their simple manufacturing structure, low cost of production, and energy-saving capacity (a key element for the manufacturing of most weather instruments), being commonly used by National Meteorological Services, airports, industries, farmers, and private individuals to measure the rain depth and intensity [2][23][25]. In hydrological research, they are the most common gauges used to measure precipitation, which is one of the main variables for runoff models, calibration of distributed precipitation measurements [3][4][26], downscaling of remote sensing precipitation models [6][27], radar calibration [7][28][29], basin water balance, flood models [30], structure design, and profitability in different projects (hydroelectrical generation, dams, irrigation, city planning, etc.) [2][9].

Despite the advantages of TBRs, their main drawbacks are due to measurement errors and uncertainties originating in the operation of the equipment itself, as well as by external agents, which impacts on measurement reliability. Numerous studies in recent years have focused on explaining the nature of these measurement biases and have proposed different calibration methodologies and strategies to reduce the measurement uncertainty in TBRs, and some book chapters have addressed this topic [31][32]. However, there are no review articles on TBR measurement uncertainties, calibration, or error reduction strategies. This is the main objective, with the purpose of gathering the knowledge developed in the area and making it more accessible.

According to [32], all instruments have biases and uncertainties, but in precipitation, their quantification and adjustment are more complex than for other environmental variables due to the variability of hydrometeors. However, this aspect is often forgotten by managers of operational monitoring networks and data users; consequently, biases are forwarded through applications or modeling, resulting in a lack of reliability [26][33][34]. These biases are usually considered by correction models that modify the measured precipitation, adding biases generated by wind, wetting, evaporation, and mechanical biases [35].

TBR rain measurements are affected by systematic biases due to instrumental, environmental, and management sources. In general, an underestimation of total rainfall can be observed, due to the difficulty of TBRs to catch the exact amount of water falling over the projection of the measurement area on the ground (wind, evaporation, splashing, and wetting phenomena) and to correctly measure the amount of water collected by its funnel (mechanical biases). In TBRs, the main sources of measurement biases are those caused by wind and mechanical biases [32][36].

2.1. Instrumental Error

The mechanical characteristics that benefit the operation of TBRs also generate a systematic mechanical bias that underestimates rainfall as the rainfall intensity (RI) increases. According to [24], this phenomenon is due to the water lost during the tipping movement of the buckets. During this movement, some water is not measured since the movement starts at that instant when a given bucket's volume is reached. However, the bucket tipping rotation requires an amount of time that generates a time window where some rainwater is added as an unmeasured surplus (**Figure 2**). In addition, according to [2], there is another source of surplus caused by the drop triggering the tipping movement (D), with a certain fraction of its volume that exceeds the V_t , both related to RI . As the RI increases, the water flow in the funnel and the size of D increases. However, the surplus due to D can be considered negligible in contrast to that caused by the time the bucket takes to tip [2][37].



Figure 2. Water falling on the bucket during the tipping movement as an unmeasured surplus. Source: [2].

The volume of water lost during the tipping movement is related to the flow rate out of the funnel which, in turn, depends on the RI . If a constant increase in the RI is assumed, the flow rate would increase as the RI does, and therefore, so would the losses. However, they also depend on the tipping time, which decreases as the RI increases (especially at a high RI), caused by water constantly falling and impacting the rocker arm, accelerating its movement, which also generates a decrease in the V_t by reducing the kinetic energy needed to tip. The reduction of these two parameters results in a compensation effect, which offsets part of the losses; therefore, the increase in the volume of water lost during the tipping movement as a function of the increase in the RI follows a curved pattern [2][38].

Regarding the effects of the RI in TBR measurements, three regions were observed by [2][38]. The first region corresponds to a very low RI , where the flow rate falling from the funnel orifice is too low that does not have enough time to fall into the bucket in motion, so no extra water is added during the tipping time. In the second region, the flow rate generated by the RI is fast enough to add some water as it drops into the bucket during the tipping time and produces an underestimation in the measurements. The third region is observed at a high RI above a threshold where the drip-falling flow becomes a continuous stream and adds not only unmeasured water to the bucket during the tipping time, but also a constant thrust on the rocker arm; this generates a reduction in the V_t and tipping time, resulting in compensation of the underestimation effect generated by the unmeasured water falling into the bucket during the tipping time.

The magnitude of the biases depends on the TBR design characteristics, such as the size of the funnel orifice, the size of the funnel, the size of the buckets, and the instrument resolution [2][24][39]. For example, these biases are caused by the time the bucket takes to tip, and they will appear after a certain RI , since at a very low RI , the funnel flow rate is too low and the time window generated by the tipping time is not long enough to generate a measurement overshoot, which depends on the TBR characteristics. The magnitude of this no tipping time bias or first region varies from one TBR model to another depending in the specific characteristic, as well as the continuous stream threshold [2].

Since the biases are related to the *RI*, calibration strategies as a function of the *RI* are used to reduce their impact on the measurement. Likewise, there are other sources of instrumental error in the buckets' self-functioning mechanism: drag variations, friction force variation in the fixed axis, variability in *D* size, the interaction of falling droplets with tipping bucket balance, changes in falling water direction, leveled errors, an incomplete evacuation of water from the tipping bucket or funnel, the buckets' volume variation, water origin, initial conditions of the buckets, wetting loss to the internal wall of the gauging funnel, evaporation, splashing, mechanical blockages, and logging errors. These sources do not depend on the *RI* and calibration cannot avoid them; however they can be reduced by proper equipment management and maintenance [2][24][30][40][41][42][43]. Moreover, a random unexplained variation, not related to the *RI*, has been identified by several authors [2][30][36][40][41][44][45][46][47][48], which can be significant and could be explained by a combination of the sources previously mentioned and other sources originating from environmental agents (e.g., wind) and human error [2][40]. Nevertheless, as [39] affirmed, these random errors are small compared to those derived from *RI* or wind.

2.2. External Sources of Bias

These are the biases caused by external agents, not directly related to the TBR operating mechanism, such as losses from evaporation, wetting, splashing, funnel clogging, colonization for animals or insects, and wind effects [32][36][45][46][48][49][50][51][52]. Among all of these, the last one is the most relevant source of error in many precipitation monitoring sensors. According to [23], the effect of wind is caused by the interaction between the gauge body and the airflow. The rain gauge behaves as a "bluff-body" when impacted by the wind that produces airflow deformations around it, which results in significant acceleration and vertical velocity components above the collector that deviate the trajectories of the hydrometeors (**Figure 3**) and induces a significant reduction in their performance [23][32][43][51][53].

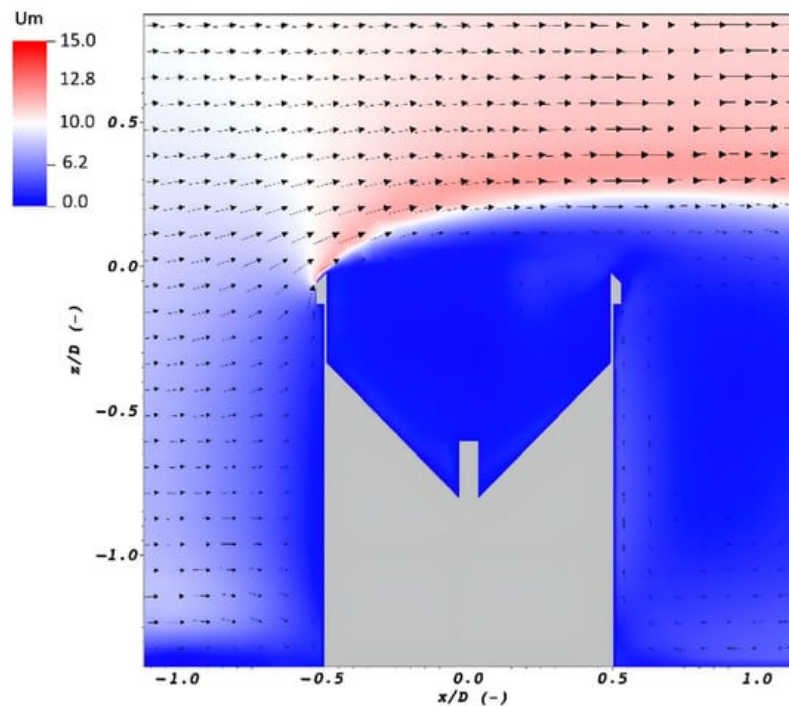


Figure 3. A sample section of the airflow field (velocity magnitude, U_m (m s^{-1})) along the vertical symmetry of a TBR at a horizontal wind speed of 10 m s^{-1} simulation. The arrows represent the time-averaged magnitude and direction of the airflow. Source: [43][51].

Wind biases can cause approximately 2–10% and 10–50% undercatch for liquid and solid precipitation, respectively. It depends on the gauge geometry, the wind speed, the type of precipitation, and its characteristics such as particle distribution, size, and precipitation intensity [51].

2.3. TBR Management and Limitations

TBR biases are generally defined as instrumental and environmental; however, researchers also consider TBR management as an important source of measurement biases, since proper TBR management can either reduce biases or favor their effects. The importance of instrumental management is not usually taken into account during the operation of rainfall monitoring networks or for data users; thus, errors propagate through applications or modeling and the results are affected by limited reliability, since most historic recorded rainfall series have never been corrected and are affected by significant biases and uncertainties [23][26][33][34].

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