

THE EFFECTS OF URBAN ENVIRONMENTS AND AIR POLLUTION ON PRECIPITATION MICROPHYSICS: AN EXPLORATORY STUDY USING DISDROMETERS IN BELGIUM

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PREFACE

Someone once made the comparison between a master's thesis and a marathon, as both require strong motivation and persistence to reach the finish line. My "marathon" started 2.5 years ago, when I first encountered the interesting field of hydrometeorology and precipitation microphysics for my bachelor's thesis. The rather complex processes surrounding such a banal phenomenon as rain intrigued me, and made me want to explore these concepts in greater detail the following years. This curiosity ultimately brought me to investigate the impacts of environmental drivers on rainfall microphysics, which keep puzzling researchers to this day. Now, being at the end of this race, I would like to express my gratitude to those whose support and encouragement have helped me cross the finish line.

First and foremost, I would like to sincerely thank my promoter, Prof. dr. Kwinten Van Weverberg. He has guided me throughout the entire period with insightful feedback and constructive discussions. Beyond continuously offering his expertise, his endless enthusiasm and unwavering confidence have motivated me to elevate this thesis to a higher level and constantly give it my all. I would not be the researcher I am today without his support.

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ABSTRACT

Urbanisation and air pollution are increasingly recognised as important factors influencing precipitation microphysics, yet their combined impact on raindrop size distributions (DSDs) remains uncertain. This thesis investigates how urban land cover and particulate air pollution affect rainfall microphysical properties using multi-year disdrometer observations at three urban-edge sites near Brussels, Ghent and Liège. Measurements from three disdrometers were combined with ERA5 wind data, land cover information and gridded air quality datasets. The analysis focuses on temporal variability in rainfall characteristics, urban influences on downwind precipitation, and relationships between particulate matter (PM_{10} and $PM_{2.5}$) and rainfall microphysics. After quality control and instrument evaluation, DSD parameters were derived and rainfall events were classified into stratiform and convective regimes. Urban effects were quantified by relating wind-direction-dependent urban fraction to rainfall characteristics. Air pollution influences are assessed using correlations with particulate matter concentrations. The results show that the OTT Parsivel² disdrometer delivers the most robust measurements, while the Thies LPM systematically overestimates small drops and the Biral VPF-730 exhibits unresolved internal calibration issues. The baseline analysis reveals a geographic contrast in rainfall microphysics. Although summer rainfall shows a more intense and convective character at all sites, higher drop concentrations in Ghent may indicate a stronger marine influence, whereas the lower concentrations in Brussels and Liège suggest a more continental character. Urban influences on rainfall characteristics are generally weak and inconsistent between sites. Although rainfall occurrence tends to increase downwind of urban areas, rainfall intensity and mean drop size generally decrease near Brussels and Liège, while Ghent shows limited or slightly positive intensity impacts. Air pollution impacts are regime-dependent. At the daily scale, particulate matter concentrations are associated with lower rainfall intensity and smaller drop sizes, whereas convective events under polluted conditions tend to exhibit larger drops and increased kinetic energy. These relationships persist after accounting for the confounding effects of pressure and wind speed. This suggests general suppression of warm-rain processes, particularly for $PM_{2.5}$, along with possible aerosol invigoration during convective events, especially for PM_{10} . Overall, this study highlights that precipitation microphysics in Belgium are primarily controlled by large-scale meteorological variability, while urban and air pollution effects act as subtle, secondary modifiers with strong site- and regime-dependent behaviour.

SAMENVATTING

Verstedelijking en luchtvervuiling worden steeds vaker erkend als belangrijke factoren die neerslagmicrofysica beïnvloeden, maar hun gecombineerde impact op regendruppelgrootteverdelingen (DSD's) blijft onduidelijk. Deze thesis onderzoekt hoe stedelijk landgebruik en luchtvervuiling een effect hebben op de microfysische eigenschappen van regen, op basis van disdrometerwaarnemingen op drie meetlocaties aan de stadsrand nabij Brussel, Gent en Luik. Metingen van de drie disdrometers werden gecombineerd met ERA5-winddata, landgebruiksgegevens en geïnterpoleerde datasets van luchtkwaliteit. De analyse richt zich op temporele variabiliteit van neerslagkarakteristieken, stedelijke invloeden op benedenwindse neerslag en relaties tussen fijnstofconcentraties (PM_{10} en $PM_{2.5}$) en neerslagmicrofysica. Na kwaliteitscontrole en evaluatie van de instrumenten werden DSD-parameters afgeleid en neerslagevents geïnterpreteerd in stratiforme en convectieve regimes. Stedelijke effecten werden gekwantificeerd door de windrichtingsafhankelijke verstedelijgingsgraad te koppelen aan neerslagkenmerken. Luchtvervuilingseffecten werden geanalyseerd via correlaties met fijnstofconcentraties. De resultaten tonen aan dat de OTT Parsivel² disdrometer de meest betrouwbare metingen oplevert, terwijl de Thies LPM systematisch kleine druppels overschat en de Biral VPF-730 onopgeloste interne kalibratieproblemen vertoont. De basisanalyse onthult een geografisch contrast in microfysica van neerslag. Hoewel zomerse neerslag op alle locaties een intenser en convectief karakter heeft, wijzen hogere druppelconcentraties in Gent wellicht op een sterkere maritieme invloed, terwijl de lagere concentraties in Brussel en Luik duiden op een meer continentaal karakter. De stedelijke invloed op neerslag is over het algemeen zwak en inconsistent tussen de locaties. Hoewel de kans op neerslag meestal toeneemt benedenwinds van steden, nemen de neerslagintensiteit en gemiddelde druppelgrootte doorgaans af nabij Brussel en Luik, terwijl Gent beperkte of licht positieve effecten op de intensiteit vertoont. De invloed van luchtvervuiling is regimeafhankelijk. Op dagelijkse tijdschaal zijn fijnstofconcentraties geassocieerd met lagere regenintensiteit en kleinere druppelgroottes, terwijl convectieve events onder vervuilde omstandigheden samenhangen met grotere druppels en verhoogde kinetische energie. Deze relaties houden stand na correctie voor verstoringen door factoren zoals windsnelheid en luchtdruk. Dit wijst op algemene onderdrukking van warme regenprocessen, vooral door $PM_{2.5}$, en mogelijke aerosolgeïnduceerde intensivering tijdens convectieve events, vooral door PM_{10} . Samengevat toont deze studie dat neerslagmicrofysica in België sterk gecontroleerd wordt door grootschalige meteorologische variabiliteit, terwijl stedelijke invloeden en luchtvervuiling subtielere, secundaire factoren zijn met een sterk locatie- en regimeafhankelijk karakter.

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LIST OF ABBREVIATIONS

AMD:	Area weighted mean diameter
CCN:	Cloud condensation nuclei
CSI:	Critical success index
DSD:	Drop size distribution
ECMWF:	European Centre for Medium-Range Weather Forecasts
FAR:	False alarm rate
KE(R):	Rainfall kinetic energy (rate)
LISA:	Local Indicators of Spatial Association
LWC:	Liquid water content
MM:	Method of moments
MLE:	Maximum likelihood estimation
MSLP:	Mean sea level pressure
OLS:	Ordinary least squares
PBL:	Planetary boundary layer
PM:	Particulate matter
POD:	Probability of detection
QC:	Quality control
RH:	Relative humidity
RMI:	Royal Meteorological Institute
RMSE:	Root mean square error
SEM:	Standard error of the mean
SPW:	Société Public de Wallonie
UDI:	Urban dry island
UHI:	Urban heat island
URI:	Urban rain island
VMD:	Volume weighted mean diameter

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1. INTRODUCTION

1.1 Context of the topic

Rainfall is one of the most important phenomena for life on Earth, sustaining natural ecosystems and human agriculture. However, precipitation is not solely based on the amount of water reaching the surface. The size, concentration and fall velocity of raindrops strongly influence how rainfall interacts with the atmosphere and how it affects soils, vegetation and urban areas upon reaching the ground. Therefore, rather than viewing rainfall as a volume of water, it can be analysed as a population of distinct, individual drops. This is known as the raindrop size distribution (DSD), describing the number of raindrops as a function of size. They are typically measured by disdrometers, which record the diameter and velocity of falling particles. DSDs provide insight into the processes leading up to the rainfall and are widely used in meteorology and hydrology. They play an important role in flood predictions, agriculture, and estimating rainfall intensity from radar signals as well as rainfall attenuation of microwave radiocommunication (Fiser, 2010; Liao *et al.*, 2020; Van Weverberg *et al.*, 2026). Furthermore, DSDs are commonly used in numerical weather models to better predict extreme rainfall events (Michaelides *et al.*, 2009). However, uncertainties in DSD retrievals, owing to the large variability in space and time of the distributions, often lead to errors in weather models when integrated (Jaffrain, 2012; Q. Yang *et al.*, 2019). Consequently, it is crucial to thoroughly understand the factors that influence raindrop sizes, but disdrometer data are scarce due to the high cost of the equipment (Fiser, 2010). In recent decades, increasing attention has been given to the influence of cities and air pollution on precipitation processes. Previous studies suggest that both factors can alter rainfall characteristics and DSDs, although the associated processes are complex and still poorly understood (Lalonde *et al.*, 2023; Tao *et al.*, 2012; Q. Yang *et al.*, 2022; Y. Zhang *et al.*, 2017). This knowledge gap causes uncertainties in observations, simulations and predictions of rainfall (Q. Yang *et al.*, 2022), highlighting the importance of further research on these subjects.

1.2 Societal relevance

Variations in rainfall characteristics strongly influence natural and human systems, affecting flood risks, erosion, water management and weather predictions. DSDs are widely used in weather and climate models to represent precipitation processes and improve rainfall estimation. Aerosols from air pollution, for example, can strongly alter DSDs through aerosol-cloud interactions (ACI). These interactions remain one of the largest uncertainties in the assessment of future climate change, as aerosols can either suppress or enhance rainfall depending on

environmental conditions (Alexandri *et al.*, 2023). Additionally, the influence of urban influence on precipitation has become increasingly important as the global urban population has grown rapidly over the past decades. In 2025, around 58% of the world population lived in urban areas, compared to only 20% in 1950, and is projected to rise to 67% by 2050 (United Nations, 2025). Meanwhile, the extent of the built-up area has increased twice as fast as the increase in population. As urban areas typically enhance rainfall, more people will be exposed to flood risks. At the same time, rapid urban development increases pollutants, leading to further changes to rainfall patterns. Beyond atmospheric modelling and flood risks, DSDs are also useful for environmental applications. Derived variables such as kinetic energy are essential for research on rainfall interception of vegetation, soil infiltration, soil erosion, and damage to infrastructure such as wind turbines (Jaffrain, 2012; Tilg *et al.*, 2020). The intensity of splash erosion, for example, is strongly related to raindrop sizes (Tilg *et al.*, 2020). Finally, this research is particularly relevant in the Belgian context due to the installation of a new disdrometer and the limited existing research on the other disdrometers in the country.

1.3 Structure and research objectives

This thesis aims to provide a clear and structured assessment of two largely debated factors impacting precipitation, being urbanisation and aerosols. The main research question is: *“How do urban areas and air pollution influence precipitation microphysics and drop size distributions in Belgium?”* To answer this, the following sub questions will be addressed:

- What are the characteristic raindrop size distributions and rainfall microphysical properties observed in Belgium?
- How do DSD characteristics vary between precipitation regimes and across temporal scales?
- What is the influence of urbanisation on downwind precipitation microphysics?
- How do particulate matter concentrations influence precipitation microphysics?
- To what extent do meteorological conditions confound observed urban and aerosol relationships?

Following the introduction, the literature review provides the theoretical background necessary for this study. It first introduces fundamental atmospheric processes responsible for rainfall formation and DSD variation, after which the statistical representation and measurements of DSDs are discussed. Then, the chapter examines different precipitation regimes as well as the influence of aerosols and urbanisation on rainfall microphysics, and addresses the main research gaps in the literature. The methodology section describes the study area, the

instrumental overview and the processing and validation of precipitation measurements. The section further discusses the derivation of DSD parameters, the classification of rainfall regimes, the various supportive environmental datasets, and the statistical methods used. The results section presents the evaluation of the disdrometer performance and the observed variability in DSDs, including temporal patterns and statistical distributions. The section then investigates the relationships between urbanisation, air pollution and rainfall microphysics. The discussion interprets the results in relation to the existing literature and the underlying physical mechanisms. The uncertainties and confounding factors are discussed, as well as recommendations for further research. Finally, the conclusion summarises the main findings and answers the research questions.

2. LITERATURE REVIEW

2.1 Moist atmospheric processes and precipitation microphysics

2.1.1 *Fundamentals of atmospheric moisture*

Precipitation microphysics entails the small-scale processes within clouds that lead to precipitation, as well as the properties of precipitation particle populations, including their sizes, velocities and concentrations (McFarquhar, 2022). Before precipitation can occur, water must be present. Water can be found in the atmosphere in gaseous, liquid and solid form, and can transform from one phase to the other through evaporation, condensation, freezing, melting, sublimation, and deposition. These transitions occur by absorbing or releasing latent energy, which plays a fundamental role in atmospheric thermodynamics (Shuttleworth, 2012). Along with a wide range of gases, such as nitrogen gas (N_2), oxygen gas (O_2) and argon (Ar), the atmosphere also contains a variable amount of water vapour (H_2O) (Moene & Dam, 2014). Unlike the other gases, water vapour concentrations vary strongly in space and time, typically ranging between 0 and 5%.

The particles contained in these gases all exert pressure on the air, thus contributing to the total atmospheric pressure. The contribution of water vapour is referred to as the vapour pressure (e). The maximum amount of water vapour that air can contain depends on the temperature, as given by the Clausius-Clapeyron equation. This equation states that saturation vapour pressure (e_s) increases exponentially with temperature, increasing moisture capacity with roughly 6-7% per °C warming (Bohren & Albrecht, 2023). This means that warm air can contain substantially more water vapour than cold air before reaching saturation.

Relative humidity (RH) expresses how close air is to saturation and is defined as the ratio between the actual vapour pressure and the saturation vapour pressure ($RH = \frac{e}{e_s} \cdot 100$) (Shuttleworth, 2012). When the air is said to be saturated with respect to water vapour, the saturated vapour pressure (e_s) is reached, and the relative humidity is 100%. Adding more water vapour will lead to condensation of the excess vapour into liquid water. A related quantity is the vapour pressure deficit (VPD), which represents the difference between the saturated vapour pressure and the actual vapour pressure ($VPD = e_s - e$) (Shuttleworth, 2012). The VPD describes the atmospheric demand for moisture, where high VPD values indicate dry air with a strong capacity to absorb additional water vapour, thereby increasing evaporation, while low values indicate moist air close to saturation.

Saturation can be reached by either increasing the amount of water vapour in the air, or by lowering the air temperature, thus decreasing e_s (Shuttleworth, 2012). In the atmosphere, the second process commonly occurs through adiabatic cooling (no external energy exchange). Air parcels can rise freely via convective uplift when they are warmer and thus less dense than the environment, or they can be forced upward mechanically by topography or frontal systems (Shuttleworth, 2012). When an air parcel rises, the surrounding atmospheric pressure decreases with altitude. To reach an equilibrium with the environment, the air parcel expands, thereby decreasing internal energy and lowering temperature. Further cooling then leads to condensation and the formation of clouds.

2.1.2 Precipitation formation processes

Precipitation originates from a sequence of microphysical processes that begin with cloud formation and lead to the growth of hydrometeors large enough to fall to the surface. When moist air cools until the saturation vapour pressure is reached, water vapour condenses onto cloud condensation nuclei (CCN), forming microscopic cloud droplets, although homogeneous nucleation can occur without CCN on rare occasions (Jaffrain, 2012). These droplets then grow according to the so-called Köhler curve, which describes the balance between curvature and solute effects: drop curvature increases the equilibrium vapour pressure and thus inhibits growth of very small droplets, whereas dissolved solutes lower the vapour pressure and promote growth (Appendix 1). As a result, only droplets that exceed a critical size can grow spontaneously under supersaturated conditions (i.e. relative humidity exceeding 100%), while smaller droplets tend to evaporate (Köhler, 1936).

In warm clouds (containing only the liquid phase), further growth mainly occurs through collision-coalescence, whereby larger droplets capture smaller ones and rapidly increase in mass (Low & List, 1982). This process consists of two stages: autoconversion, where cloud droplets ($< 50 \mu\text{m}$) collide and merge with other cloud droplets to form small raindrops, thus initiating rainfall; and accretion, where these small raindrops continue to grow by collecting additional cloud droplets, determining the intensity of rainfall (Wu *et al.*, 2018). In cold clouds, on the other hand, the Wegener-Bergeron-Findeisen process dominates, whereby lower saturation vapour pressure over ice causes water vapour to deposit onto ice particles (Storelvmo & Tan, 2015). This leads to ice particle growth at the expense of supercooled water droplets. This growth eventually makes the particles heavy enough to overcome air resistance from updraft within the cloud (Raabe *et al.*, 2025). They then fall from the cloud as precipitation, such as rain, snow, or hail.

The combined result of condensation, collision–coalescence, and ice-phase processes determines not only the formation of precipitation, but also the resulting distribution of particle sizes. During their descent, additional processes further alter the DSD. Because larger drops have higher terminal fall velocities, they reach the surface more efficiently than smaller drops, leading to a sedimentation size sorting and a relative enhancement of large drops near the surface compared to the distribution within the clouds (Milbrandt & Yau, 2005). At the same time, collisions between drops occur due to different fall velocities, leading to coalescence (increasing the drop size) or breakup (producing multiple smaller drops) (Ulbrich, 1983). In addition, large drops may become aerodynamically unstable and undergo spontaneous breakup. These microphysical processes continuously modify the number and size of falling drops, thus shaping the observed drop size distributions (DSDs) at the surface. Testud *et al.* (2001) suggest that the equilibrium between collisional coalescence and breakup leads to a stable DSD, forming the basis of analytical DSD models.

The terminal fall velocity v_T of liquid raindrops as a function of diameter D was first determined experimentally by Gunn and Kinzer (1949). Although bigger drops have a higher fall velocity, an asymptote of 9.2 m/s is reached for drops with a diameter larger than 5 mm. Raindrops preserve their spherical shape until a diameter of 1 mm is attained, after which the drops become flattened ellipsoids (Tilg *et al.*, 2020). The additional gravitational force caused by the greater mass of bigger drops is therefore counteracted by the increased air resistance due to a bigger surface area. Atlas (1973) later approximated the observations of terminal fall velocity theoretically using the following formula:

$$v_T = \begin{cases} 3,78D^{0,67}, & x < 3 \text{ mm} \\ 9,65 - 10,3e^{-0,6D}, & x \geq 3 \text{ mm} \end{cases} \quad (1)$$

The theoretical fall velocity represents the terminal velocity under still-air conditions. In natural conditions, however, deviations can occur due to wind and turbulence (Tilg *et al.*, 2020). Observational studies have shown that increased wind speeds lead to a broader distribution of fall velocities compared to calm conditions, caused by asymmetric drop shapes and enhanced breakup (Montero-Martínez & García-García, 2016; Thurai *et al.*, 2019). Furthermore, Equation 1 only applies to raindrops falling near the surface. At higher altitudes, lower air pressure, and therefore less air resistance, must be accounted for (Atlas *et al.*, 1973).

2.2 Drop size distributions (DSDs): moments, bulk variables and statistical models

2.2.1 DSD moments and bulk variables

Raindrop size distributions, or DSDs, are represented by the number concentrations $N(D)$ of raindrops as a function of diameter. This can be expressed as: $N(D) = \frac{dN}{dD \cdot dV}$, where dN is the number of drops within the diameter interval dD , considered over a given volume dV . All macroscopic properties of precipitation can be calculated as moments of $N(D)$:

$$M_k [m^{-3}mm^{-k}] = \int_{D_{min}}^{D_{max}} N(D) \cdot D^k \cdot dD \quad (2)$$

The various moments, along with their statistical and physical properties, are listed in Table 1. In this context, R^* represents a quantity that is closely linked to precipitation intensity and is defined by Joss & Gori (1978). By integrating the drop size distribution over the full spectrum of diameters, a wide range of integral bulk variables can be derived (Liao *et al.*, 2020). These variables summarise the macroscopic properties of the total raindrop population, despite its underlying microscopic variability in drop size and fall velocity.

Among these are drop size metrics such as the volume-weighted mean diameter (VMD) (Tilg *et al.*, 2020), the area-weighted mean diameter (AMD; also known as the effective diameter) (Smith, 2003) and the standard deviation of the mass spectrum (σ_m) (Smith *et al.*, 2019). It should be noted that the equivalent term mass-weighted mean diameter is also common in the literature to denote VMD, as volume and mass are proportional for liquid drops. The symbol D_m is also widely used for this quantity, however, the terminology adopted here follows Tilg *et al.* (2020). VMD represents the diameter that characterises the mass of the drop distribution and is frequently used as a characteristic drop diameter in studies on rainfall microphysics (Alcoba *et al.*, 2022; Peinó *et al.*, 2024; Tilg *et al.*, 2020). Conversely, AMD is often used in radiation remote sensing studies, as optical and infrared instruments are most sensitive to the surface area of the particles (Blanchard *et al.*, 2017; Guyot *et al.*, 2015). σ_m gives an indication of the variation of raindrop sizes.

In addition to these characteristic diameters, several physically relevant bulk variables can be directly related to moments of the DSD. The total number concentration N_T corresponds to the zeroth moment (Table 1), whereas the liquid water content (LWC) is proportional to the third moment ($\propto D^3$), reflecting the total mass of water (Testud *et al.*, 2001). Rainfall rate R , which incorporates the diameter-dependent fall velocity, scales

approximately with the 3.67th moment, assuming v_T scales with $D^{0.67}$ (Equation 1) (Fiser, 2010). The kinetic energy (KE) of rainfall scales with drop mass (D^3) and the square of the fall velocity ($\propto D^3 v^2 \sim D^{4.34}$). Since this kinetic energy flux is strongly correlated with rainfall rate, empirical KE–R power fits can be employed to accurately calculate kinetic energy from rainfall rates (Testud *et al.*, 2001; Tilg *et al.*, 2020).

Radar reflectivity Z is a fundamental variable in radar meteorology and is directly measured by weather radars. Under the assumption of Rayleigh scattering (scattering of diameters much smaller than the radar wavelength) and spherical particles (Uijlenhoet *et al.*, 2003), it is proportional to the sixth moment ($\propto D^6$), making it highly sensitive to larger drops (Smith, 2003; Z. Yang *et al.*, 2019). Because Z is not a direct measure of rainfall rate, empirical Z – R relationships ($Z = a \cdot R^b$) are required to convert reflectivity into quantitative precipitation estimates (Jaffrain, 2012). The prefactor a reflects the shape of the normalised DSD and tends to decrease when VMD increases and concentration decreases (Uijlenhoet *et al.*, 2003). The exponent b determines how the DSD changes with rain rate, with higher exponents indicating stronger increases in reflectivity. Although these Z – R relations vary strongly between climate regions and rainfall regimes (Loh *et al.*, 2020), a common standard is the Marshall–Palmer (1948) relationship $Z = 200R^{1.6}$.

Table 1:

Moments of DSDs and their interpretation.

Moment	Statistical property	Physical quantity
0	—	Total drop concentration (N_T)
1	Mean	—
2	Variance	Total surface area
3	Skewness	Total volume (LWC)
4	Kurtosis	R^*
5	Hyperskewness	—
6	Hyper-tailedness	Reflectivity factor (Z)

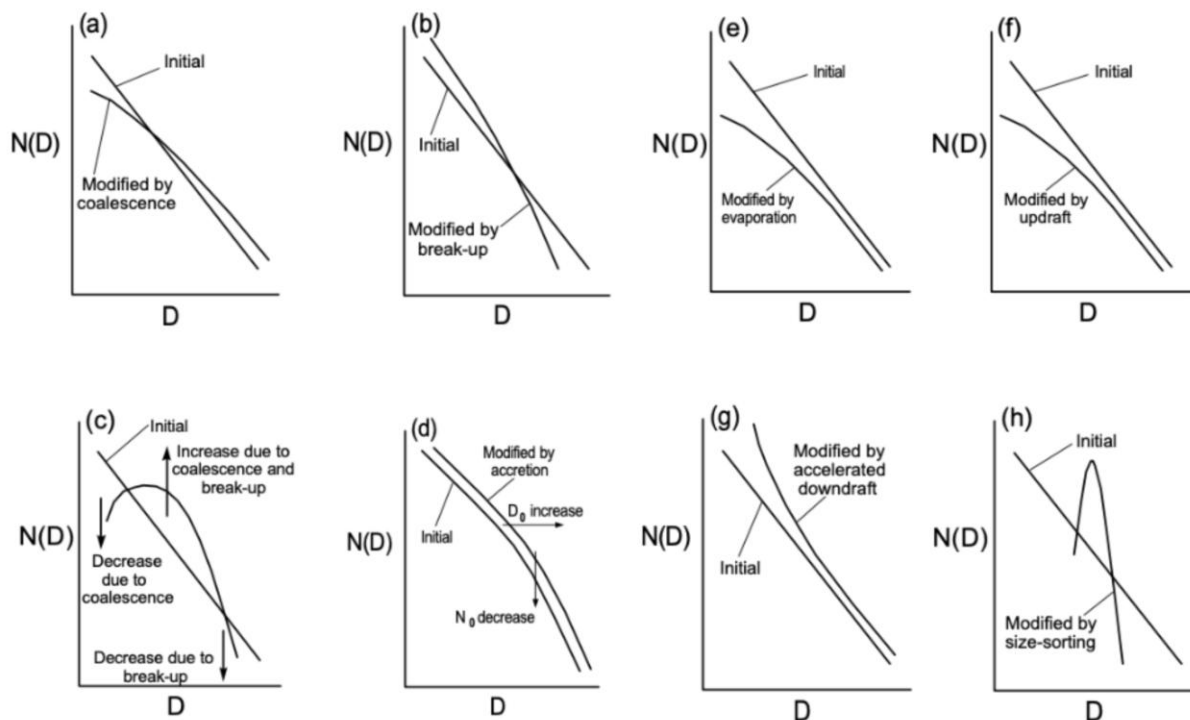
Note. Adapted from “Raindrop Size Distributions: Exponential or Gamma—Does the Difference Matter?” by P. L. Smith (2003), *J. Appl. Meteorol. Climatol.*, 58(4), 787–796 ([https://doi.org/10.1175/1520-0450\(2003\)042%3C1031:RSDEOG%3E2.0.CO;2](https://doi.org/10.1175/1520-0450(2003)042%3C1031:RSDEOG%3E2.0.CO;2))

The shape of the DSD is not static but is continuously modified by microphysical processes, each affecting different parts of the spectrum, as shown on Fig. 1. Collision–coalescence reduces the number of small drops, while increasing the number of larger drops, thus shifting the distribution towards larger diameters. As a result,

the total number concentration N_T decreases, while the VMD increases. In contrast, breakup processes fragment large drops into smaller ones, leading to an increase in small drop concentration and a reduction in large drops. This results in an increase in N_T and a decrease in VMD. When both processes act simultaneously, they tend to narrow the distribution, with coalescence dominating at small diameters and breakup at large diameters. Accretion, meaning the growth of existing drops through the collection of small droplets, increases the drop sizes (higher VMD), without substantially changing the concentration (N_T remains unchanged), as these cloud droplets are not reflected in the DSD. Evaporation and updrafts preferentially remove smaller drops, resulting in a relative increase in larger drops (higher VMD) and a lower N_T , while downdrafts tend to have the opposite effect. Finally, size sorting during fall redistributes drops according to their fall velocity, often leading to a narrower distribution and reduced N_T , while the impact on the VMD is less certain.

Figure 1:

Schematic representations of the effects of microphysical cloud processes on resulting DSDs. The depicted processes are (a) coalescence, (b) breakup, (c) combination of coalescence and breakup, (d) accretion, (e) evaporation, (f) updraft, (g) downdraft and (h) size sorting.



Note. Adapted from “Cloud Microphysical Properties, Processes, and Rainfall Estimation Opportunities”, by Rosenfeld, D. and Ulbrich, C. W. (2003), *Meteorol. Monogr.*, 30(52), 237 ([https://doi.org/10.1175/0065-9401\(2003\)030%3C0237:CMPPAR%3E2.0.CO;2](https://doi.org/10.1175/0065-9401(2003)030%3C0237:CMPPAR%3E2.0.CO;2))

2.2.2 Statistical distributions of DSDs

The raindrop size distribution, or DSD, is a central concept in this study. Representing DSDs with statistical distributions is relevant for several reasons. First, measurement instruments such as disdrometers are sensitive to noisy drop counts, particularly in the largest diameter classes due to the small sampling area (Testud *et al.*, 2001). Random fluctuations in sparse counts may therefore distort integral parameters, especially those based on higher moments such as Z , which are more sensitive to large drops. In radar meteorology, such models are essential to convert indirect observations, such as reflectivity and phase shift, into precipitation intensity (Illingworth & Mark Blackman, 2002; Testud *et al.*, 2001). In climate models and weather prediction, bulk microphysics schemes represent the phase transitions between different hydrometeor types and determine rainfall distributions in the models. To remain computationally efficient, these schemes rely on statistical particle size distributions to describe hydrometeor populations (Milbrandt & Yau, 2005). In addition, these distributions provide a standardized framework to compare different rain types using a limited number of characteristic parameters (Testud *et al.*, 2000). The main distributions proposed to date are the negative exponential, gamma, and lognormal distributions.

Marshall and Palmer (1948) defined a relationship in which drop concentration decreases exponentially with increasing diameter. This can be written as

$$N(D) = N_0 \cdot e^{-\Lambda \cdot D} \quad (3)$$

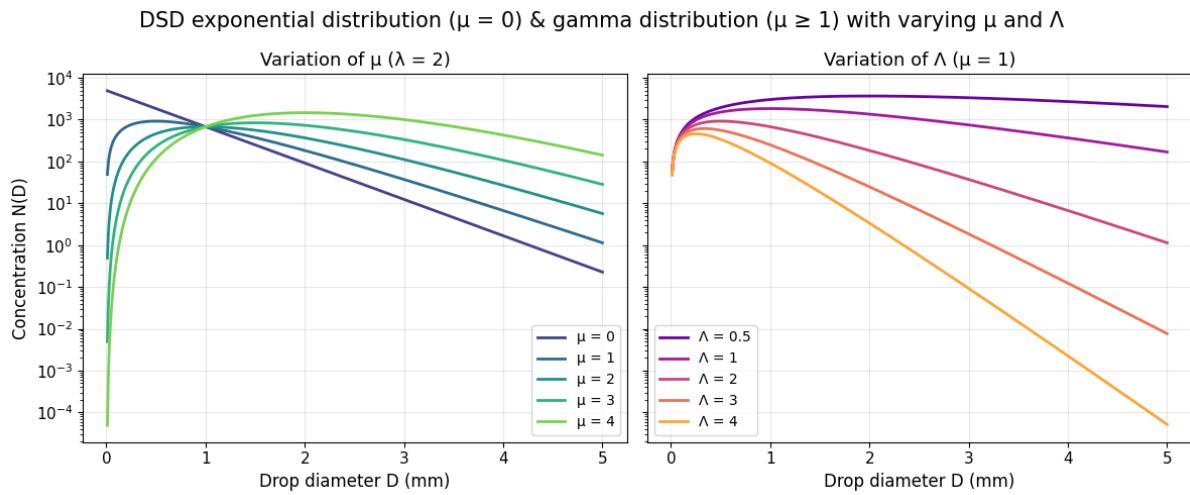
where $N(D)$ ($\text{m}^{-3}\text{mm}^{-1}$) is the number of drops with diameter between D and $D + \delta D$, D (mm) is the drop diameter, N_0 ($\text{m}^{-3}\text{mm}^{-1}$) is a concentration parameter determining the amount of very small drops, and Λ (mm^{-1}) is a slope parameter that depends on rainfall intensity. Due to its mathematical simplicity, the negative exponential distribution is easy to apply, but it is inadequate in representing small raindrops (Marshall & Palmer, 1948). Observations generally indicate fewer drops with diameters smaller than 1.5 mm than predicted by the distribution. This discrepancy is partly caused by wind effects and evaporation of small drops below the cloud base (Smith, 2003). The more flexible gamma distribution is expressed as

$$N(D) = N_0 \cdot D^\mu \cdot e^{-\Lambda \cdot D} \quad (4)$$

and introduces a shape parameter μ to the exponential distribution (Smith, 2003). Equation 4 also shows that the exponential distribution is a special case of the gamma distribution when the shape parameter equals zero. Figure 2 illustrates the gamma distribution with varying parameter values, where a higher μ shifts the peak toward larger diameters and a higher Λ leads to a steeper falloff, resulting in a sharper decline in the concentration of large drops.

Figure 2:

Graph of gamma distribution shapes for different values of μ and Λ (author's own analysis and visualisation using Python).



Although more complex, the gamma distribution is more flexible and better represents smaller drops. A known limitation is that the intercept parameter N_0 lacks physical meaning, since its dimension strongly depends on the shape parameter μ (Testud *et al.*, 2001). For $\mu = 0$, N_0 is expressed in m^{-4} , whereas for $\mu = 2$, it is expressed in m^{-6} (Testud *et al.*, 2000). Because N_0 and Λ are not independent physical quantities but are related to variables such as liquid water content (LWC, expressed in kg m^{-3}), mean diameter (VMD), and distribution shape, their interpretation is not straightforward. Normalization of the gamma distribution addresses this issue by ensuring that a given property remains constant when μ changes. One approach replaces the empirical intercept parameter N_0 with a function of the total drop concentration N_T (m^{-3}), corresponding to the zeroth moment, expressed as

$$N_T = \int_{D_{min}}^{D_{max}} N(D) dD = N_0 \frac{\Gamma(\mu + 1)}{\Lambda^{\mu+1}} \quad (5)$$

(Clark, 1974; Illingworth & Mark Blackman, 2002). The distribution is then written as

$$N(D) = N_T \frac{\Lambda^{\mu+1}}{\Gamma(\mu + 1)} D^{\mu} \cdot e^{-\Lambda \cdot D} \quad (6)$$

where the gamma function $\Gamma(x)$ represents the factorial function $(x - 1)!$ extended to continuous x . An advantage of this formulation is that drop concentrations do not decrease drastically with increasing μ . Alternatively, the intercept can be normalized with respect to the liquid water content. Testud *et al.* (2001) proposed a normalised intercept parameter N_w (m^{-4}), defined solely by LWC and VMD:

$$N_w = \frac{256 \cdot LWC}{\pi \cdot \rho \cdot VMD^4} \quad (7)$$

The normalized gamma distribution then becomes

$$N(D) = N_w \frac{\Gamma(4)}{16} \frac{(4 + \mu)}{\Gamma(4 + \mu)} \frac{D}{VMD} e^{-(4+\mu) \cdot \frac{D}{VMD}} \quad (8)$$

(Illingworth & Mark Blackman, 2002; Testud *et al.*, 2000, 2001). The constant is chosen such that N_w corresponds to the intercept parameter (N_0) of a distribution that would follow an exponential distribution if it had the same liquid water content (LWC) and volume-weighted mean diameter (VMD) as the measured distribution. The normalized intercept parameter is therefore a way to describe the density of drop concentration on a standardised scale, regardless of the shape of the drop size distribution (Testud *et al.*, 2001). This facilitates physical interpretation of the results. Under this normalization, precipitation intensity R remains nearly constant when μ changes, which is not the case with drop concentration normalization (Equation 6). This implies that the parameters N_w , VMD, and μ independently control the absolute drop concentration, the mean volumetric diameter, and the shape of the distribution, respectively. An important drawback of normalization is that the Z - R relationship ($Z = a \cdot R^b$) cannot be used to infer information about the shape parameter μ , since b remains constant after normalization (Illingworth & Mark Blackman, 2002).

2.2.3 Parameter determination

One of the most widely used methods to fit distribution parameters to observed drop size distributions is the method of moments (MM) (Smith, 2003; Testud *et al.*, 2001; Ulbrich & Atlas, 1998). Depending on the chosen distribution, two, three, or four moments are required to determine the parameters. This method is highly sensitive to the extremes of the drop spectrum. High-order moments such as M_6 depend on the presence of only a few very large drops, which can easily be missed or overestimated due to the small sampling area of measurement instruments (Fiser, 2010; Smith, 2003). Conversely, low-order moments such as M_0 and M_1 are often unreliable because of measurement errors affecting very small drops. In practice, M_2 , M_3 , and M_4 are commonly used to estimate the parameters. The method is widely applied because of its computational simplicity.

Another method, generally considered statistically superior, is maximum likelihood estimation (MLE) (Marzuki *et al.*, 2012). This approach determines the parameters that maximize the probability of representing the observed data. MLE yields lower systematic errors and lower variability in parameter estimates than MM, but it is computationally more complex and requires the prior specification of a strict distribution (Smith *et al.*, 2019). Of the two methods, MM is more sensitive to bin size, especially when the total drop concentration N_T is small. However, the bias decreases markedly when N_T exceeds 10^3 and, for large N_T , can even be lower than that of MLE (Marzuki *et al.*, 2012). The bias of MLE is less sensitive to sample size, but it tends to underestimate parameters when bin widths are large.

2.2.4 Characteristics and limitations of parametric fits

Despite its strong simplification, the negative exponential distribution has proven to be a good representation for light to moderate rainfall (Testud *et al.*, 2001). This is largely because the shape of the DSD is strongly controlled by coalescence and breakup processes (Srivastava, 1971). At low rainfall intensity, coalescence dominates and the distribution tends toward an exponential form. At higher intensities, the gamma distribution performs better, as it captures the contribution of large-drop breakup more effectively. Smith (2003) note, however, that for estimating bulk quantities such as liquid water content (LWC), rainfall intensity (R), or reflectivity factor (Z), the additional complexity of the gamma distribution provides only limited improvement over the negative exponential distribution. The normalized gamma distribution, by contrast, offers a clearer physical interpretation and independent parameters. In addition to these two distributions, the lognormal and

Rayleigh distributions are also reported in the literature (Ojo *et al.*, 2022; Testud *et al.*, 2001), but they often show weaker performance in applications such as rainfall intensity simulation (Ojo *et al.*, 2022).

The parameters μ and Λ are not independent. The μ - Λ relationship reflects the mean behaviour of DSD parameters and allows the gamma DSD model to be simplified by explicitly linking two of the three parameters (Zhang *et al.*, 2003). Similarly, the ratio between volume-weighted mean diameter (VMD) and area-weighted mean diameter (AMD) provides a general measure of the DSD shape. This ratio equals $4/3$ for a negative exponential distribution and decreases when μ increases, following $\frac{\mu+4}{\mu+3}$ (Smith, 2003).

2.3 Precipitation regimes and measurements

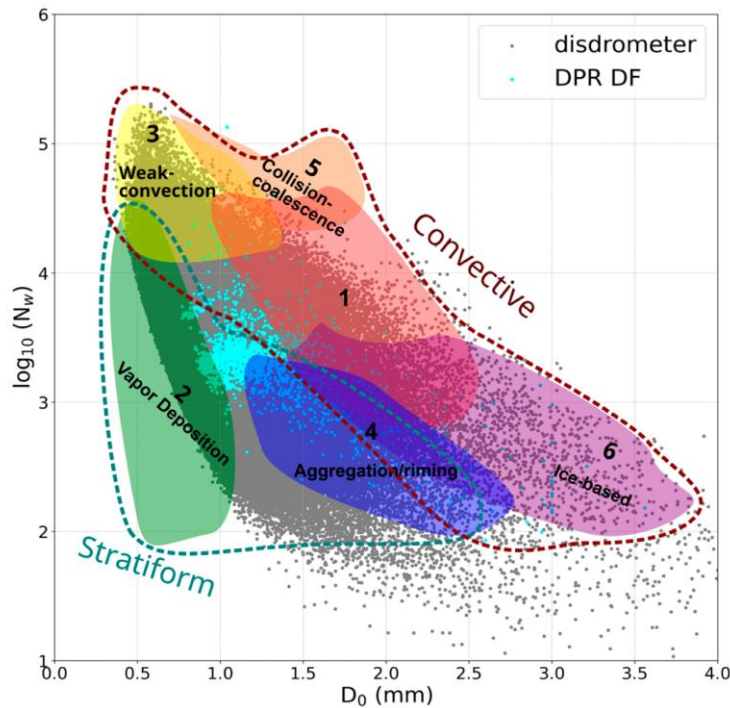
2.3.1 Precipitation regimes

Precipitation is typically classified into either stratiform or convective precipitation (Z. Yang *et al.*, 2019). Convective regimes are characterised by strong vertical wind speeds, low areal coverage and high rainfall intensities (Loh *et al.*, 2020; Z. Yang *et al.*, 2019). Conversely, stratiform regimes have weak upward motions, extensive areal coverage with pronounced horizontal homogeneity and low rainfall intensities. Though stratiform and convective precipitation are the most common types, some studies distinguish other types such as frontal precipitation, having similar conditions as stratiform regimes (Jaffrain, 2012), or transitional precipitation, having more mixed characteristics (Jaffrain, 2012; Uijlenhoet *et al.*, 2003). Owing to the differing characteristics of stratiform and convective rain, the regimes have distinct typical Z–R relationships, with convective rain generally having higher prefactors and different microphysical processes. Rainfall regimes can be distinguished from the behaviour of the VMD and the normalised drop concentration scale parameter N_w (Peinó *et al.*, 2024). In VMD- $\log_{10}(N_w)$ space, convective events are typically associated with larger drops (high VMD) and higher concentrations (high N_w), while stratiform rain tends to exhibit smaller drops and lower concentrations (Fig. 3). Moreover, dominant processes leading to precipitation during a convective or stratiform event can be deduced from the two variables. Warm cloud processes, such as collision–coalescence and weak or shallow convection, generally produce smaller drops with higher concentrations. In contrast, cold cloud processes involving ice-based mechanisms, such as the Wegener–Bergeron–Findeisen process and aggregation and riming of ice crystals, tend to result in larger drops with lower concentrations. Further structure can be differentiated within the convective regime, based on the origin of rainfall. Bringi *et al.* (2003) have identified a maritime and a continental cluster within the convective regime of the VMD- $\log_{10}(N_w)$ space. Here, the maritime

cluster is characterised by higher drop concentrations and smaller drop sizes, associated with warm cloud processes. In contrast, the continental cluster shows lower concentrations and larger drop sizes and is associated with cold-cloud processes.

Figure 3:

Scatter plot of raindrop size distributions in the VMD- $\log_{10}(N_w)$ space, overlaid with rainfall regimes and microphysical dominant processes regions.



Note. Adapted from “Validation of GPM DPR rainfall and Drop Size Distributions using disdrometer observations in the Western Mediterranean” by E. Peinó *et al.*, (2024), *Remote Sensing*, 16(14), 2594 (<https://doi.org/10.3390/rs16142594>)

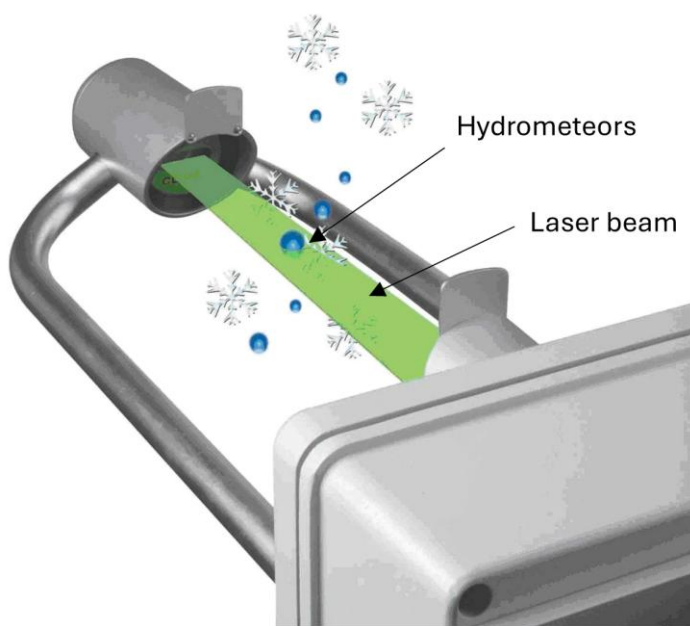
2.3.2 Measurement of DSDs and instrument limitations

Whereas DSDs were formerly measured using manual techniques, a disdrometer is nowadays the standard instrument for observations (Kathiravelu *et al.*, 2016). Disdrometers automatically measure the diameter and velocity of falling particles at high temporal resolution. Several disdrometer types exist, including acoustic, displacement, optical, and two-dimensional video disdrometers, each based on different measurement principles. Among these, laser-optical disdrometers are often used due to their ability to accurately differentiate between liquid and solid hydrometeors (atmospheric water particles such as raindrops and snowflakes)

(Jaffrain, 2012; Kathiravelu *et al.*, 2016). The measurement principle of an optical disdrometer is illustrated in Figure 4, where particle sizes and fall velocity are derived from the attenuation of a laser beam signal as drops pass through the sampling area and scatter the light.

Figure 4:

Schematic of a laser-optical disdrometer and its measurement technique.



Note. Adapted from “Laser Precipitation Monitor: Instruction for Use” by Thies Clima, (2022), Adolf Thies GmbH & Co. KG (https://www.thiesclima.com/db/dnl/5.4110.xx.x00_Laser_Precipitation_Monitor_eng.pdf).

Observational measurements from disdrometers are subject to several errors and limitations. A fundamental limitation is the small sampling area of the disdrometer (typically around 50 cm²), which means that only a fraction of the rainfall is captured at a given time. This leads to sampling variability and noisy drop counts, causing slightly different measurements even at collocated disdrometers (Jaffrain, 2012; Testud *et al.*, 2001). Additional uncertainties arise from the measurement principle of optical disdrometers. When multiple drops pass through the laser beam simultaneously, they may be recorded as a single drop with an unrealistic fall velocity (Frasson *et al.*, 2011). This phenomenon, known as coincidence, becomes particularly important at high rainfall intensities (Guyot *et al.*, 2015). Furthermore, spatial inhomogeneity of the laser beam, with higher intensity near the centre, can lead to systematic biases in drop size estimation: drops passing through the centre may be slightly overestimated in size, while those near the edges may be underestimated (Jaffrain, 2012). This

effect is magnified by drops that only partially cross the laser beam at the edge, further reducing the measured size.

Environmental factors also influence measurements. Wind and turbulence can alter drop trajectories and affect the detection of small drops (Tilg *et al.*, 2020). In addition, splashing effects, where drops fragment into artificially small drops after impact on the sensor, may cause the counting of non-natural raindrops. Disdrometers may also register non-hydrometeoric particles such as insects, spiders or dust, further contributing to measurement noise (Jaffrain, 2012). Finally, instrument-specific differences introduce a source of uncertainty when comparing datasets. For example, the Thies laser-optical disdrometer has been shown to be more sensitive to small drops ($D < 0.6$ mm), whereas the OTT Parsivel exhibits higher sensitivity to larger drops, leading to systematic differences in observed DSDs (Guyot *et al.*, 2019).

To mitigate these issues, various correction and filtering procedures are typically applied. Effective sampling areas are adjusted depending on drop size (larger for bigger drops) to account for the reduced probability of fully crossing the sampling area, thus correcting edge cases (Jaffrain & Berne, 2011). The most relevant correction used to eliminate incorrect measurements caused by splashing, coincidence or non-hydrometeoric particles involves filtering out drops whose velocity deviates significantly from the theoretical fall velocity (Jaffrain, 2012).

2.4 Influence of air pollution and aerosols on precipitation

2.4.1 Aerosols and particulate matter

Air pollution consists of aerosols and trace gases, such as ozone, nitrogen dioxide and sulfur dioxide (C. He *et al.*, 2024; Penner *et al.*, 2001). Atmospheric aerosols, defined as liquid or solid particles suspended in the atmosphere, are commonly quantified using particulate matter (PM) metrics based on aerodynamic diameter (Shihab, 2024). Aerosols may be classified as primary, when directly emitted from a source, or secondary, when formed in the atmosphere through chemical reactions (Harrison *et al.*, 1997). PM_{2.5} refers to fine particulate matter with diameters smaller than 2.5 μm , while PM₁₀ includes particles smaller than 10 μm . Fine particles are primarily associated with anthropogenic combustion processes, including transport, industry and agriculture, and commonly consist of elemental carbon and secondary particles such as ammonium sulphate and ammonium

nitrate (Harrison *et al*, 1997). Coarse particles generally have a natural origin, such as mineral dust, sea salt and biogenic particles.

Surface PM concentrations are occasionally used as a proxy for atmospheric aerosol loadings, particularly within the planetary boundary layer (PBL) where interactions between the earth's surface and atmosphere are strongest (Li *et al*, 2017; Plocoste, 2022). Across Western Europe, PM concentrations have generally declined, due to strict emission regulations for transport and industry, as well as the introduction of alternative energy sources, with reported decreases up to 7.8% yr⁻¹ (Alikhani Faradonbeh *et al*, 2021; C. Li *et al*, 2016).

Aerosol loadings can also be estimated via remote sensing measurements, including the aerosol optical depth (AOD), which measures to what extent aerosols absorb or reflect light along a specific atmospheric path at a given wavelength (Arikan & Yildiz, 2023). Satellite observations provide extensive spatial coverage, although active sensors such as lidar are necessary to separate aerosol reflectance from surface and cloud interference (Arikan & Yildiz, 2023; S. Li *et al*, 2017; Winker *et al*, 2009), since most passive sensors struggle with this decoupling. Additional uncertainties for AOD values arise for strongly absorbing aerosol types and under conditions with optically thick clouds (Arikan & Yildiz, 2023; Penner *et al*, 2001). The relationship between AOD and surface PM concentrations is not always straightforward. While some studies report strong correlations (Li *et al*, 2017), others find weaker relationships, which, however, tend to strengthen when accounting for relative humidity (Fu *et al*, 2022). This occurs because aerosols reflect and absorb more radiation under humid conditions due to hygroscopic growth.

2.4.2 Influence of aerosols on cloud and rainfall microphysics

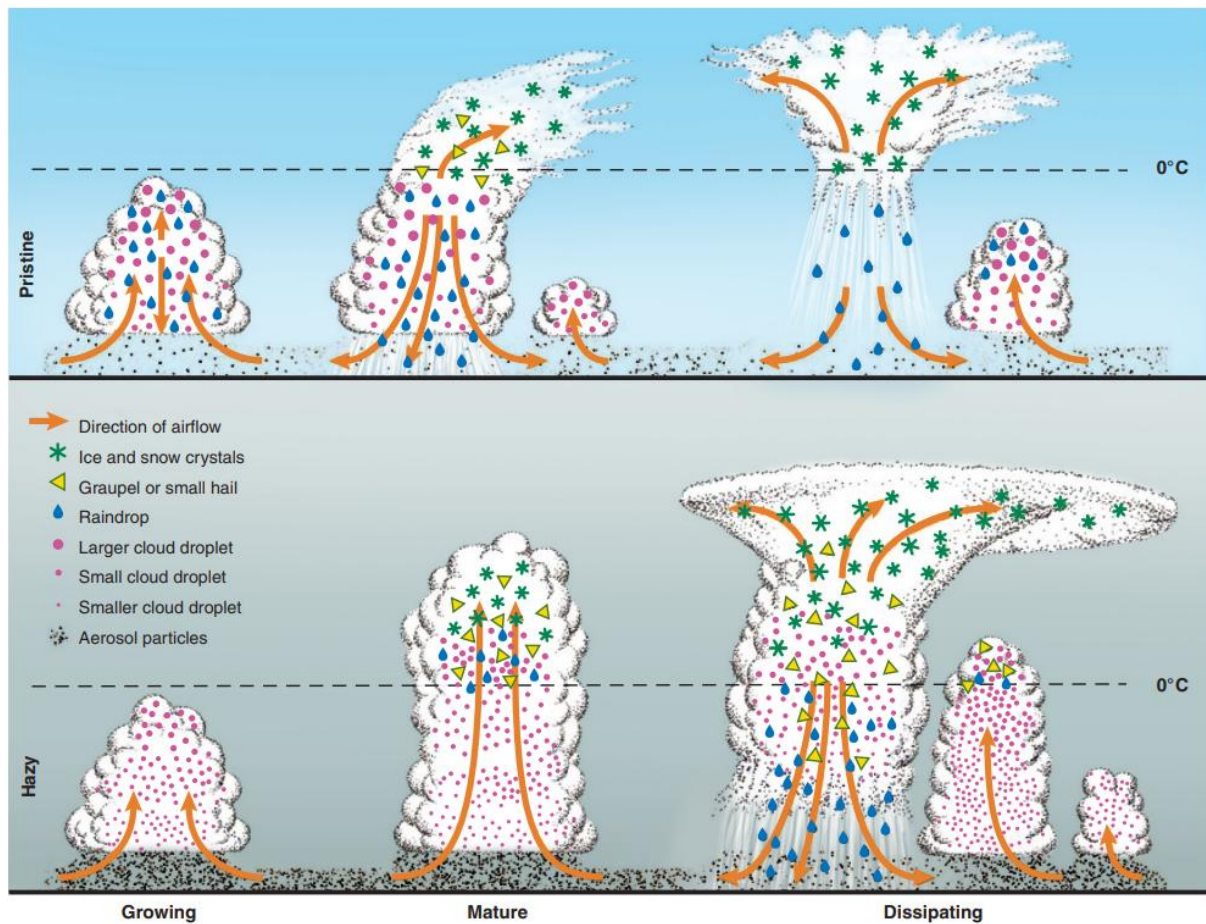
Air pollution undergoes complex interactions with weather dynamics, with aerosols exerting a particularly significant impact on atmospheric processes (C. He *et al*, 2024). Aerosols influence cloud and precipitation formation through both direct radiative effects and indirect cloud microphysical effects. The direct effects arise from their interaction with radiation, as aerosols can either scatter or absorb incoming solar radiation depending on their composition (Penner *et al*, 2001). Whereas many aerosol types, such as sulfates, nitrates and sea salt, tend to scatter solar radiation, others exhibit strong absorption properties, most notably black carbon, which is produced during incomplete combustion of fossil fuels. The magnitude of these radiative effects is also size-dependent, with particles of the accumulation mode (aerodynamic diameter between 0.1 and 1 µm) exerting the strongest influence on shortwave radiation (Matus *et al*, 2019). Overall, the combined direct radiative effect of

aerosols tends to cool the climate system (Penner *et al*, 2001), which can suppress the development of convective clouds by reducing the amount of energy available at the surface (De Sales *et al*, 2019).

Indirect effects, in contrast, refer to aerosol-induced changes to cloud properties through microphysical pathways (Penner *et al*, 2001). Aerosols can act as cloud condensation nuclei (CCN) on which cloud droplets can form (Quinn *et al*, 2008), or less commonly, as ice nucleating particles (INP), allowing the direct formation of ice crystals (Kanji *et al*, 2017). Consequently, an increase in aerosol concentration leads to a larger number of smaller cloud droplets. This enhances cloud reflectivity (albedo), as smaller droplets scatter incoming radiation more efficiently (Twomey, 1977). The resulting radiative effects can suppress convective activity, as cooling air below and warming air above the cloud stabilise the atmosphere (Fan *et al*, 2013). Hygroscopic aerosol types such as sulfates are highly soluble and therefore act as efficient CCN, strongly enhancing cloud albedo. In contrast, black carbon is comparatively less soluble and strongly absorbs incoming solar radiation. Furthermore, the reduction in droplet size decreases the efficiency of collision-coalescence, thereby slowing droplet growth (Rosenfeld, 1999). This size reduction suppresses the formation of warm-cloud precipitation and delays the onset of precipitation, thus increasing cloud lifetime, horizontal extent and liquid water content (Albrecht, 1989; Heikenfeld *et al*, 2019). The delayed formation of raindrops also enables continued vertical development of the cloud. An increased number of CCN leads to more numerous, smaller droplets, which collectively provide a larger surface area for condensation. Sustained condensation enhances latent heat release and can strengthen convective updrafts (Cotton & Walko, 2021). At the same time, smaller droplets are more easily transported upward due to their lower fall velocities (Loftus & Cotton, 2014), allowing a larger fraction of cloud water to reach supercooled levels. Once in the supercooled region, droplets freeze and release a substantial amount of additional latent heat. This additional energy can strongly enhance convective updrafts and cloud growth, increasing the likelihood of cloud tops overshooting into the stratosphere. This invigoration effect can lead to deep convective clouds (DCC) with more intense precipitation at a later stage (Figure 5) (Andreae *et al*, 2004; Rosenfeld *et al*, 2008). On the other hand, smaller drops in polluted clouds are more prone to evaporation, thereby limiting the transport of cloud water to supercooled levels and preventing invigoration of precipitation (Rosenfeld *et al*, 2008).

Figure 5:

Schematic of convective development of clouds in a pristine (top) and polluted (bottom) atmosphere.



Note. Adapted from “Flood or Drought: How Do Aerosols Affect Precipitation?” by Rosenfeld *et al.*, (2008), *Science*, 321(5894), p.1310 (<https://doi.org/10.1126/science.1160606>)

2.4.3 Aerosol impacts on rainfall and DSDs

The combined impact of aerosols on precipitation is still ambiguous and varies depending on aerosol composition and concentration, as well as meteorological conditions (C. He *et al.*, 2024). Aerosol processes impacting warm clouds are generally well understood and tend to inhibit rainfall (Fan *et al.*, 2016). The effect on mixed-phase clouds such as DCCs is less conclusive. Some studies found that aerosols can enhance precipitation intensities due to microphysical invigoration of convective updrafts (Fan *et al.*, 2020; Lin *et al.*, 2021; Su *et al.*, 2020), especially for clouds with a warm cloud base (Han *et al.*, 2022). On the other hand, other studies report that aerosols suppress convection and precipitation intensity through radiative effects (Z. Li *et al.*, 2016; L. Lin *et al.*, 2018; Qian *et al.*, 2009; Rosenfeld & Woodley, 2001). To address these conflicting results, a non-monotonic

relationship between aerosol concentration and precipitation change is observed by some studies, where microphysical invigoration causes an initial increase in precipitation until an optimal concentration, after which radiative suppression lead to a slow decrease in precipitation when aerosol concentrations are increased further (Guo *et al.*, 2019; Koren *et al.*, 2014; Liu *et al.*, 2019; Zang *et al.*, 2023). However, this relationship is not universally observed. Teller and Levin (2006) found that precipitation rates from convective clouds decrease with increasing aerosol concentrations, while Han *et al.* (2022) found type-dependent relations: marine aerosols exhibit a non-monotonic relationship with rainfall rates, dust aerosols lead to a general increase and smoke particles to a general decrease. The role of aerosol types on rainfall microphysics effects is however less well understood, as another study found a general increase in rain rates for black carbon and a decrease for dust particles (Xiao *et al.*, 2025).

By altering microphysical processes within clouds, aerosols also influence drop sizes and the associated DSDs. Several studies report an increase in mean raindrop sizes with increasing aerosol loadings (Meher *et al.*, 2024; Michibata & Suzuki, 2020; Seela *et al.*, 2026; Xiao *et al.*, 2025; Yang *et al.*, 2022). Yang *et al.* (2022), for example, report 20% larger drop sizes and 12% lower drop concentrations under high aerosol loadings. These effects are robust for both convective and stratiform rain, although they are stronger in summer than in winter. Meher *et al.* (2024) report similar findings for pre-monsoonal rainfall, with increased mean drop sizes and decreased drop concentrations observed in both convective and stratiform rain. These findings may appear counterintuitive given that the indirect effects of aerosol favour the formation of large numbers of small cloud drops (Albrecht, 1989). However, the inverse relationship between size and concentration for cloud droplets and raindrops can be explained as follows. Fewer cloud droplets efficiently coalesce into many moderate-sized raindrops. In contrast, high cloud droplet concentrations suppress warm-rain coalescence (Qian *et al.*, 2008). As a result, precipitation forms predominantly through ice processes, producing fewer but larger raindrops (Andreae *et al.*, 2004). When warm cloud rainfall does occur, raindrops tend to be smaller and in higher concentrations (Chen *et al.*, 2021; Nguyen-Dinh Hoang *et al.*, 2025; Qian *et al.*, 2009). An important exception is giant CCN (> 1 μm diameter), mostly from salt and dust particles, which cause larger cloud droplets and enhance warm rain formation (Rosenfeld *et al.*, 2008).

Aerosols can alter the occurrence and dominance of microphysical processes. In highly polluted conditions, size sorting is more pronounced: the smaller droplets evaporate preferentially, thus reducing the occurrence of small raindrops (Findeisen *et al.*, 2015). At the same time, breakup processes are less pronounced than in pristine conditions (Seela *et al.*, 2026), indicating a shift towards larger drops. Furthermore, accretion becomes more

dominant due to the high count of small cloud droplets that readily adhere to the falling raindrops (Michibata & Suzuki, 2020). Similarly, the removal of aerosol particles caused by falling raindrops, or wet scavenging, also plays an important role: while pristine environments are mostly self-perpetuating, by the constant wet scavenging keeping the aerosol levels low (Fan *et al.*, 2016), polluted environments can build up due to the delayed onset of rainfall, followed by intensified precipitation that removes large amounts of aerosols (Zang *et al.*, 2023). This effect is further enhanced by the increased occurrence of intensive rainfall containing larger drops, which are more efficient in scavenging aerosol particles (Ebert *et al.*, 1998).

2.5 Effects of urbanisation on precipitation

2.5.1 Urban heat island (UHI) effect

Cities can significantly influence the local climate. One of the most well-known urban climate phenomena is the urban heat island (UHI) effect, whereby urban areas experience higher temperatures than surrounding rural areas, typically around 1 to 3°C (Liu & Niyogi, 2019). The UHI effect is generally most pronounced at night and caused by increased energy absorption, anthropogenic warming and reduced vegetation cover in cities (Sui *et al.*, 2025). During the day, materials contained in urban surfaces such as buildings and pavements absorb and retain large amounts of shortwave and longwave radiation due to their low albedo and high specific heat capacity (Johnson *et al.*, 2021). At night, this heat is slowly released to the atmosphere, thus suppressing nocturnal cooling, especially in windless and cloud-free conditions. Consequently, air temperature differences between urban and rural areas are typically higher during the night, although surface temperature contrasts can reach extreme values during summer days (Voogt & Oke, 2003). Furthermore, in densely built cities, street canyons (narrow streets with large buildings) limit the capacity for radiation to escape, effectively trapping the heat near the surface (Han *et al.*, 2014). The UHI effect is further intensified by increased sensible heat fluxes due to the general lack of vegetation, which would otherwise provide a cooling effect through evapotranspiration (Birungi *et al.*, 2024), as well as anthropogenic emission of heat, such as transport and residential heating (Han *et al.*, 2014).

The intensity of the UHI effect depends strongly on city size and geographical setting. Larger cities experience stronger UHI effects, caused by greater anthropogenic heat release in cities with larger populations and increased heat retention in cities with larger surface areas (Zhou *et al.*, 2013). Geographic location also plays an important role. Coastal cities generally exhibit milder UHI effects than continental cities because of the

moderating sea effects. For example, a Belgian study found that inland cities such as Hasselt and Liège experience greater heat stress than cities of a similar size located closer to the coast, such as Bruges and Ghent, respectively (Wouters *et al.*, 2017). In temperate climates, UHI tends to be more intense during the day in summer, due to pronounced solar radiation as well as vegetational cooling in the suburbs, while the nocturnal intensity is higher during winter, owing to the increased anthropogenic heating (Zhou *et al.*, 2014).

2.5.2 *Urban modification of rainfall*

Urban areas are known to influence precipitation patterns and intensities, although the magnitude of this effect depends strongly on urban structure and geographic location. Some cities receive more precipitation than upwind areas, referred to as urban rain islands (URI), while others are drier than upwind areas, known as urban dry islands (UDI). Overall, most cities and areas downwind tend to receive higher precipitation intensities, with a meta-analysis indicating average increases of 16 to 18% (Liu & Niyogi, 2019). The intensification of urban rainfall is primarily attributed to increased thermal convection: a strong UHI effect can induce a thermal low-pressure area, drawing moisture from surrounding areas and transporting it vertically. When relative humidity is sufficiently high, these convective updrafts may increase rainfall (Han *et al.*, 2014; Luo *et al.*, 2022; Torelló-Sentelles *et al.*, 2025). Given the limited availability of vegetation for evapotranspiration, urban-induced rainfall increases rely heavily on dissipation of artificial water from domestic activities such as washing and cooking, as well as moisture advected from surrounding rural areas (Luo *et al.*, 2022). At the same time, increased surface roughness in cities also alters atmospheric flow. Buildings and other urban structures decelerate winds and enhance mechanical turbulence, leading to convergence of air and moisture accumulation (Han *et al.*, 2014). This mechanism is inferior to the UHI-induced effect for rainfall over cities (Han *et al.*, 2014), but is important for downwind intensification of rainfall, especially under high background wind speeds (Ding *et al.*, 2025).

While thermally and mechanically induced convection are important for the initiation of rainfall, aerosols play an important role in the further development of rain formation, as discussed in Section 2.4. In Belgium, aerosol particles are strongly associated with urban areas, with particulate matter concentrations being significantly correlated with large urban areas and population densities (Fierens *et al.*, 2016). The combined effect of the urban-induced dynamical changes and aerosol effects significantly alters raindrop size distributions. Enhanced convection in urban environments is often associated with larger drop sizes (higher VMD) and lower normalized intercept parameters N_w , indicating a shift towards more intense rainfall (Ma *et al.*, 2019). In addition, microphysical processes are altered, with intensified warm-phase invigoration (Fan *et al.*, 2020) and riming,

although their net effect depends on meteorological conditions such as convective available potential energy (CAPE), relative humidity and wind shear (Han *et al.*, 2014).

Despite a general predominance of URIs, UDIs can also occur. UDIs are most commonly associated with weak, but still positive, UHI, combined with strong background wind speeds (Torelló-Sentelles *et al.*, 2025). The weak UHI leads to higher vapour pressure deficits and shallow PBL heights, thus limiting turbulence and vertical motion. The combination of limited updrafts and lack of moisture causes a general suppression of rainfall over urban areas. Such conditions are most common in continental cities, particularly at night, due to the limited moisture advected towards the city (Sui *et al.*, 2025). Coastal cities, on the other hand, often experience substantial precipitation increases due to interactions with moisture-laden sea-breeze circulations. Furthermore, UDIs also occur in complex terrains (such as mountainous regions), where cities located in valleys receive less rainfall than surrounding hillslopes (Sui *et al.*, 2025).

The magnitude and spatial structure of these urban-induced rainfall effects depend strongly on urban characteristics. Larger cities generally exhibit stronger increases in rainfall intensity than smaller ones (Torelló-Sentelles *et al.*, 2024). Compact, densely built cities tend to produce more concentrated and intense rainfall, whereas more open built cities are associated with spatially dispersed precipitation patterns with multiple small hot spots (Yang *et al.*, 2024). City shape can also play a role, as circular and elongated cities lead to a stronger precipitation enhancement than triangular-shaped cities (Yang *et al.*, 2024; Zhang *et al.*, 2022). Globally, around 63% of cities experience rainfall increases (URIs), though regional differences are pronounced and closely related to the humidity of the climate. Tropical cities of sub-Saharan Africa generally experience substantially higher rainfall accumulations compared to their surroundings, with 85% of cities showing URIs, compared to only 15% showing UDIs (Sui *et al.*, 2024). In temperate regions such as Europe, the distribution is 64% URIs and 36% UDIs, with overall effects that are generally weaker and more dependent on urban structure (Sui *et al.*, 2024). In some dry continental regions, UDIs even make up the majority. As for seasonal variation, the URI is most pronounced in the summer in most regions (Sui *et al.*, 2025), although the effect is seen year-round in temperate maritime climates such as the Dutch coast (Daniels *et al.*, 2016). In summer, the thermally induced convection dominates, while the mechanically induced convection dominates in winter.

2.6 Literature summary

In summary, rainfall intensity and drop size distributions are regulated by the interaction of cloud microphysical processes, including collision–coalescence, breakup, evaporation and ice processes. Previous studies demonstrate that DSD characteristics vary strongly between precipitation regimes and can be represented using statistical distributions such as the gamma or negative exponential distribution. However, observational uncertainties related to disdrometer measurements and parameter estimation remain significant limitations. The literature further indicates that both urbanisation and aerosols can substantially alter precipitation processes. Urban environments may either enhance or suppress rainfall through changes in thermal convection, surface roughness, moisture convergence and planetary boundary layer dynamics. Though the main drivers are largely known, the overall effects remain poorly understood due to the lack of empirical quantification and challenges in generalisation owing to each city's unique geographical context. Anthropogenic aerosols from air pollution influence cloud microphysics by altering droplet formation, collision efficiency and convective growth of clouds. Similar to the urban effects, aerosol effects on precipitation remain uncertain, with both suppression and enhancement of rainfall reported depending on aerosol type, concentration and background meteorological conditions. Moreover, studies simultaneously considering precipitation regimes, urbanisation and air pollution impacts on DSDs are scarce. This study aims to address these research gaps by analysing precipitation microphysics and DSDs in Belgium using disdrometer observations.

3. METHODOLOGY

3.1 Study area and instruments

The analyses in this thesis are based on observations from three disdrometers located in Belgium, which continuously record rainfall intensity and raindrop size distributions (DSDs). The instruments are situated south or southeast of three major urban areas: Ghent, Brussels, and Liège (Fig. 6). The first instrument is an OTT Hydromet Parsivel² optical disdrometer, operated by the Department of Geography at Ghent University and located at the ILVO site in Merelbeke-Melle. This instrument has been operational since May 2024, and records drops using 32 diameter bins and 32 velocity bins, at a one-minute frequency. The second instrument is a Biral VPF-730 present weather sensor, operated by the Royal Meteorological Institute (RMI) and located in Uccle (Brussels), operational since May 2020. The instrument operates at a five-minute frequency, using 21 diameter bins and 16 velocity bins to characterise drops. The third instrument is a Thies Clima Laser Precipitation Monitor (LPM), operated by the University of Liège and located in Sart-Tilman, operational since January 2006. This disdrometer operates at a one-minute frequency and records drops with 20 diameter and 20 velocity bins. For convenience, these instruments are hereafter referred to as OTT, Biral, and Thies, respectively.

The disdrometers comprise three different models and two types. The Biral VPF-730 is a forward scatter meter, which measures the light scattering of small particles suspended within the sampling volume and of larger particles passing through it (Biral, 2022). In contrast, the OTT Parsivel² and Thies LPM are optical disdrometers that measure the attenuation of a laser beam caused by falling particles (OTT, 2017; Thies Clima, 2007). Because these instruments rely on different measurement principles, differences in the retrieved drop size distributions (DSDs) may partly reflect instrumental effects rather than purely atmospheric variability.

All three sites are located south of their respective urban areas (Table 2) and are influenced by local topography. The cities of Ghent, Brussels and Liège are situated in river valleys (Scheldt, Senne, and Meuse, respectively) and lie at lower elevations than the corresponding disdrometer sites. The disdrometers in Uccle and Sart-Tilman are located on elevated terrain south of their respective cities, whereas topographic variation in the area around Ghent and Merelbeke-Melle is relatively limited. These elevation differences may influence local airflow patterns and orographic effects, which are relevant for precipitation formation and drop size distributions.

In addition to the disdrometers, three nearby rain gauges are used for validation of the precipitation measurements. Furthermore, data from three automatic weather stations of the RMI synoptical network are used to provide additional meteorological variables for the air pollution analysis. These record weather parameters such as air temperature, relative humidity, wind speed and pressure at a ten-minute frequency (Rosillon *et al.*, 2024).

Figure 6:

Map of disdrometer distribution in Belgium. Map CRS is Lambert 72 (EPSG: 31370) and grid CRS is WGS84 (EPSG:4326). Altitude is expressed in mTAW. Basemap is Mapbox Voyager.

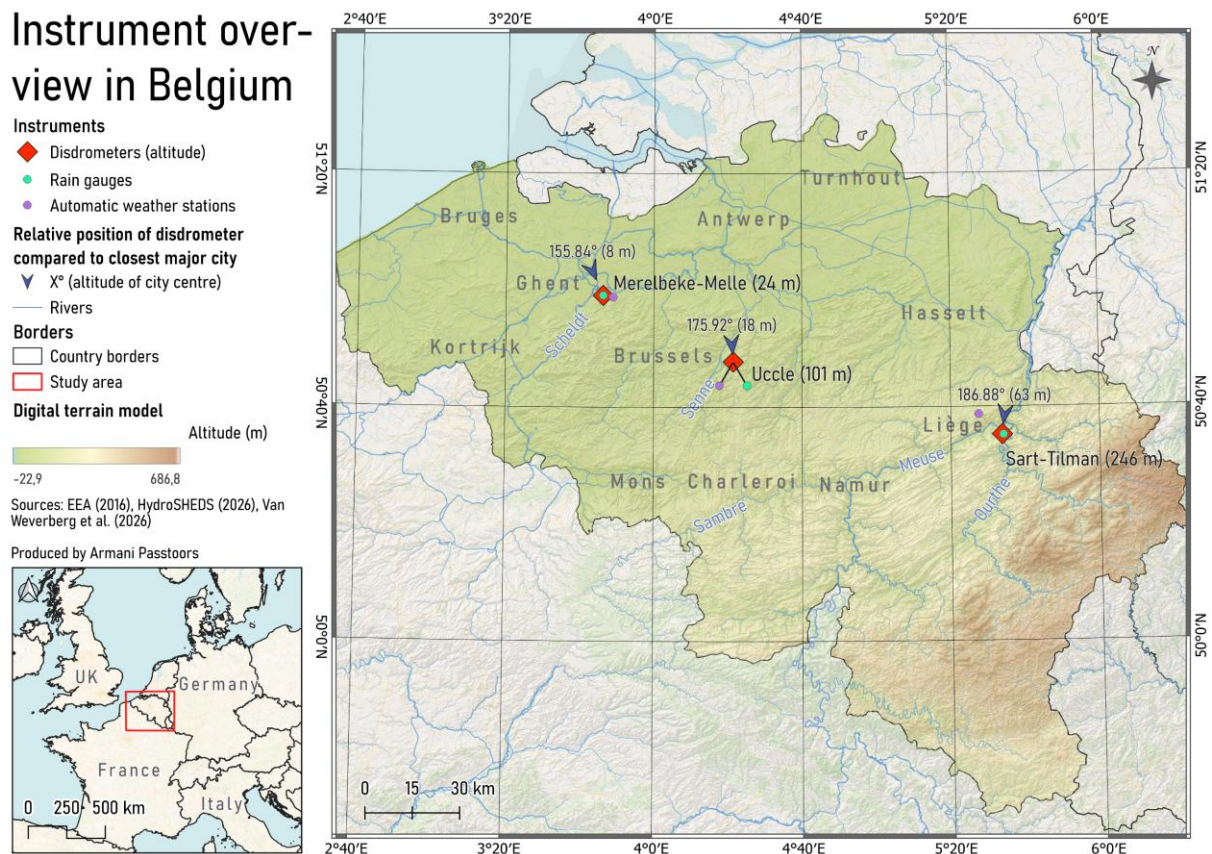


Table 2:*Overview of the disdrometers.*

#	Model	Type	Location	Coordinates*	Distance to city center (km)†	Relative position†
1	Biral VPF-730	Forward scatter disdrometer	Uccle	50°47'48"N 4°21'30"E	5.57	175.92° (S)
2	OTT Parsivel ²	Laser-optical disdrometer	Merelbeke-Melle	50°59'07"N 3°46'17"E	8.48	155.84° (SSE)
3	Thies LPM	Laser-optical disdrometer	Sart-Tilman	50°35'13"N 5°33'49"E	6.22	186.88° (S)

*Coordinates are expressed in WGS84 (EPSG: 4326)

†Relative to the nearest major city, namely Brussels, Ghent and Liège for disdrometers 1, 2 and 3, respectively, using the Grand Place, the Korenmarkt and the Place Saint-Lambert as reference points for the city centre

3.2 Disdrometer data

3.2.1 Extraction and data quality check

The processing consists of three main steps: (1) extraction of raw spectra, (2) quality control and filtering, and (3) derivation and calibration of DSD variables. Since the three disdrometers are produced by different manufacturers, each uses a slightly different data format and extraction procedure. From all data files, the raw drop size spectra, defined as matrices of drop counts as a function of diameter and fall velocity, as well as the reported precipitation intensity, were extracted for each time interval. The spectra were subsequently subjected to thorough filtering and quality control (Fig. 7). Because disdrometers measure all particles and hydrometeors passing through the sampling area, a correction is required to remove non-rain particles from the data.

First, all spectra were filtered using a binary mask to retain only diameter–velocity bins corresponding to liquid precipitation. Two sets of masks were tested and compared. The first set of masks was derived from the Biral manual (Biral, 2022) and from a scientific study for the OTT and Thies instruments (Adirosi *et al*, 2023), as their manuals do not provide explicit masks. The second, more uniform set was constructed by selecting diameter–velocity bins for which the mean fall velocity deviates by at most 33% from the theoretical fall velocity of raindrops (Equation 1), with a maximum absolute deviation of 1.5 m s^{-1} . These thresholds were determined by calibrating the filtered mean fall velocities against theoretical values. As shown in Fig. 8, this second set (calculated masks) allows a larger tolerance for small drops, while imposing stricter constraints on larger drops.

Figure 7:

Overview of the quality checks for the disdrometer data.

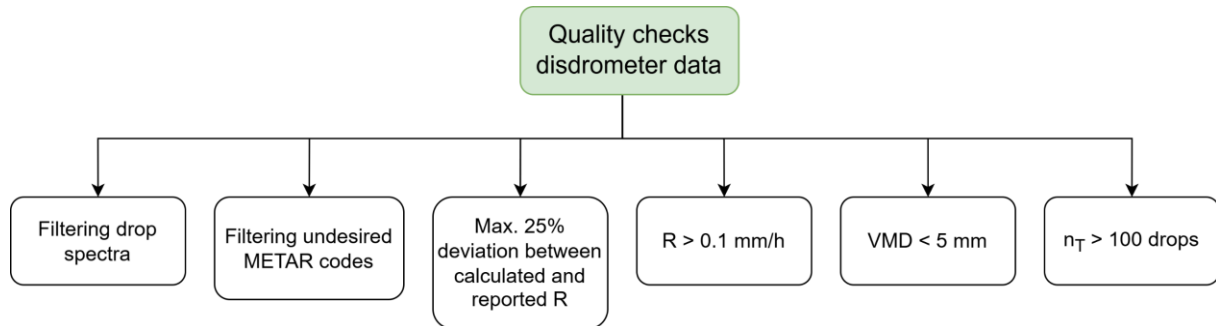
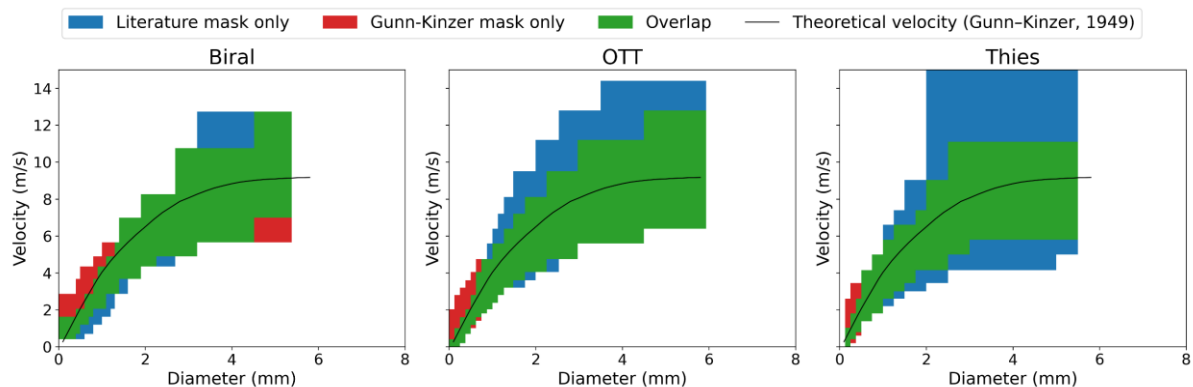


Figure 8:

Comparison of masks derived from literature (blue) and from the theoretical fall velocity (Gunn-Kinzer mask; red). Overlap between the masks is shown in green. The theoretical fall velocity derived by Gunn and Kinzer (1949) is illustrated with a solid black line.



Other filters include the omission of periods with low rainfall intensity ($R < 0.1 \text{ mm h}^{-1}$), low total drop counts ($n_T < 100$), and unrealistically high VMD values ($VMD > 5 \text{ mm}$). These criteria account for the majority of removed samples. The selected thresholds were chosen to retain physically representative rainfall while excluding periods dominated by very few large drops, which can lead to unstable DSDs. Inspection of the filtered samples showed substantial overlap between these criteria, indicating that many removed periods simultaneously exhibited low drop counts, low rainfall intensity and large VMD values. Additionally, filtering of METAR codes was applied to remove periods associated with non-liquid hydrometeors (Appendix 2). Although solid precipitation

is theoretically already excluded through the drop spectra filtering, the METAR filter acts as a secondary consistency check. After filtering, the drop size distribution $N(D)$ ($\text{m}^{-3} \text{mm}^{-1}$) was derived from the drop spectra using the following formula:

$$N(D) = \frac{n(D, v)}{A_{eff}(D) \cdot \Delta D \cdot \Delta t \cdot v(D)} \quad (9)$$

where $n(D, v)$ is the number of drops in a diameter-velocity bin, $A_{eff}(D)$ the effective sampling area (m^2), ΔD the diameter bin width, Δt the sampling time (s), and $v(D)$ the fall velocity of drops in the bin (m s^{-1}). The sampling time is five minutes for Biral and one minute for OTT and Thies. The effective sampling area corrects the nominal sampling area for the reduced probability that larger drops fully pass through the sensing area, and is defined as follows:

$$A_{eff}(D) = A \left(1 - \frac{D}{w}\right) \quad (10)$$

where A is the nominal sampling area (m^2), D is the diameter (m), and w is the laser width (m) (Ghiggi *et al.*, 2026). Rainfall rate (R ; mm h^{-1}) can then be calculated from the DSD, using the following formula:

$$R = 6\pi \cdot 10^{-4} \sum_i N(D_i) \cdot v(D_i) \cdot D_i^3 \cdot \Delta D_i \quad (11)$$

where $N(D)$ is expressed in $\text{m}^{-3} \text{mm}^{-1}$, $v(D)$ in m s^{-1} and D in mm (Ghiggi *et al.*, 2026).

For the laser-optical disdrometers, OTT and Thies, A_{eff} can be calculated directly using Equation 10. For Biral, however, the parameters A and w are not provided and were therefore estimated by minimizing the difference between the reported precipitation intensity and the precipitation intensity derived directly from the DSD, using Equation 11. In contrast to this physically based correction, the internal Biral processing applies an empirical calibration factor derived from comparisons between measured and reference precipitation accumulations (Biral, 2022). This factor represents a linear bulk scaling of the precipitation totals and is not explicitly linked to the sampling geometry or the underlying drop size distribution. As a result, it does not address potential inconsistencies in the shape of the DSD. Given that this study relies on higher-order moments of the DSD (e.g. reflectivity Z and volume-weighted mean diameter VMD), such a linear correction does not provide additional

value for the validation of the DSDs. Moreover, since all DSD-derived variables are computed directly from $N(D)$, a correction applied only to the aggregated rainfall rate cannot be translated back into a correction of $N(D)$ itself.

Therefore, a uniform methodology is adopted for all instruments, with the effective sampling area calculated using Equation 10 for OTT and Thies and estimated for the Biral sensor as described above (see Appendix 3 for estimation of sampling area). While this approach also introduces an empirical component, it is applied at the calculation of the DSDs and is thus more relevant for robust further analysis. Nevertheless, as this formulation is primarily developed for optical disdrometers, its application to a forward-scatter instrument such as Biral introduces additional uncertainty in the derived DSD parameters, particularly because the empirically estimated A_{eff} may not fully capture instrument-specific detection characteristics.

3.2.2 Data validation

After preprocessing, the data were validated both externally and internally. External validation consists of comparison with independent rain gauge measurements, while internal validation assesses consistency between disdrometer-derived variables. For external validation, three rain gauges located in the vicinity of each disdrometer were used (Table 3). The rain gauge in Melle (operated by the Department of Geography at UGent) is collocated with the disdrometer and records cumulative rainfall at one-minute resolution. The rain gauges in Uccle and Sart-Tilman (part of the Service Public de Wallonie (SPW) network) (Delobbe *et al.*, 2006) are located further away and operate at a five-minute resolution. All rainfall data were aggregated to a common temporal resolution of five minutes prior to comparison. Rain gauge intensities were compared with both the reported disdrometer precipitation and the precipitation derived from the DSD (Equation 11), expressed in mm h^{-1} . Internal validation was performed by comparing reported and DSD-derived precipitation intensities to detect potential calibration or measurement inconsistencies. Since several key variables are derived from the DSD, consistency between these two estimates is essential to ensure reliable results. Performance during rainy periods was quantified using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute and relative bias. These metrics were computed for time intervals with rainfall intensity exceeding 0.1 mm h^{-1} . Rain detection skill was evaluated using the probability of detection (POD), false alarm rate (FAR), and critical success index (CSI), defined as:

$$POD = \frac{a}{a + c}; FAR = \frac{b}{a + b}; CSI = \frac{a}{a + b + c}, \quad (12)$$

where a represents hits (rain detected by both instruments), b false alarms (rain detected only by the disdrometer), and c missed events (rain detected only by the rain gauge) (Mahtour *et al.*, 2011). Rain occurrence was defined as a rainfall intensity greater than 0.1 mm h⁻¹.

Table 3:

Overview of the rain gauges used for validation.

#	Model	Type	Temporal resolution	Location	Distance to disdrometer* (m)
1	OTT Pluvio ² L	Weighing precipitation gauge	5 min	Uccle	115
2	OTT WAD 200 / 314	Weighing precipitation gauge	1 min	Merelbeke-Melle	1
3	OTT Pluvio ² L	Weighing precipitation gauge	5 min	Sart-Tilman	410

*Relative to the nearest disdrometer, being disdrometer Biral, OTT and Thies for rain gauge 1, 2 and 3 respectively (see Table 2)

3.2.3 Calculation of DSD parameters and complementary variables

From the calculated N(D) concentrations, a set of microphysical variables were derived, including characteristic drop diameters (VMD, AMD) and mass distributions (σ_m), concentration metrics (n_r , N_r), and physical quantities such as kinetic energy (KE, KE(D), KER), liquid water content (LWC), normalized intercept parameter (N_w) and reflectivity (Z), listed in Table 4. The volume-weighted mean diameter VMD (mm) is calculated based on Bringi *et al.*, (2003):

$$VMD = \frac{\sum N(D) \cdot D^4 \cdot \Delta D}{\sum N(D) \cdot D^3 \cdot \Delta D} = \frac{M_4}{M_3}, \quad (13)$$

where M_k denotes the k-th moment of the drop size distribution (Equation 2). The area-weighted mean diameter AMD (mm) is calculated based on Smith (2003):

$$AMD = \frac{M_3}{M_2}, \quad (14)$$

and the standard deviation of the mass spectrum σ_m (mm) is calculated based on Smith *et al.* (2019)

$$\sigma_m = \sqrt{\frac{M_3 \cdot M_5 - M_4^2}{M_3^2}}. \quad (15)$$

The total drop concentration N_T is calculated using Equation 5 and the total drop count n_T is calculated as a simple sum:

$$n_T = \sum n_{ij}, \quad (16)$$

where i and j denote diameter and velocity bins respectively. Following the equations in Tilg *et al* (2020), KE ($J m^{-2}$) is calculated using this equation:

$$KE = \frac{\rho_w \cdot \pi}{12} \sum_i \sum_j \frac{n_{ij} \cdot D_i^3 \cdot v_j^2}{A_{eff}(D_i)}, \quad (17)$$

where A_{eff} (m^2) is the effective area and ρ_w ($kg m^{-3}$) is the density of water. $KE(D)$ ($J m^{-2} mm^{-1}$) is calculated using

$$KE(D_i) = \frac{\rho_w \cdot \pi}{12} \sum_j \frac{n_{ij} \cdot D_i^3 \cdot v_j^2}{A_{eff}(D_i) \cdot \Delta D_i}, \quad (18)$$

and KER ($J m^{-2} h^{-1}$) is obtained by scaling KE to an hourly rate:

$$KER = \frac{3600}{t} KE, \quad (19)$$

where t (s) is the disdrometer sampling time. N_w (m^{-4}) is calculated using Equation 7 and LWC ($g m^{-3}$) is calculated based on Hagen & Yuter (2003)

$$LWC = \frac{\rho_w \cdot \pi \cdot M_3}{6}. \quad (20)$$

The reflectivity factor Z (dBZ) is calculated as

$$Z = 10 \cdot \log_{10}(M_6) . \quad (21)$$

However, this is a Rayleigh approximation, as it only considers Rayleigh scattering of raindrops (Ulbrich, 1983). When drops become larger, Mie scattering plays a significant role, and frequency needs to be considered. In this case, the equivalent radar reflectivity Z_e is used (Testud *et al*, 2001). Since reflectivity is primarily used for regime classification, the Rayleigh approximation is considered sufficient.

In addition to these microphysical variables, two temporal rainfall metrics were defined to characterize rainfall occurrence and persistence. The rain fraction (ϕ_r) is defined as the fraction of time with recorded rainfall within a given period:

$$\phi_r = \frac{n_{rain}}{n_{total}} , \quad (22)$$

where n_{rain} are the number of time steps with a rain rate exceeding 0.1 mm h^{-1} . This metric represents the proportion of time during which rainfall occurs. Furthermore, the rain frequency (f_r) is defined as the fraction of aggregated periods classified as rainy:

$$f_r = \frac{N_{rainy}}{N_{total}} , \quad (23)$$

Where a period is considered rainy if at least one rainy observation is recorded within that period. While ϕ_r quantifies temporal persistence of rainfall at the native temporal resolution (one or five minutes), f_r describes the probability of rainfall at an aggregated timescale (e.g., daily aggregation).

Table 4:

Overview of the different microphysical variables used and their corresponding equations.

Rainfall microphysics variables				
Name	Symbol	Unit	Type	Equation
Rainfall rate	R	mm h ⁻¹	Scalar	11
99 th percentile of rainfall rate	R99	mm h ⁻¹	Scalar	-
Rainfall frequency	f _r	-	Scalar	23
Rainfall fraction	φ _r	-	Scalar	22
Number concentration	N(D)	m ⁻³ mm ⁻¹	Array	9
Total concentration	N _T	m ⁻³	Scalar	5
Total drop number	n _T	-	Scalar	16
Volume-weighted mean diameter	VMD	mm	Scalar	13
Area-weighted mean diameter	AMD	mm	Scalar	14
Standard deviation of the mass spectrum	σ _m	mm	Scalar	15
Liquid water content	LWC	g m ⁻³	Scalar	20
Rainfall kinetic energy per area	KE	J m ⁻²	Scalar	17
Rainfall kinetic energy per diameter	KE(D)	J m ⁻² mm ⁻¹	Array	18
Rainfall kinetic energy rate	KER	J m ⁻² h ⁻¹	Scalar	19
Normalized intercept parameter	N _w	m ⁻⁴	Scalar	7
Reflectivity factor	Z	dBZ	Scalar	21

3.2.4 Statistical modelling

Statistical modelling is used to characterise the shape of the DSDs. To analyse the shape (μ) and slope (Λ) parameters, the DSDs were fitted to a negative exponential distribution (Equation 3) and a concentration-normalized gamma distribution (Equation 6) using both the method of moments (MM) and maximum likelihood estimation (MLE). These parameters are useful alongside the data-driven microphysical variables, as they represent the total behaviour of the DSDs. μ (-) and Λ (mm⁻¹) were calculated using the VMD and AMD (assuming a gamma distribution form of the DSD), corresponding to M_2 , M_3 and M_4 (see Appendix 4 for full derivation):

$$\mu = \frac{3 \cdot VMD - 4 \cdot AMD}{AMD - VMD} \quad (24)$$

$$\Lambda = \frac{1}{VMD - AMD} \quad (25)$$

3.2.5 Precipitation regime classification

Precipitation events were determined at ten-minute intervals (ten consecutive one-minute intervals) for OTT and Thies, and as 30-minute intervals (six consecutive five-minute intervals) for Biral. An event was only retained if rainfall intensity exceeded 0.1 mm h^{-1} during at least 50% of the interval. The difference in length reflects the different native sampling intervals of the instruments. The 50% threshold represents a trade-off between capturing short-lived convective events, which may only occur during part of the interval, and ensuring sufficient data points to compute robust variability metrics such as the standard deviation. Two rainfall regimes were distinguished, namely convective and stratiform, following the classification methodology of Wang *et al.* (2021). This classification is based on two criteria: a rainfall variability threshold of $\sigma_R = 1.5 \text{ mm h}^{-1}$ and a rainfall intensity threshold of $R = 5 \text{ mm h}^{-1}$. Here, σ_R is defined as the standard deviation of rainfall intensity within the event window. A rainfall event is classified as convective when both $\sigma_R > 1.5 \text{ mm h}^{-1}$ and $R > 5 \text{ mm h}^{-1}$, and as stratiform when both conditions are not met.

Instead of applying a fixed rain rate threshold, the intensity criterion is expressed in terms of reflectivity using instrument-specific Z–R relationships. This approach is motivated by the fact that Z scales with D^6 and is therefore more sensitive to the presence of large drops than rain rate, which scales with $D^{3.67}$ (Fiser, 2010). As a result, rainfall events with similar intensities may correspond either to large concentrations of small drops or smaller concentrations of large drops. Expressing the intensity criterion using reflectivity reduces the likelihood of classifying high intensity rainfall dominated by relatively small drops as convective. While fixed reflectivity thresholds in the range of 30–40 dBZ are commonly used in the literature to identify convective precipitation (Lee *et al.*, 2021; Uijlenhoet *et al.*, 2003), they implicitly assume a universal Z–R relationship. To account for instrument-specific differences in DSD characteristics, the reflectivity threshold is instead derived separately for each instrument as the Z value corresponding to $R = 5 \text{ mm h}^{-1}$. However, since the reflectivity threshold is derived from a fixed rainfall intensity, it remains an intensity criterion rather than a purely microphysical criterion. The VMD-log10(Nw) space is therefore used as an independent microphysical validation.

3.3 Supportive environmental data

3.3.1 ERA5 data

To gain information on wind direction and speed, hourly ERA5 reanalysis gridded data (0.25° spatial resolution) of wind speed in longitudinal direction (u) and latitudinal direction (v) was used (Copernicus Climate Change Service (C3S), 2025). ERA5 is a reanalysis product of the European Centre for Medium-Range Weather Forecasts (ECMWF) that combines observations with numerical models to produce a consistent reference dataset (Hersbach *et al.*, 2020). The analysis was conducted at the 850 hPa pressure level (approximately 1.5 km above sea level), which is commonly used to represent large-scale low-tropospheric circulation while minimizing the influence of surface friction and local boundary-layer processes (Maier, 2015). The wind direction was calculated using the formula from Stull (2016):

$$\alpha = \text{atan2}(u, v) + 180^\circ, \quad (26)$$

where α represents the meteorological wind direction (i.e. the direction from which the wind originates), expressed in clockwise degrees from north.

3.3.2 LCZ data and urbanisation factors

Land cover information was obtained from the Ecoclimap Second Generation (SG) dataset, with a spatial resolution of 0.0028° (approximately 300 m) (Bessardon *et al.*, 2024). This dataset includes 23 natural land cover classes as well as 10 urban classes from local climate zone classifications, originally distinguished by Stewart & Oke (2012). For convenient physical interpretation in further analyses, the 33 cover types were grouped into ten superclasses based on vegetation characteristics for the natural classes and based on building density and urban fraction for the urban classes (see Table 5).

Table 5:

Ecoclimap SG land cover classes and division into ten superclasses.

Land cover classes			
#	Cover type	Urban fraction	Superclass
1	Sea and oceans	0.0	Water & bare soil
2	Lakes	0.0	
3	Rivers	0.0	
4	Bare land	0.0	
5	Bare rock	0.0	
6	Permanent snow	0.0	
7	Boreal broadleaf deciduous	0.0	Forest
8	Temperate broadleaf deciduous	0.0	
9	Tropical broadleaf deciduous	0.0	
10	Temperate broadleaf evergreen	0.0	
11	Tropical broadleaf evergreen	0.0	
12	Boreal needleleaf evergreen	0.0	
13	Temperate needleleaf evergreen	0.0	
14	Boreal needleleaf deciduous	0.0	
15	Shrubs	0.0	Grassland
16	Boreal grassland	0.0	
17	Temperate grassland	0.0	
18	Tropical grassland	0.0	
19	Winter C3 crops	0.0	Crops
20	Summer C3 crops	0.0	
21	C4 crops	0.0	
22	Flooded trees	0.0	Marsh
23	Flooded grassland	0.0	
24	LCZ1: compact high-rise	0.9	Compact built
25	LCZ2: compact midrise	0.9	
26	LCZ3: compact low-rise	0.9	
27	LCZ4: open high-rise	0.7	Open built
28	LCZ5: open midrise	0.7	
29	LCZ6: open low-rise	0.6	
30	LCZ7: lightweight low-rise	0.9	Large low-rise
31	LCZ8: large low-rise	0.9	
32	LCZ9: sparsely built	0.3	Sparsely built
33	LCZ10: heavy industry	0.6	Heavy industry

3.3.3 Air quality data (PM_{2.5}, PM₁₀)

Air pollution data for PM₁₀ and PM_{2.5} (particulate matter with diameters smaller than 10 and 2.5 μm , respectively, expressed in $\mu\text{g m}^{-3}$) were obtained from the Belgian Interregional Environment Agency (IRCEL-CELINE, 2024) and used as a proxy for aerosol loading in the lower atmosphere. These data consist of daily mean concentrations from a network of 82 ground monitoring stations, interpolated to a 4×4 km grid covering Belgium using the Residual Interpolation optimised for Ozone (RIO) (Fierens *et al.*, 2016). This interpolation technique accounts for spatial variability in pollution levels, particularly near emission sources (Janssen *et al.*, 2008). PM₁₀ data are available for the period 1997 – 2024, while PM_{2.5} data are available for 2008 – 2024. It should be noted that surface PM concentrations may not fully represent aerosol conditions at cloud level. Nonetheless, they provide

a useful approximation of aerosol loading and are regularly used as a proxy in atmospheric studies (Cordero, 2025).

3.4 Analyses

3.4.1 *Software overview*

Data preparation, processing and analysis were largely executed in Python using a Jupyter Notebooks environment. These Notebooks were run on the Tier-2 High-Performance Computing (HPC) infrastructure of Ghent University (Vlaams Supercomputer Center (VSC), 2026), allowing high-speed computations on the server. On the other hand, QGIS served as the main tool for spatial analysis and map visualisation.

3.4.2 *Statistical tests*

In addition to distribution fitting of DSDs, statistical tests were used to evaluate differences between groups and relationships between variables. The normality of the data is assessed using the Shapiro-Wilk normality test (Salkind, 2007). As rainfall variables are frequently non-normally distributed, nonparametric tests were used: the Kruskal-Wallis test for multi-group comparisons and the Mann-Whitney U test for pairwise comparisons, as alternatives to the analysis of variance (ANOVA) and the independent t-test respectively (Okoye & Hosseini, 2024). Correlations were evaluated using Spearman's rank correlation instead of Pearson correlation when normality assumptions are not met (Zar, 2005). Statistical significance is indicated in figures using asterisks, where * stands for $p < 0.05$, ** for $p < 0.01$ and *** for $p < 0.001$. Regression relationships were estimated using ordinary least squares (OLS), and error bars represent either the standard error of the mean (SEM) or the standard deviation, as specified in the corresponding figure captions.

3.4.3 *Temporal analysis*

The first analysis focused on identifying temporal variations in rainfall characteristics derived from the disdrometers. The data were stratified into diurnal and seasonal periods. Four diurnal periods were defined, each lasting six hours: night (00:00–06:00), morning (06:00–12:00), afternoon (12:00–18:00), and evening (18:00–24:00). In addition, four meteorological seasons were considered: winter (December–February), spring (March–May), summer (June–August), and autumn (September–November), following meteorological seasons in the

Northern Hemisphere (Trenberth, 1983). Differences in rainfall characteristics (e.g. R, VMD, KE) between periods were assessed using pairwise Mann–Whitney U tests.

3.4.4 Urban wind direction analysis

To evaluate the influence of urban areas on downwind rainfall, a wind direction analysis was conducted using a circular buffer with a radius of 10 km centred on each disdrometer. Since urban effects on precipitation are known to decay rapidly with distance (Yang *et al.*, 2024), saturating beyond 20 km (Zhang *et al.*, 2025), this radius was chosen as it is large enough to contain the city centre in all three cases, but small enough to retain an urban footprint. The buffer was subdivided into 32 wind sectors (11.25° resolution) to provide a detailed characterisation of upwind conditions. For each sector, the fractional cover of each land use class was calculated. These fine-scale sectors allow a more precise separation of urban influences from other directional confounding factors, such as topography or sea effects.

Urban and suburban extents of the examined cities were delineated following the moving-window method of Zhou *et al.* (2014) using a 3×3 pixel (0.9×0.9 km) neighbourhood mean urban fraction. Based on the thresholds used by Wouters *et al.* (2017), grid cells with a mean urban fraction exceeding 0.5 were classified as urban, while values between 0.25 and 0.5 were classified as suburban.

To match the temporal resolution of ERA5 wind data, disdrometer observations were aggregated to hourly values. For rainfall events (convective or stratiform), which span shorter durations (10 or 30 minutes), the nearest hourly ERA5 wind record was assigned. For each site, the nearest ERA5 grid cell was selected, and each rainfall observation was assigned to an upwind sector based on wind direction. This allowed linkage between rainfall characteristics and upwind land cover. Urban influence was then assessed using Spearman correlations between land cover fractions (including urban fraction) and rainfall or microphysical variables. The analysis was further stratified by season (summer and winter) and by wind speed. Several studies suggest stronger urban rainfall intensification over urban areas under weak background wind conditions and over downwind areas under strong background wind conditions (Sui *et al.*, 2025; Torelló-Sentelles *et al.*, 2025). Therefore, wind-speed stratification was used based on the location of each disdrometer with respect to the urban area, where urban-favourable conditions are defined as lower-than-average wind speeds for stations within urban areas and higher-than-average wind speeds for stations located outside them. Theoretically, urban effects should be most pronounced under these conditions.

3.4.5 Air pollution analysis

To characterise the local PM environment surrounding the disdrometer sites, domain-wide mean concentrations of particulate matter (PM_{10} and $PM_{2.5}$) over Belgium were calculated. In addition to visual inspection of the interpolated mean concentrations, a hot spot analysis was performed using the Local Moran's I statistic (Zhang *et al.*, 2008) to assess local spatial autocorrelation in mean particulate matter concentration. This method identifies statistically significant clusters and spatial outliers, referred to as Local Indicators of Spatial Association (LISA), and classifies them into four types: high–high (clusters of high values), low–low (clusters of low values), high–low (high values surrounded by low values), and low–high (low values surrounded by high values). The analysis is primarily used to determine the spatial context of the disdrometer locations, to see whether the instruments are situated within regional hotspots or near strong spatial gradients. The spatial weights matrix is defined using a distance-based threshold. To determine the appropriate spatial scale, the analysis is repeated for a range of distances in increments of 2 km, and the optimal distance is selected based on the maximum standardized z-score of spatial autocorrelations. It should be noted that the PM concentrations are based on RIO-interpolated data derived from 82 ground-based stations. Consequently, part of the observed spatial autocorrelation reflects the interpolation itself, rather than the underlying concentrations. However, the disdrometer locations are situated relatively close to monitoring stations (0.03 km for Biral, 6.68 km for OTT and 2.97 km for Thies), limiting the uncertainty from interpolation.

Disdrometer rainfall data were aggregated to daily data or rainfall events (convective or stratiform) and combined with daily mean particulate matter concentrations. Each day is then labelled as low, intermediate or high PM concentration, based on terciles. Terciles were computed for the period 2006 – 2024 for PM_{10} and 2008 – 2024 for $PM_{2.5}$. A common period for all instruments is used to ensure comparability between days with matching labels of different disdrometers. Since PM concentrations have dropped steadily in the past decades in Europe (Alikhani Faradonbeh *et al.*, 2021), instruments with a shorter temporal coverage (e.g. OTT) are skewed toward days with low or intermediate PM levels, as high PM events occur less often in recent years. For the same reason, PM_{10} period starts in 2006 (thus omitting 1997 – 2005), aligning with the beginning of the data coverage for Thies. Differences in rainfall characteristics between PM categories were evaluated using median differences and the Kruskal–Wallis test. To account for confounding factors, a Spearman partial correlation analysis is executed, which quantifies the association between two variables after statistically controlling for the effects of one or more covariates. In this study, mean sea level pressure (MSLP) and wind speed were used as covariates.

High PM concentrations often occur under stable atmospheric conditions, associated with high pressure and low wind speeds, which limit ventilation and thus cause accumulation of pollutants (Chen *et al.*, 2021; C. He *et al.*, 2024; Q. Yang *et al.*, 2022). Meanwhile, these conditions are conducive to overall dry conditions with localised intense rainfall and larger mean drop sizes. As a result, these effects confound the pure aerosol impacts and need to be accounted for when isolating aerosol effects. MSLP and wind speed at the surface were obtained from three nearby ground-based weather stations, located 0.03, 3.18, and 9.84 km from the Biral, OTT, and Thies instruments, respectively. To estimate the uncertainty of the partial correlations, confidence intervals were calculated using bootstrap resampling with 1000 iterations.

4. RESULTS

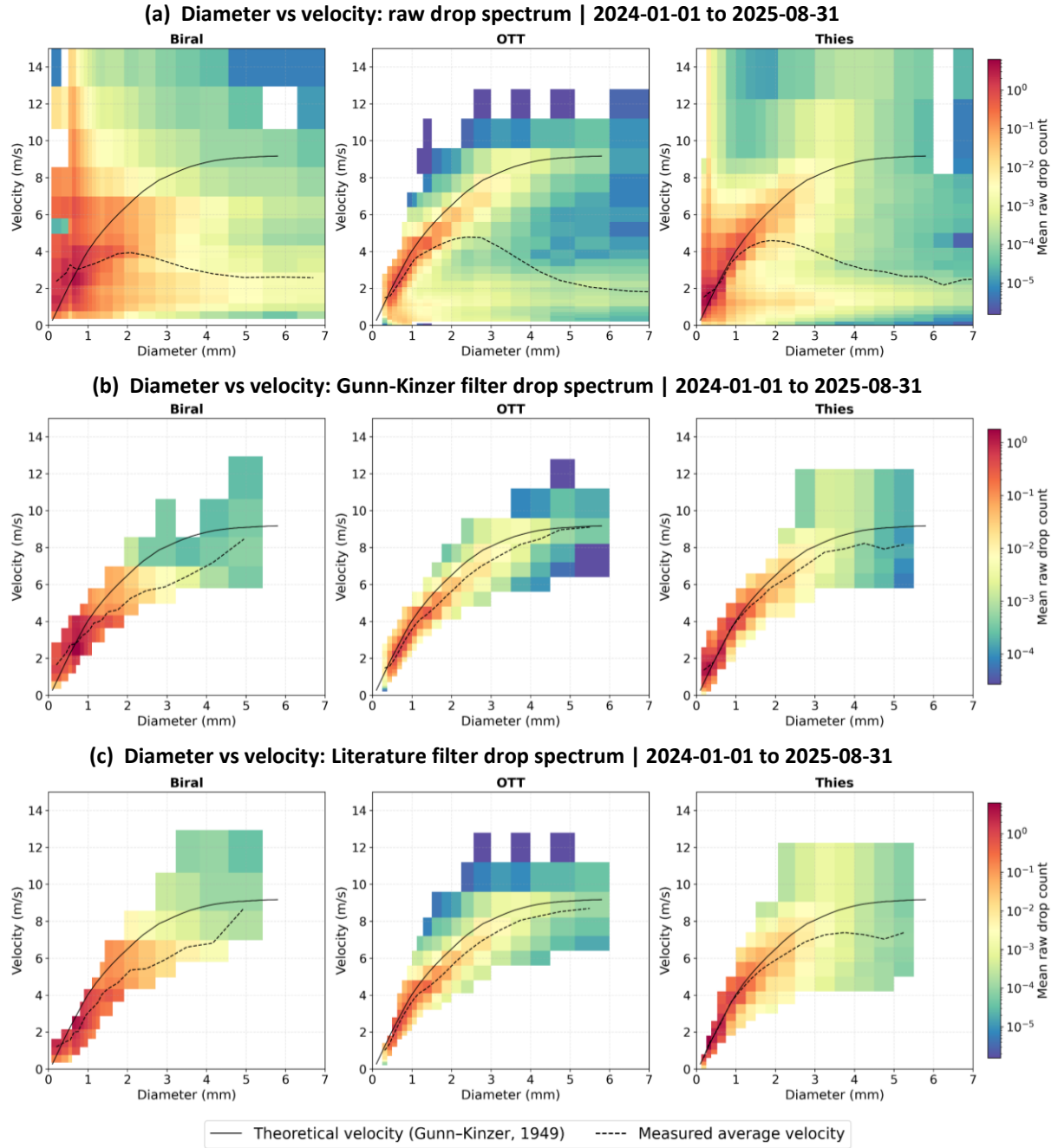
4.1 Assessment of disdrometer performance

4.1.1 Internal validation

Before conducting further analyses, the disdrometer data were evaluated to assess their internal consistency and reliability. This was first done by comparing measured diameter-velocity relationships with theoretical fall velocities of raindrops. The raw drop spectra, representing the collection of all recorded particles, show substantial deviations from theoretical values (Fig. 9, top row). Larger particles ($D > 0.5$ mm) tend to exhibit lower fall velocities than theoretical raindrops, while small particles ($D < 0.5$ mm) often show slightly higher velocities. These discrepancies are most pronounced for the Biral instrument, which displays considerable noise in the form of small, fast particles and large, slow particles. After applying the filtering procedure to retain only diameter-velocity bins corresponding to liquid precipitation (drizzle and rainfall), the agreement with theoretical fall velocities improves markedly. The filtered spectra closely follow the expected velocity-diameter relationship, indicating that the quality control effectively removes non-rain particles. Differences between the literature-based and calculated masks are minor, although the calculated masks yield slightly better agreement with the theoretical curve (Fig. 9).

Figure 9:

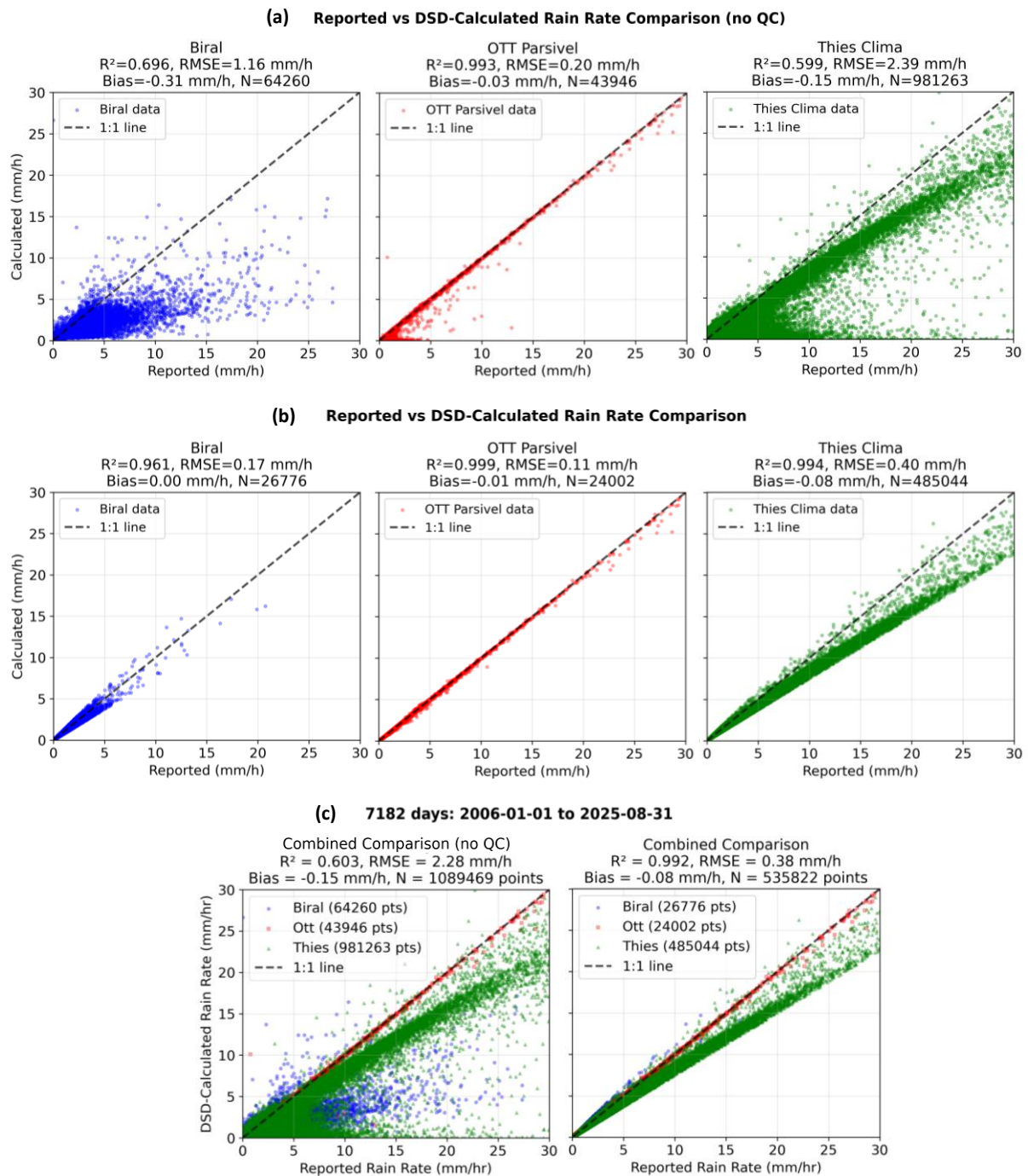
Heatmaps of (a) raw drop spectra and drop spectra after filtering for liquid precipitation with the (b) Gunn-Kinzer and (c) literature masks. The theoretical fall velocity from Gunn and Kinzer (1949) is shown with a solid line and the mean velocity with a dashed line.



Internal accuracy was further evaluated by comparing reported rainfall intensities with those derived from the DSDs (Equation 11). Prior to quality control, substantial deviations are present, particularly for Biral and Thies (Fig. 10). After applying the full quality control procedure, agreement improves considerably. For these instruments, the root mean square error (RMSE) decreases by approximately 85%, while correlation with reported values increases substantially. In contrast, the OTT disdrometer already shows strong agreement before quality control, with improvements of around 45% in RMSE after filtering. Overall, these results highlight the importance of quality control, particularly for Biral and Thies, where raw measurements are strongly affected by noise.

Figure 10:

Scatter plots of reported and DSD-calculated rain rates in native temporal resolution with (a) and without (b) quality control as listed in Fig. 7. Filtering the drop spectra for liquid precipitation is, however, applied in both scenarios. Panel titles show agreement metrics of the two rain rate variables. The bottom panels (c) depict the combined scatter plots of the three instruments without (left) and with quality control (right). QC denotes quality control.



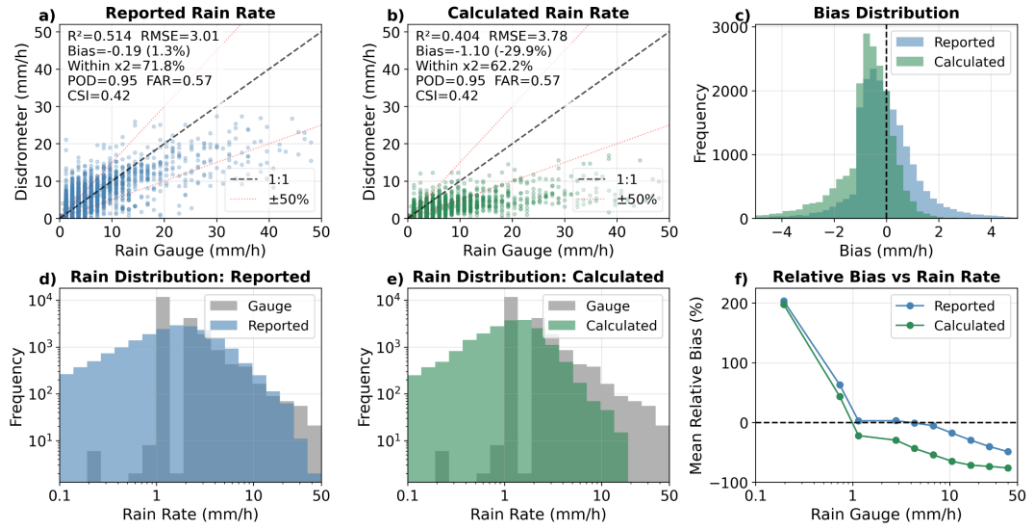
4.1.2 External validation with rain gauges

To enable consistent comparison, all measurements were aggregated to a common five-minute temporal resolution and expressed as rainfall intensity (mm h^{-1}). The performance of the disdrometers was then evaluated against nearby rain gauges. Among the three instruments, OTT shows the best overall agreement with the reference rain gauge measurements, characterised by a high correlation and critical success index (CSI), and low RMSE (Fig. 11g, h). Although the relative bias is elevated at very low rain rates, it decreases rapidly beyond 0.3 mm h^{-1} and remains stable at higher intensities (Fig. 11l). In contrast, Biral exhibits a systematic underestimation of rainfall, which becomes more pronounced at higher intensities. This underestimation is evident in both reported and DSD-derived rain rates, although it is stronger for the latter. The negative bias increases sharply beyond approximately 3 mm h^{-1} (Fig. 11f). Although the probability of detection (POD) is the highest of all three instruments (95%, compared to 61% for OTT and only 32% for Thies), the false alarm rate (FAR) is also quite high with 57% (Fig. 11a, b). Thies shows weak agreement with the corresponding rain gauge, with a low correlation ($R^2 = 0.277$) and a substantial negative bias (-17.3%). This is also reflected in its low POD and high FAR. Despite this, the overall rainfall distribution is comparable to that of the rain gauge, particularly for intermediate intensities (Fig. 11 p, q), and the total accumulated rainfall over the study period differs by only 0.33%. This suggests that discrepancies are mainly related to timing and variability rather than rainfall amounts (Fig. 11).

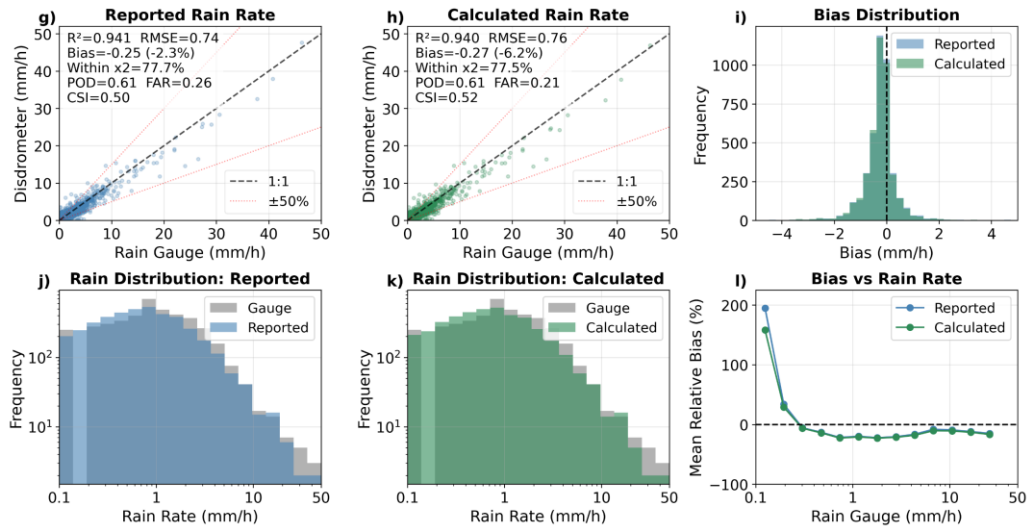
Figure 11:

Comparison of rain rates measured by the disdrometer and rain gauge. Rain rates are expressed in mm h^{-1} and computed from five-minute aggregated measurements. Periods with missing data from either instrument were omitted. Drop spectra were filtered using the calculated masks. Only intervals shown where both instruments recorded rainfall. To account for temporal deviation, the correlation is shown for the best-identified time lag, which was found through testing lags up to 24 hours in five-minute steps. The first column (panels a, d, g, j, m and p) shows scatter plots and histograms of the reported rain rates (blue) of the disdrometers, while the second column (panels b, e, h, k, n and q) shows the comparison of the calculated rain rates (green). Grey bars on the histograms stand for rain gauge values. Additionally, performance metrics are shown in the top left corner of the scatter plots. The third column (panels c, f, i, l, o and r) illustrates bias histograms and mean relative bias by rain rate.

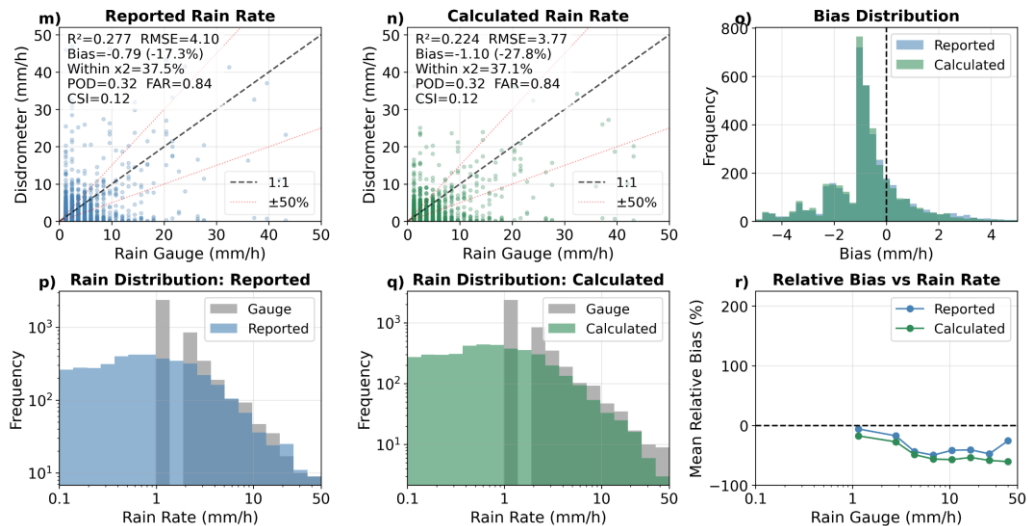
Uccle Rain Gauge vs Disdrometer (Biral) Comparison
n = 19967 | 2020-01-01 - 2025-08-31 | Gunn-Kinzer mask



Melle Rain Gauge vs Disdrometer (OTT) Comparison
n = 4125 | 2024-05-01 - 2025-08-31 | Gunn-Kinzer mask



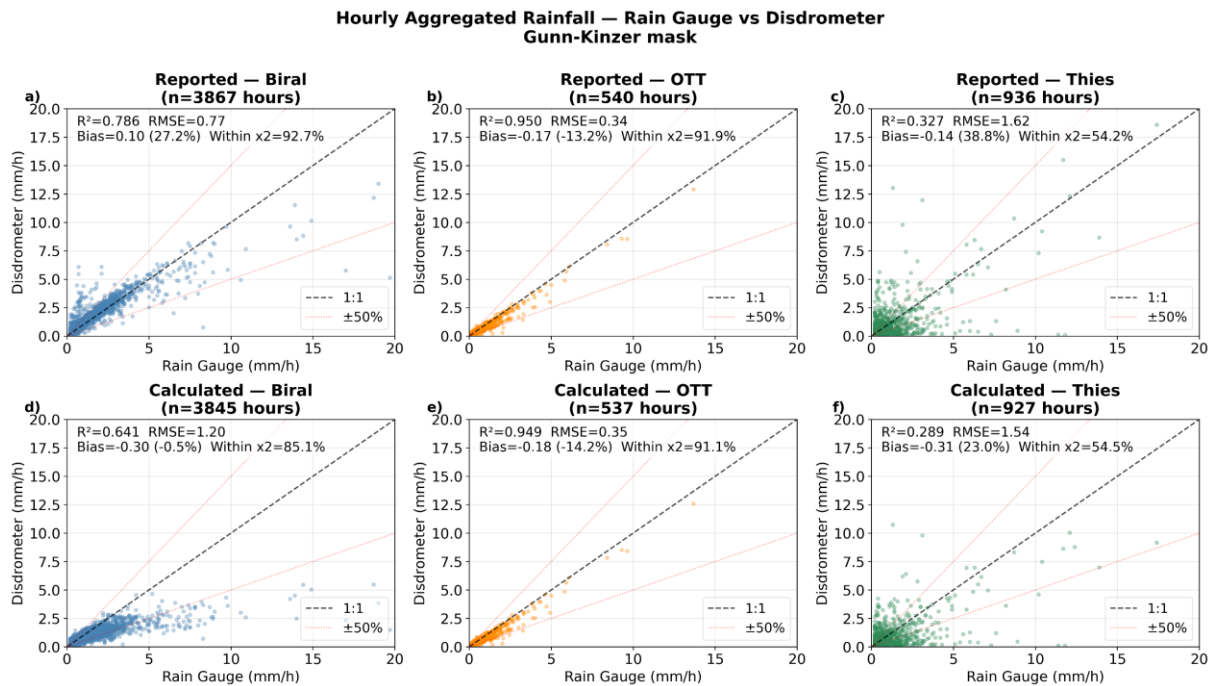
Sart-Tilman Rain Gauge vs Disdrometer (Thies) Comparison
n = 4074 | 2020-01-01 - 2025-08-31 | Gunn-Kinzer mask



After aggregating the rainy periods to hourly data by summing the five-minute rain accumulations within the hour, temporal mismatches between instruments are reduced, resulting in improved correlation for all disdrometers (Fig. 12). Nevertheless, the agreement between Thies and the rain gauge remains comparatively weak, indicating persistent inconsistencies (Fig. 12c, f). It should be noted that Fig. 11 and Fig. 12 depict the comparison using a 530-minute time lag correction, which corresponds to the highest correlation. This lag was found by systematically testing lags in five-minute intervals, up to 24 hours (see Appendix 5 for time series).

Figure 12:

Scatter plots of hourly rain rates measured by the disdrometer and rain gauge (reported: upper row; DSD-calculated: lower row [filtered with Gunn-Kinzer mask]). Performance metrics are shown in the top left corner of the graphs.

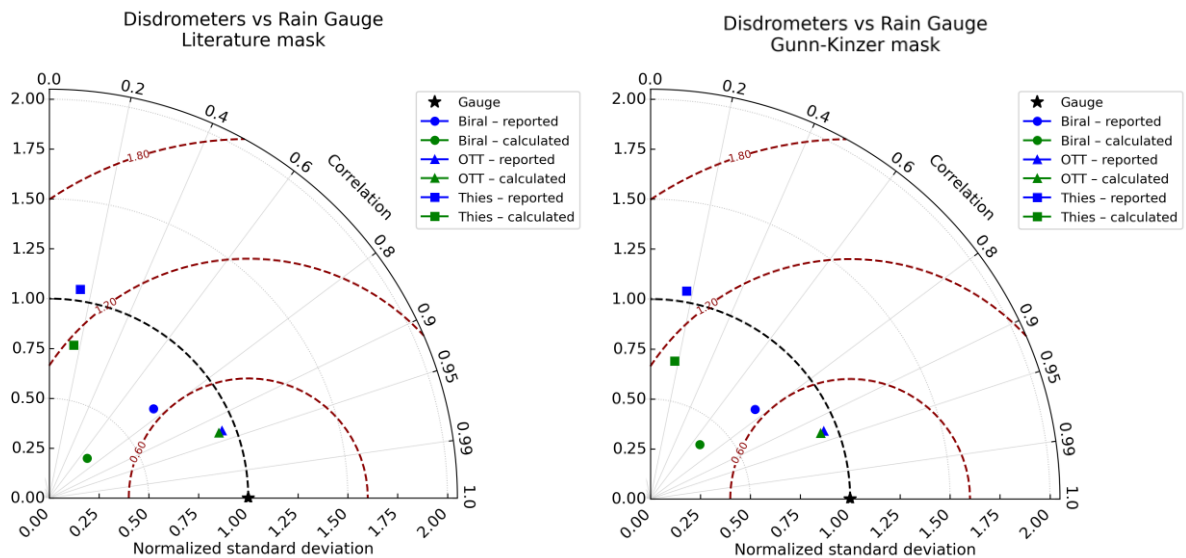


The influence of the drop spectrum filtering method (Gunn-Kinzer versus literature-based masks) is relatively minor. Across all instruments, differences in performance metrics are small. Slight improvements in RMSE are observed for Biral and Thies when using the calculated masks, while the impact on OTT is negligible. A Taylor diagram summarising the overall performance confirms these findings (Fig. 13). OTT (triangles) consistently shows the strongest agreement with the rain gauges, combining high correlation, low RMSE and a normalised standard deviation close to 1. Thies (squares) shows a comparable variance with the reference rain gauge, but very low correlation, indicating poor temporal agreement despite similar rainfall variability. Biral (circles) shows

moderate correlation but a strongly reduced standard deviation, reflecting the tendency to underestimate higher rainfall intensities.

Figure 13:

Taylor diagrams of rain rates (mm per 5 min) from disdrometers compared to the nearest rain gauge, using calculated (literature) masks for drop spectrum filtering on the left (right). Rainfall time series from the three disdrometers and three rain gauges were standardized by dividing both standard deviations (σ) and root mean square errors (RMSE) by the reference rain gauge's standard deviation. Blue symbols refer to reported rain rates and green symbols to calculated rain rates. Circles, triangles, and squares refer to Biral, OTT, and Thies, respectively.



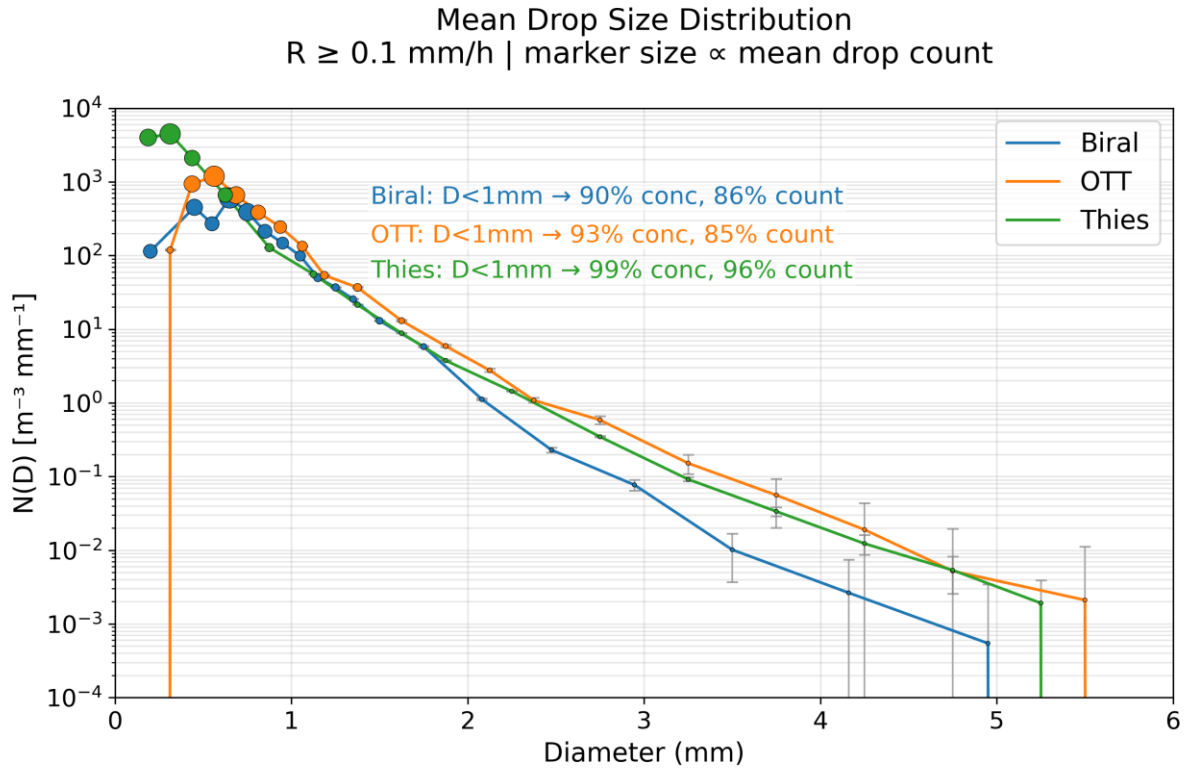
4.2 DSD structure and variability

4.2.1 Average DSD and rainfall variables

To assess inherent differences between the instruments, the overall structure of the DSDs was first compared. Despite differences in measurement principles, the three disdrometers show generally similar mean DSDs (Fig. 14). However, clear differences arise for small drop sizes. Biral and OTT exhibit DSDs that resemble a gamma distribution, with concentrations increasing up to diameters of approximately 0.5 – 0.6 mm before decreasing. In contrast, Thies follows a more exponential shape, characterised by very high concentrations of small drops and a steady decline with increasing diameter. This results in a substantially higher proportion of small drops ($D < 1$ mm) for Thies (96%) compared to Biral (86%) and OTT (85%). For intermediate drop sizes (0.5 – 2.0 mm), concentrations are comparable between all three instruments, while for larger drops, Biral shows a more rapid decrease than OTT and Thies.

Figure 14:

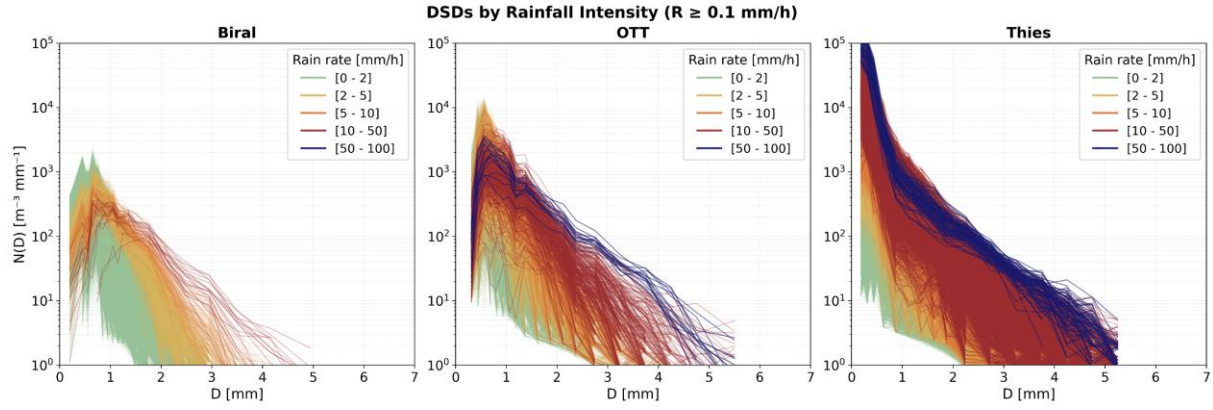
Mean raindrop size distributions per disdrometer (minimum of 0.1 mm h^{-1}). Error bars indicate the SEM. The blue line indicates the mean DSD for Biral, the orange line for OTT and the green line for Thies. Additionally, the relative contribution of drops with a diameter smaller than 1 mm to the total concentration and drop count is shown on the plot.



When stratified by rainfall intensity, the difference between the disdrometers becomes more pronounced (Fig. 15). Increasing rain rates are generally associated with broader DSDs, lower peak concentrations, and higher relative contributions from larger drops. This behaviour is consistent for Biral and OTT. However, this is not the case for Thies, where peaks are more pronounced at higher rain rates, suggesting a dominance of small drops even during intense rainfall. In addition, maximum observed rain rates for Biral are lower than for the other disdrometers, due to the longer sampling interval and high relative omission of high intensities during quality control.

Figure 15:

Individual raindrop size distributions coloured by rainfall intensity (minimum of 0.1 mm h^{-1}).



To further characterise these patterns, a range of microphysical variables derived from the DSDs were analysed. Across all instruments, rainfall intensity is strongly linked to changes in drop size characteristics. The volume-weighted mean diameter (VMD) increases with rain rate and converges towards upper limits of approximately 2.5 mm (Biral; Fig. 16a), 2.6 mm (OTT; Fig. 17a) and 2.2 mm (Thies; Fig. 18a). The VMD/AMD ratio also shows convergence, approaching values of approximately 1.2 (Biral; Fig. 16k), 1.3 (OTT; Fig. 17k) and 2.0 (Thies; Fig. 18k). Similar behaviour is observed for related variables such as the standard deviation of the mass spectrum (σ_m ; Fig. 16l – 18l), and the normalized intercept parameter (N_w ; Fig. 16j – 18j). Despite these similarities in trends, substantial differences in magnitude exist. For instance, the total number concentration (N_T) varies by orders of magnitude between instruments, with Thies (Fig. 18h, i) reporting significantly higher concentrations than Biral (Fig. 16h, i) and OTT (Fig. 17h, i).

Several robust relationships between bulk rainfall variables are also identified. Rainfall kinetic energy rate (KER) exhibits a strong power-law relationship with rain rate, with steeper scaling for Biral and OTT than for Thies. Similarly, the Z–R relationship is well described by a power law for all instruments, although with distinct coefficients for each disdrometer: the OTT relationship ($Z = 176R^{1.59}$; Fig. 17c) resembles the Marshall-Palmer relationship ($Z = 200R^{1.60}$) more than Biral ($Z = 244R^{1.47}$; Fig. 16c) and Thies ($Z = 154R^{1.68}$; Fig. 18c). VMD and AMD show a strong linear relationship, although variability is higher for Thies (Fig. 18b), reflecting periods dominated by few large drops. The kinetic energy spectrum $KE(D)$ peaks at slightly larger diameters (around 1 mm) than the concentration spectrum $N(D)$, highlighting the dominant contribution of medium-sized drops to rainfall energy (Fig. 16f – 18f). VMD decreases slightly with increasing N_T , but the relationship is weak and highly variable (Fig. 16i – 18i). Finally, liquid water content (LWC) shows a strong exponential relationship with kinetic energy (Fig. 16e – 18e) and a converging relationship with VMD (Fig. 16g – 18g).

Figure 16:

Heatmaps of microphysical relations for the Biral disdrometer (Uccle). The panels show (a) VMD vs R , (b) VMD vs AMD, (c) Z vs R , (d) KER vs R , (e) KER vs LWC, (f) $KE(D)$ vs D , (g) VMD vs LWC, (h) R vs N_T , (i) VMD vs N_T , (j) N_w vs R , (k) ratio between VMD and AMD vs R and (l) σ_m vs R . All variable pairs are fitted using power-law regression except (b), which uses linear regression, and (f). Linear and power fits are estimated through OLS regression and depicted on the graphs with a solid line. The functions and R^2 values are shown in the top left corner of the panels. The dashed lines depict the median values.

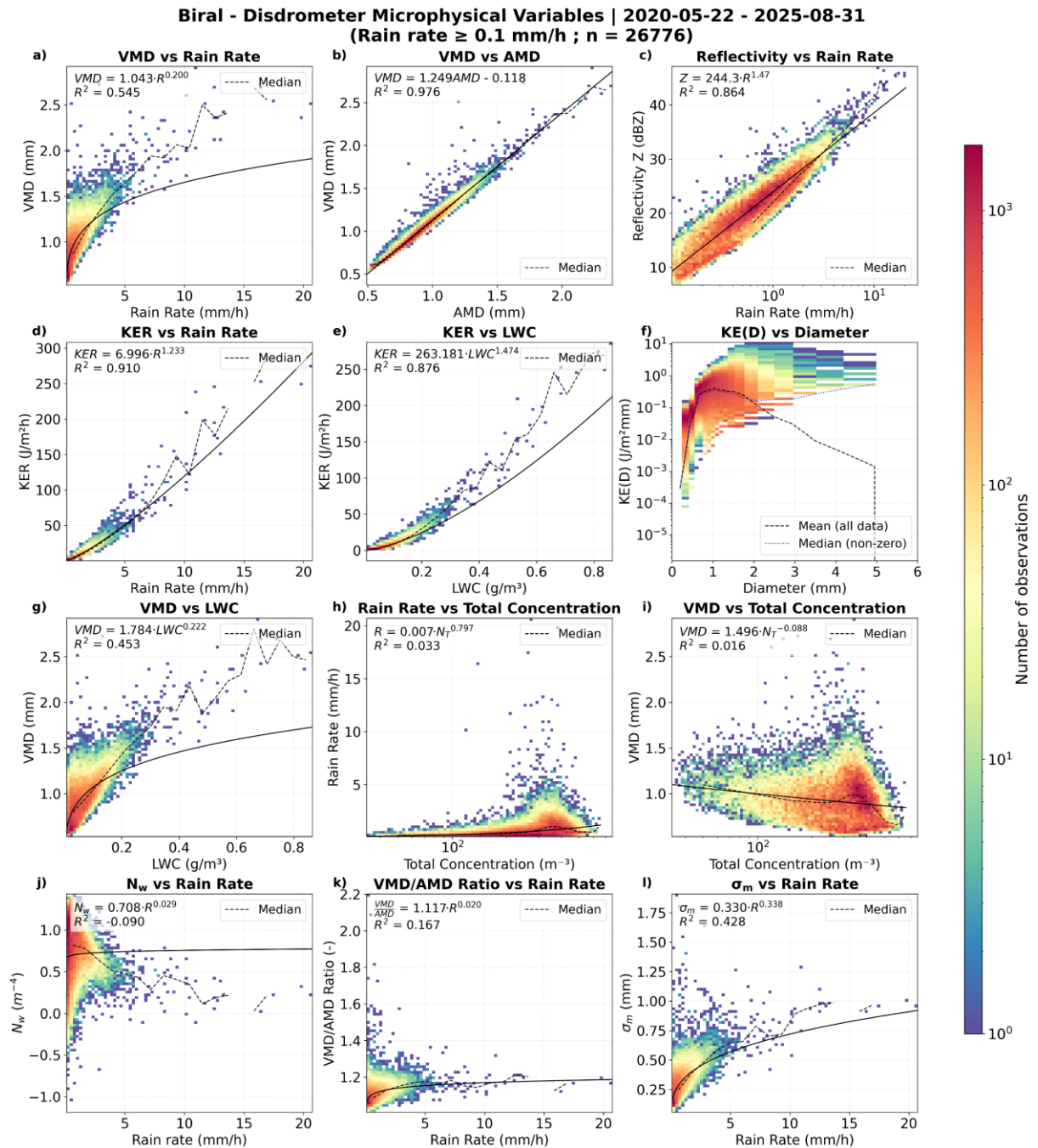


Figure 17:

Heatmaps of microphysical relations for the OTT disdrometer (Merelbeke-Melle). The panels show (a) VMD vs R , (b) VMD vs AMD, (c) Z vs R , (d) KER vs R , (e) KER vs LWC, (f) $KE(D)$ vs D , (g) VMD vs LWC, (h) R vs N_T , (i) VMD vs N_T , (j) N_w vs R , (k) ratio between VMD and AMD vs R and (l) σ_m vs R . All variable pairs are fitted using power-law regression except (b), which uses linear regression, and (f). Linear and power fits are estimated through OLS regression and depicted on the graphs with a solid line. The functions and R^2 values are shown in the top left corner of the panels. The dashed lines depict the median values.

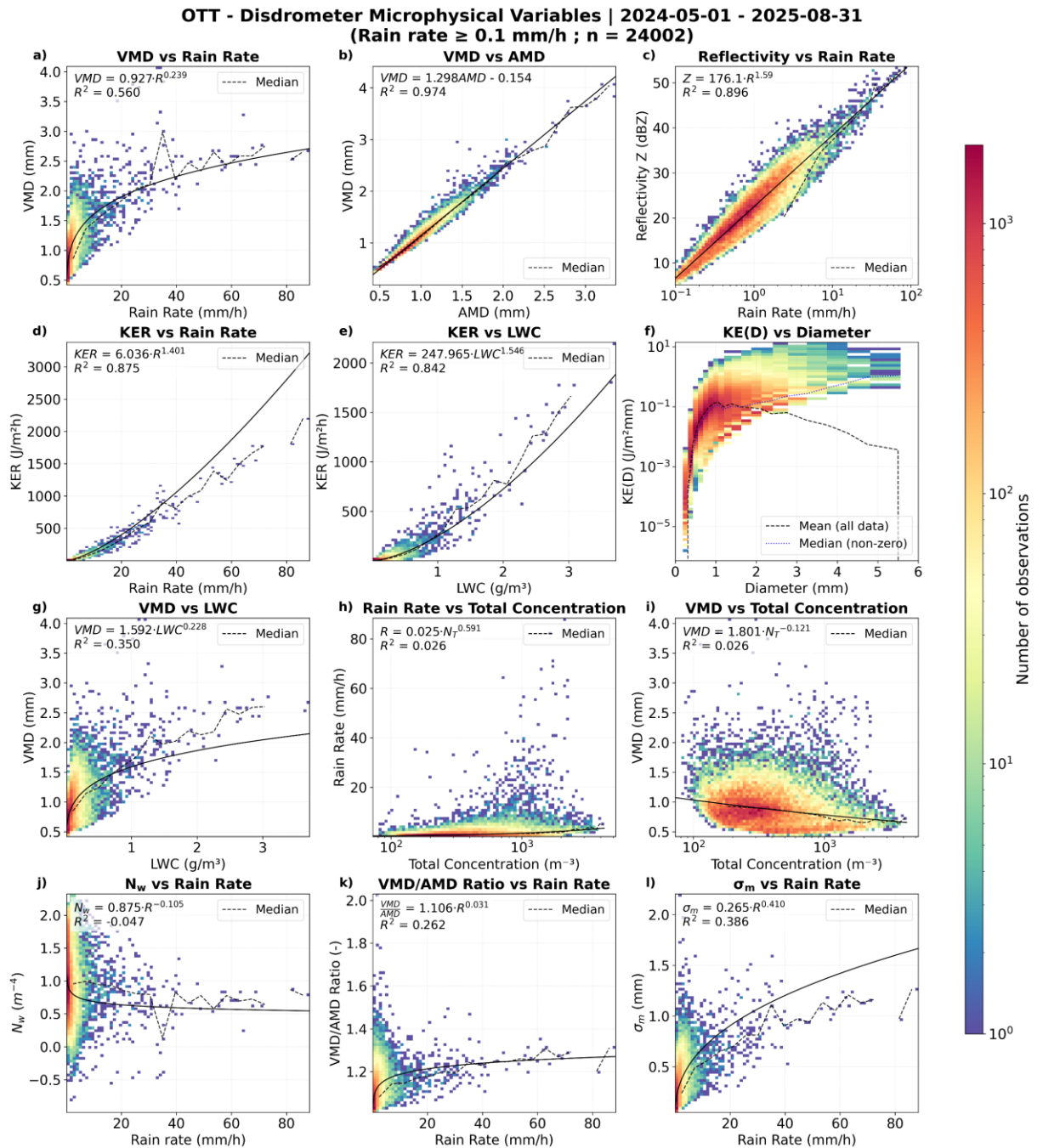
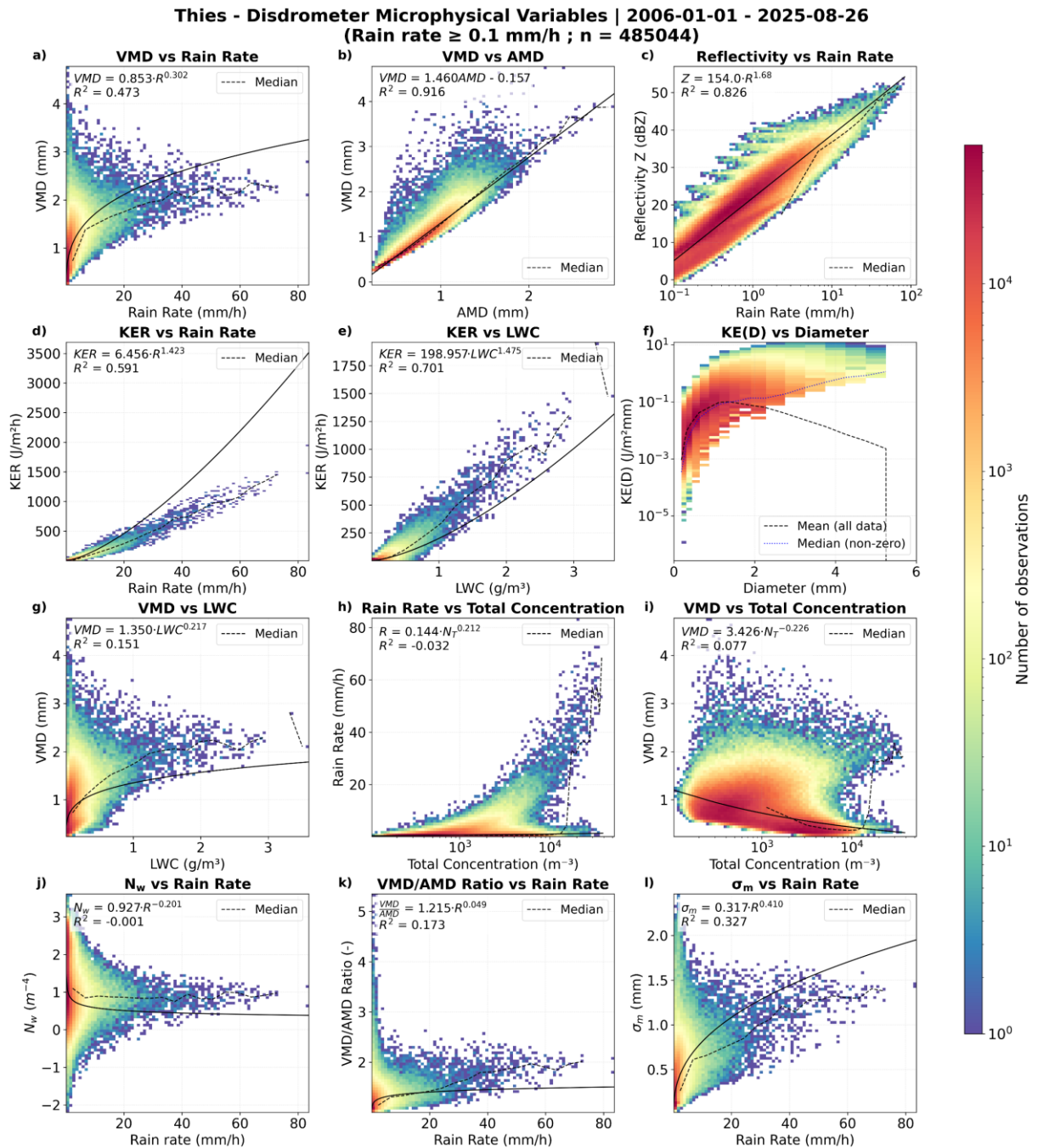


Figure 18:

Heatmaps of microphysical relations for the Thies disdrometer (Sart-Tilman). The panels show (a) VMD vs R , (b) VMD vs AMD, (c) Z vs R , (d) KER vs R , (e) KER vs LWC, (f) $KE(D)$ vs D , (g) VMD vs LWC, (h) R vs N_T , (i) VMD vs N_T , (j) N_w vs R , (k) ratio between VMD and AMD vs R and (l) σ_m vs R . All variable pairs are fitted using power-law regression except (b), which uses linear regression, and (f). Linear and power fits are estimated through OLS regression and depicted on the graphs with a solid line. The functions and R^2 values are shown in the top left corner of the panels. The dashed lines depict the median values.



The dataset was further divided into rainfall events with a duration of ten (OTT and Thies) or thirty minutes (Biral), which were classified as convective, stratiform or unclassified, using the criteria described in Section 3.2.5. Based on the instrument-specific Z-R relations, reflectivity thresholds corresponding to $R = 5 \text{ mm h}^{-1}$ were determined as 34.154 dBZ for Biral, 33.571 dBZ for OTT and 33.617 dBZ for Thies. This classification resulted in relatively few convective events for Biral. This is likely related to the quality control, which removed a substantial fraction of periods with high rain rates, thus reducing the number of periods that are eligible for convective events.

Convective and stratiform events exhibit clear differences in their drop size distributions. Convective events are characterised by significantly higher concentrations of larger drops, diverging from the overall mean DSD beyond diameters of approximately 0.6 mm (Fig. 19). In contrast, stratiform DSDs closely resemble the overall mean distribution but show a steeper decline for diameters larger than 2 mm. These differences are reflected in bulk variables: for OTT (Thies), convective events exhibit mean VMD values that are 77% (94%) higher than stratiform events, and mean rainfall intensities that are 963% (672%) higher. These regimes also occupy distinct regions in VMD– $\log_{10}(N_w)$ space. On a VMD – $\log_{10}(N_w)$ plot, the stratiform events cluster in the region of low VMD and low N_w , whereas convective events are characterised by high VMD and high N_w (Fig. 20). For Biral, however, most convective events are in the lower-right tail of the plot, associated with high VMD and low N_w , while the convective events are more evenly spread for OTT and Thies.

Figure 19:

Average DSD per precipitation regime. The blue line shows the mean DSD of all data (as shown on Fig. 14), while the orange and green lines show the mean DSD of stratiform and convective events, respectively. Sample size (n), mean VMD and rain rate (R) are shown in the legend for each category. Error bars indicate SEM.

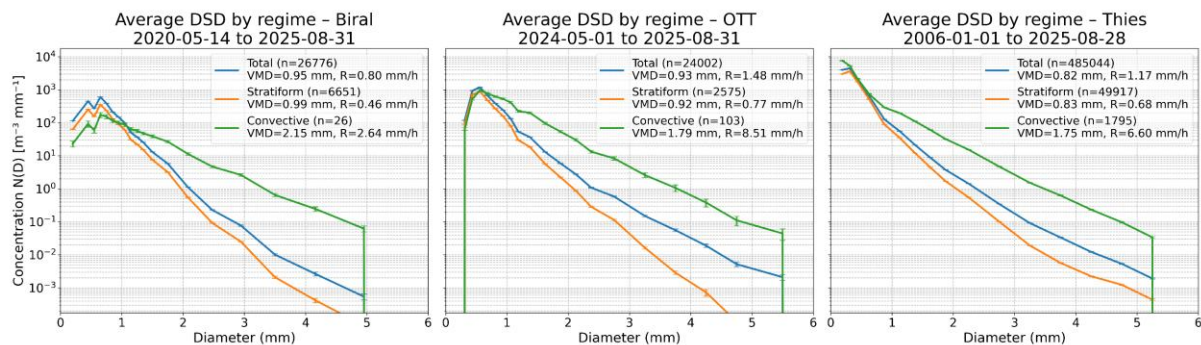
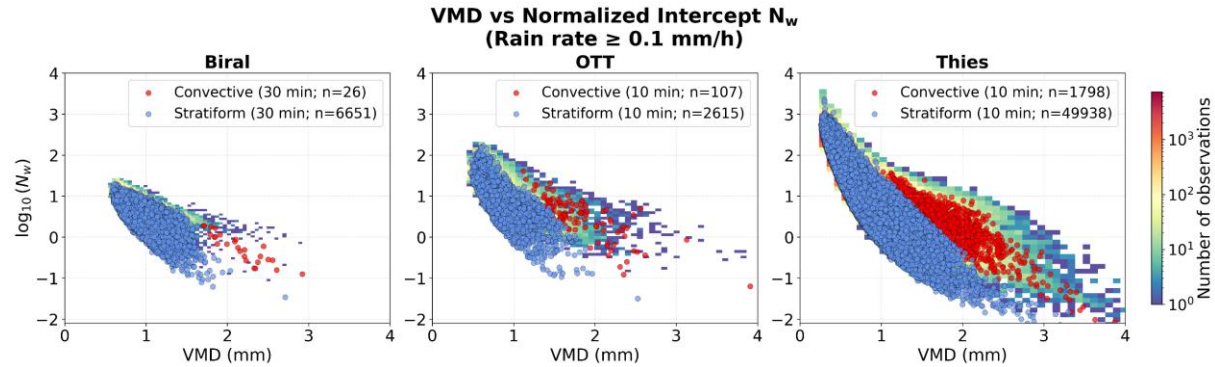


Figure 20:

Heatmap of disdrometer measurements in VMD – $\log_{10}(N_w)$ space overlaid with a scatter plot of the convective (red dots) and stratiform rain events (blue dots) per disdrometer.



4.2.2 Temporal variability of DSDs

Temporal variability in DSD characteristics reveals systematic differences at both diurnal and seasonal scales. At the diurnal scale, rainfall fraction shows only limited variation throughout the day (Fig. 21a). However, rainfall characteristics do vary between diurnal periods. Afternoon rainfall is generally more intense than nighttime rainfall, with higher median rain rates and larger drops (Table 6). This is reflected in higher median VMD values and lower total drop counts, indicating fewer but larger drops. Additionally, afternoon rainfall exhibits greater variability in both drop size and intensity, as shown by higher σ_m and elevated extreme rain rates (R99). These patterns are also reflected in lower median values of the shape (μ) and slope (Λ) parameters, resulting in a broader drop size distribution for Thies and OTT. For Biral, however, an opposite effect is found on these parameters. The signal is similar for all three instruments, but increases in drop sizes and decreases in concentrations are most pronounced for OTT.

Seasonal differences are more pronounced. Winter is characterised by more frequent rainfall events with smaller drop sizes and lower rainfall intensities (Fig. 21b). In contrast, summer rainfall is less frequent but significantly more intense, with higher median values rain rate, kinetic energy, VMD and LWC. These characteristics suggest a larger contribution of convective precipitation, which is also reflected in lower Λ values. Increases in rainfall intensity are least pronounced for Biral. Interestingly, Biral and Thies record lower total drop counts and concentrations during summer, whereas OTT shows the opposite behaviour, indicating a systematic difference between the instruments. Furthermore, Thies exhibits the strongest increase in drop sizes and is the only instrument showing a decrease in μ . Spring and autumn have comparable mean DSDs, though OTT shows more

pronounced differences for large drops. On average, autumn has higher rain rates but smaller drop sizes than spring.

Figure 21:

Average DSD variability across (a: upper row) diurnal and (b: lower row) seasonal scales. See Section 3.4.3 for definition of periods. The legend shows sample size (n), rainfall fraction (ϕ_r), mean VMD and mean rainfall rate (R). Error bars indicate SEM.

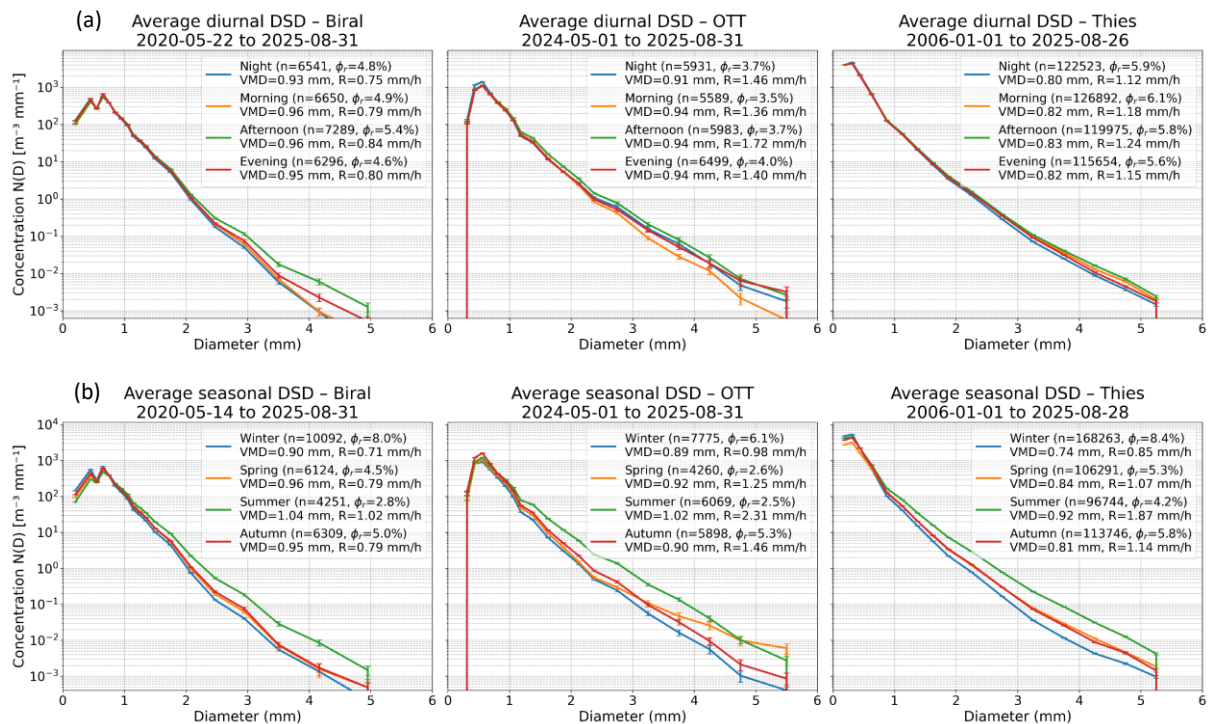
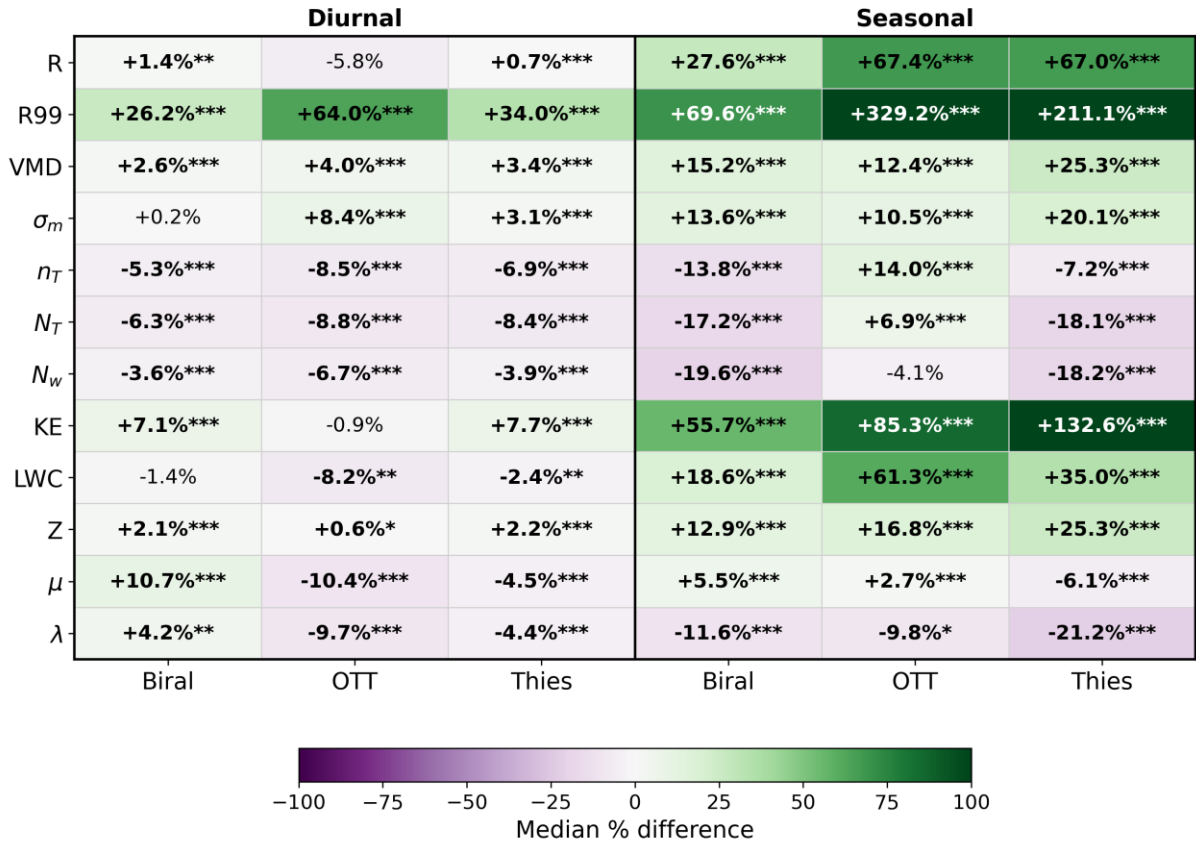


Table 6:

Median differences between diurnal (left; afternoon – night) and seasonal (right; summer – winter) periods. Bold numbers indicate significant differences ($p < 0.05$) between periods, as determined by a two-sided Mann-Whitney U test. Asterisks indicate the level of significance (: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$). Seasonal differences might be skewed for OTT, due to the short temporal coverage of the data (from May 2024 to August 2025).*

**Temporal distribution of microphysical properties: median difference
(Afternoon vs Night (Diurnal) | Summer vs Winter (Seasonal))
(* p<0.05 | ** p<0.01 | *** p<0.001)**

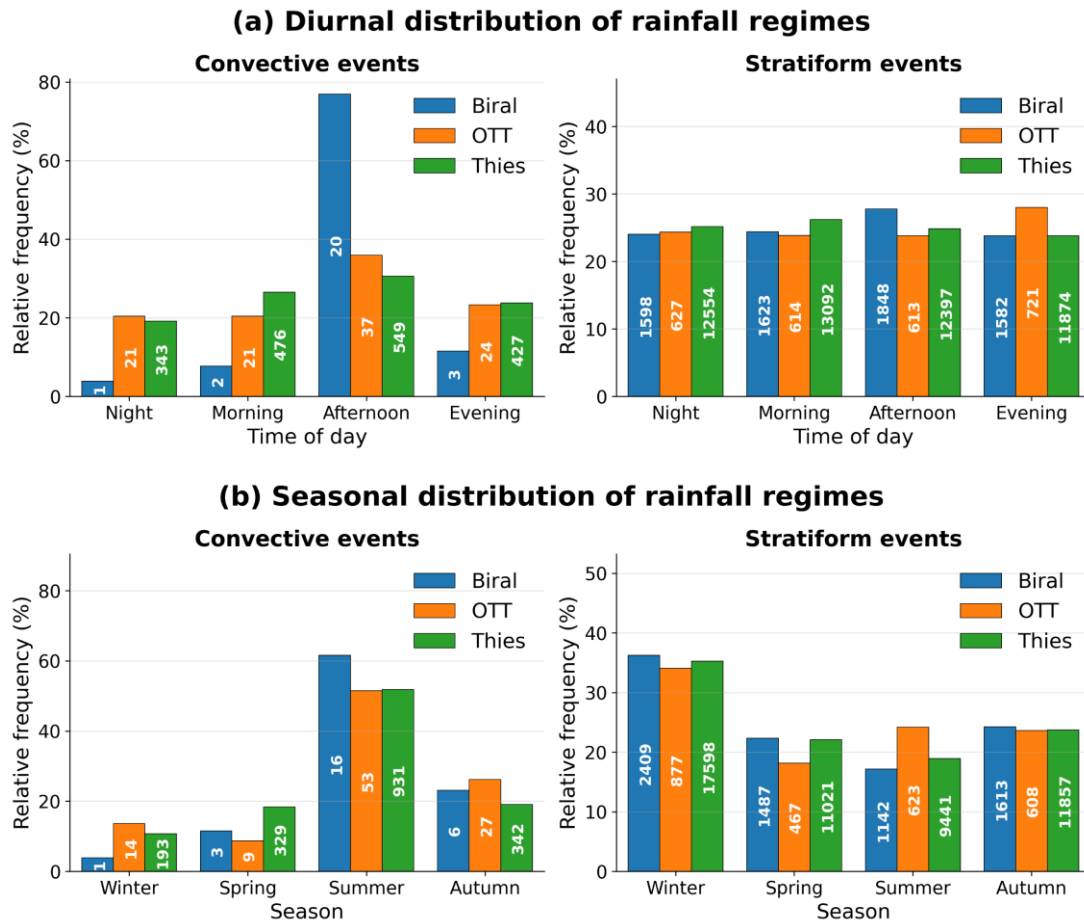


Temporal patterns also emerge when considering precipitation regimes. Convective events occur most frequently during the afternoon, while their occurrence at night is significantly less common (Fig. 22a). Stratiform events, on the other hand, seem to have no diurnal period preference, with equal occurrence rates throughout the day.

At the seasonal scale, convective events are most frequent during summer and least common in winter, whereas stratiform events have an inverse seasonal distribution, with the highest frequencies during winter and lowest in summer (Fig. 22b). Autumn stands out as a transitional period, with relatively high frequencies of both convective and stratiform events. It should be noted that the seasonal distribution for OTT may be affected by the short data period, which includes two summers but only one winter, autumn and spring.

Figure 22:

Temporal distribution of convective and stratiform events on a (a) diurnal and (b) seasonal basis. Blue, orange and green bars represent data from the Biral, OTT and Thies disdrometer, respectively. Numbers inside the bars indicate sample size. See Section 3.4.3 for definition of periods.



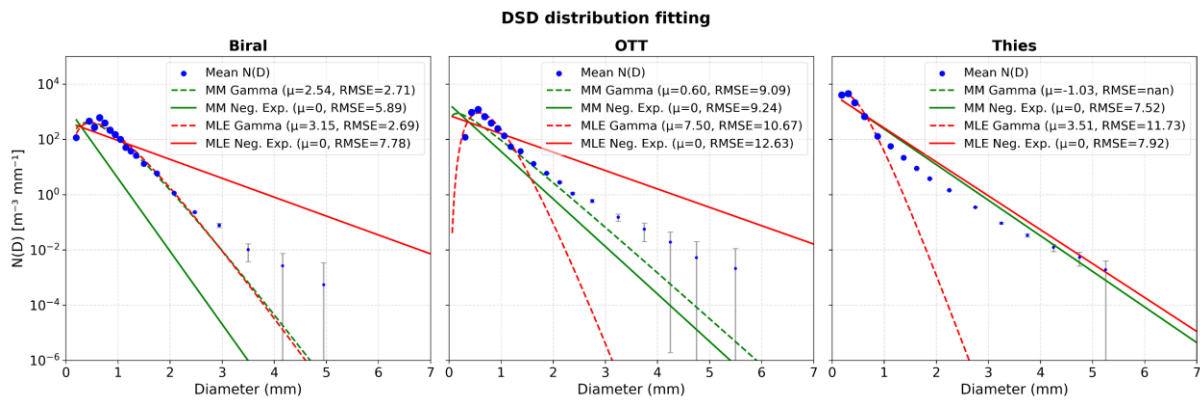
4.2.3 Statistical fitting

In addition to data-driven variables, drop size distributions were approximated using theoretical distributions to assess how well common parameterisations describe the observed spectra. This allows the drop spectra to be reduced to a few parameters, enabling simple comparison of DSDs. Statistical fitting is also useful to assess whether measured DSDs of the different instruments correspond to commonly reported functions in the literature, such as the gamma and negative exponential distribution. For Biral, the mean DSD is well represented by a gamma distribution, although larger drop sizes are slightly underestimated (Fig. 23). The difference between fitting methods (MM or MLE) is minimal. While gamma distributions also fit the OTT data best overall, the fitting method has a large influence: MM produces a low μ , resembling a negative exponential distribution with minimal

RMSE but poor representation of small drops, whereas MLE better captures the small drops but overestimates the decay rate for large drops. For Thies, the mean DSD is most closely approximated by a negative exponential distribution, with minimal differences between the fitting methods.

Figure 23:

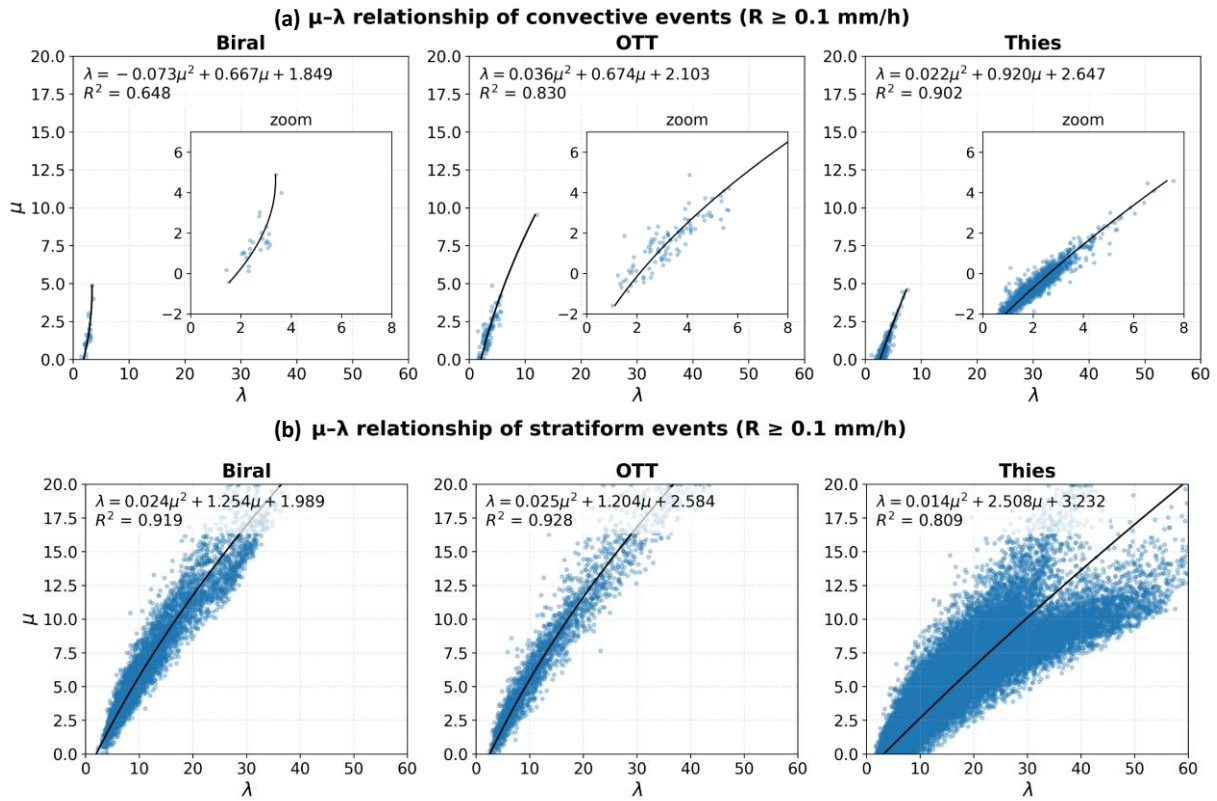
Raindrop size distributions fitted with negative exponential (dashed line) and normalised gamma distribution (solid line) using MM (green line) and MLE (red line). MM is applied on the mean DSD only, while MLE fits use all data. Distributions with $\mu < -1$ are excluded as these represent unstable and non-physical distributions that diverge for small diameters. Error bars indicate SEM and points are scaled according to sample size. Nan indicates non-existent values. The legend shows values of μ and RMSE.



The relationship between the gamma distribution parameters μ and Λ was further analysed for convective and stratiform events. The μ - Λ relationship is commonly used in climate models to reduce the number of independent DSD parameters. As this study is primarily observation-based, the relationships are only used for comparison with previous studies and between the instruments. For convective events, the μ - Λ relationship is strongest for Thies, showing the highest correlation (Fig. 24a). OTT exhibits the largest positive quadratic coefficient ($a = 0.036$), indicating a stronger increase of Λ with μ . In contrast, Biral shows a negative coefficient ($a = -0.074$) and a lower correlation, indicating a weaker relationship. For stratiform events, the μ - Λ relationships for Biral and OTT are similar and show high correlation (Fig. 24b). Thies, however, shows a more dispersed and branched pattern, resulting in a lower overall fit.

Figure 24:

Relationship between gamma distribution parameters μ and λ per disdrometer for (a) convective and (b) stratiform events, derived for every rainfall event using the MM. The values are fitted with a binomial function following Zhang et al. (2003), which is shown in the top left corner, alongside R^2 .



4.3 Urbanisation effects on DSDs and rainfall intensity

4.3.1 Geographical description

To assess potential urban influences on rainfall microphysics, the spatial distribution of land cover and urbanisation around each disdrometer was first characterised. Urbanisation in Belgium is highly heterogeneous. In Flanders, particularly in the region between Antwerp, Ghent, and Brussels, urban areas are fragmented and widespread, interspersed with extensive suburban areas (Fig. 26). This is in stark contrast with the more concentrated urbanisation found in the Netherlands to the north. In Wallonia, urbanisation is more clustered around major cities such as Liège, Namur and Charleroi, primarily along the Meuse and Sambre valleys.

Land cover also shows clear regional contrasts. The central and northwestern parts of Belgium are primarily composed of cropland (light green on Fig. 26b) and scattered patches of grassland (green) and forests (dark green). In contrast, the Campine region in the northeast and the Ardennes in the southeast are more densely forested. Clear differences in urbanisation types across the country can also be seen, with more compact urban forms in northern metropolitan areas and more open, low-density urban structures in the south.

The three examined cities (Brussels, Ghent and Liège) exhibit distinct urban and suburban structures. Brussels has the largest spatial extent and a circular form, whereas Ghent has a more rectangular shape (Fig. 25). Liège has an elongated structure, closely following the course of the Meuse, with an extensive adjacent suburban area. The Biral disdrometer in Uccle is located near the edge of the urban core of Brussels, while the disdrometers in Melle (OTT) and Sart-Tilman (Thies) are situated outside of the suburban area in more rural surroundings. These differences are important to assess urban effects, as the Biral site is more directly exposed to urban influences under low wind speeds, while the sites of OTT and Thies are more likely to be affected by urban effects under high wind speeds.

Figure 25:

Map of the delineation of the urban and suburban areas of Ghent, Brussels and Liège (Lambert 72, EPSG:31370; grid WGS84, EPSG:4286). See Section 3.4.4 for used method of delineation and Table 2 for definition of city centres. Basemap is Mapbox Voyager.

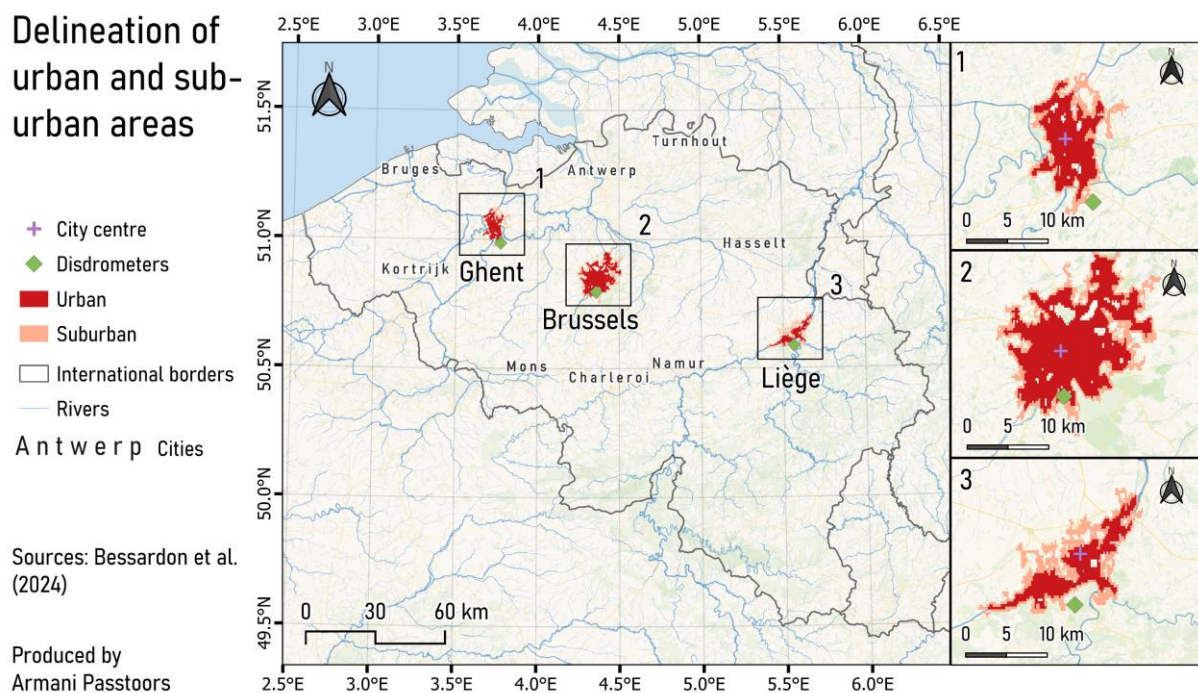
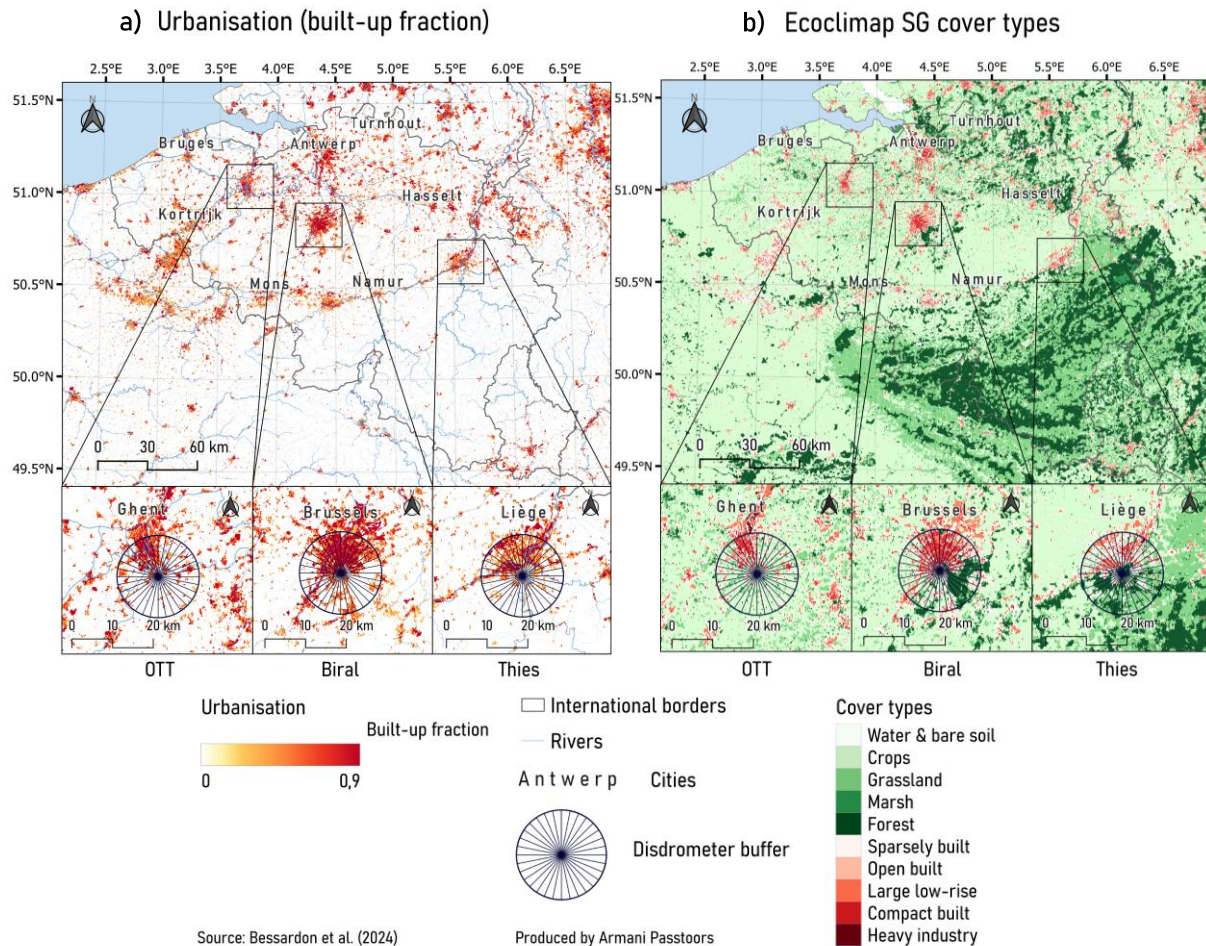


Figure 26:

Maps of Ecoclimap SG (a) built-up fraction and (b) cover types in Belgium (Lambert 72, EPSG:31370; grid WGS84, EPSG:4286).



Within the 10 km buffers around each disdrometer, clear differences in urban structure are observed. In all cases, the urban core is located roughly to the north of the measurement site, but its extent and composition vary.

The Biral disdrometer is located near the capital city of Brussels, leaving a wide footprint of high urban cover in much of the sectors from northwest to northeast (Fig. 27). The highest urban fraction occurs in the northern sectors (Fig. 27a), with compact urban areas dominating, while sparse and low-rise urban cover increases for more peripheral sectors (Fig. 27b). Western and southwestern sectors are primarily characterised by cropland, whereas forested areas are more prominent to the east and southeast, representing the large Sonian Forest (Fig. 27b).

The OTT site near Ghent shows pronounced spatial contrast in urbanisation. High urban fractions are limited to a small number of sectors, with only two exceeding 50% compact urban cover (Fig. 27a). Outside these sectors, land cover is largely homogeneous and dominated by cropland, with limited variation between sectors (Fig. 27b).

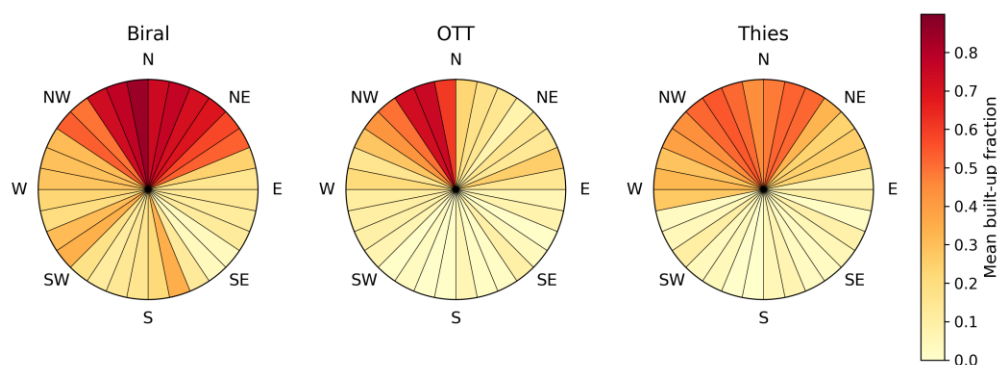
The Thies site near Liège shows a more diffuse urban pattern. The urban footprint is broader but less intense, with lower maximum urban fractions compared to Biral and OTT (Fig. 27a). The sector with the highest mean urban fraction has an urban fraction of only 0.546, while the maximum is significantly higher for OTT (0.751) and Biral (0.850). Urban areas in Liège are mostly comprised of sparsely built, open built and large low-rise areas, with compact areas in a sector never exceeding 40%. Additionally, this site is the only one among the three to contain a significant percentage of industrial area (Fig. 27b).

These spatial characteristics of urban extent, density, and land cover composition provide a basis for analysing how upwind conditions may influence rainfall characteristics at each site.

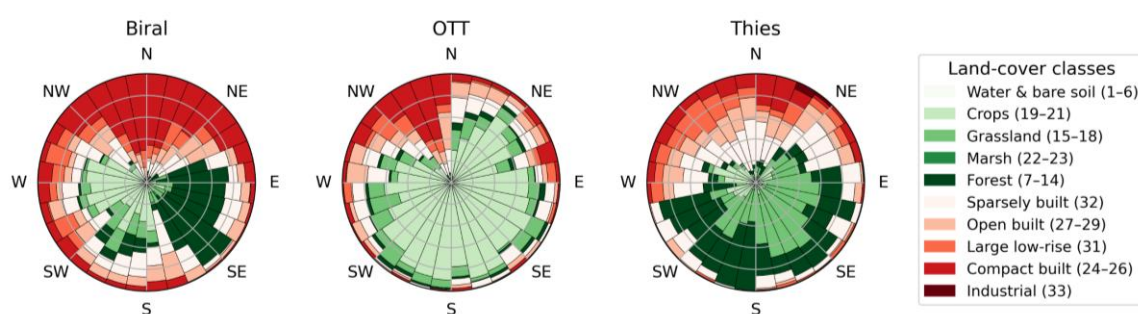
Figure 27:

Radial plots of average (a) built-up fraction (one value per sector) and (b) land cover composition (stacked radial sectors showing relative area) for each of 32 wind sectors within a 10 km radius around each disdrometer.

(a) Mean urban fraction per wind sector (within 10 km radius)



(b) Land-cover composition per wind sector (within 10 km radius)



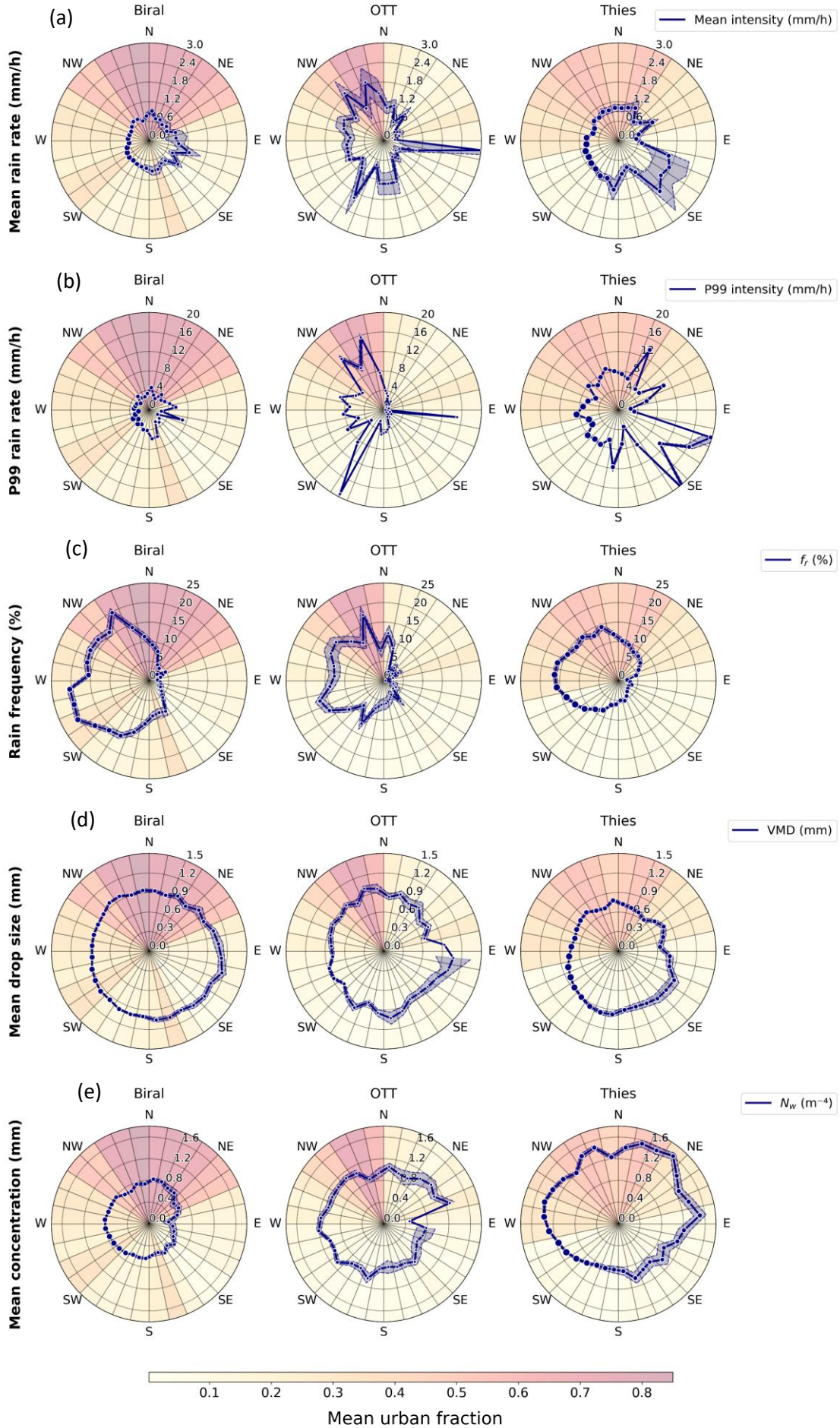
4.3.2 Urbanisation–rainfall relationships

To assess the influence of urban areas on rainfall characteristics, disdrometer observations were combined with ERA5 wind directions to determine whether rainfall occurred downwind of urban or rural sectors. Disdrometer data were aggregated to hourly resolution and linked to the corresponding upwind sector based on wind direction. For each sector, rainfall variables were averaged and compared with the sector's urban fraction.

Across all three sites, rainfall occurrence shows a clear directional dependence (Fig. 28). Rain frequency is highest for winds originating from the northwestern to southwestern (approximately 15-20% of the hours contained rainfall), while eastern and southern winds are considerably drier, only resulting in rainfall roughly 5% of the time (Fig. 28c). This uneven distribution leads to larger standard errors for sectors with less frequent rainfall. Rainfall intensity exhibits no consistent response to urban influence across the three locations. At the Ghent site (OTT), mean rainfall intensity tends to be slightly higher in sectors with a larger urban fraction, although the associated uncertainty is substantial (Fig. 28a). In contrast, no clear difference is observed for Brussels (Biral) and Liège (Thies), where intensities remain comparable between urban and non-urban sectors. Extreme rainfall, represented by the 99th percentile, follows similar but more variable patterns (Fig. 28b). Drop size characteristics also show inconsistent behaviour. Average volume-weighted mean diameter (VMD) does not differ significantly between urban and non-urban sectors for Biral and OTT, while Thies records lower VMD values downwind of more urbanised areas (Fig. 28d). Independently of urbanisation, all three instruments show higher VMD values for easterly wind sectors (Fig. 28d). The normalised intercept parameter (N_w) tends to increase slightly with urban fraction for Biral and Thies, whereas a weak decrease is observed for OTT (Fig. 28e). In general, it seems that rainfall characteristics are more governed by the direction of the dominant wind itself, rather than the associated upwind urban structure.

Figure 28:

Radial plots of average urban fraction per wind sector (10 km buffer; 32 sectors), color-coded in red, overlaid with mean values of rainfall characteristics from rainfall periods whose dominant wind direction comes from each wind sector. The connected radial points show sector-specific means of (a) rain rate, (b) 99th percentile of rain rates, (c) rain frequency, (d) VMD and (e) normalised concentration N_w . Coloured area indicates SEM for all subplots except (b). Uncertainty of (b) is estimated by means of bootstrapping. Points are scaled according to sample size.



These patterns are reflected in the correlation analysis (Table 7). When considering the full dataset, a higher urban fraction is generally associated with lower rainfall intensity, smaller drop sizes and reduced extreme rainfall for Biral and Thies, though the correlations are weak (Table 7a). The shape (μ) and slope (Λ) parameters of corresponding gamma distributions are slightly increased for these two sites, while the total concentration (N_T) and normalised concentration (N_w) increase consistently ($p < 0.001$) with urban fraction across all instruments, indicating a shift towards more numerous, smaller drops. Rainfall frequency is also slightly increased downwind of Ghent (OTT) and Liège (Thies), while no change was observed for Brussels (Biral).

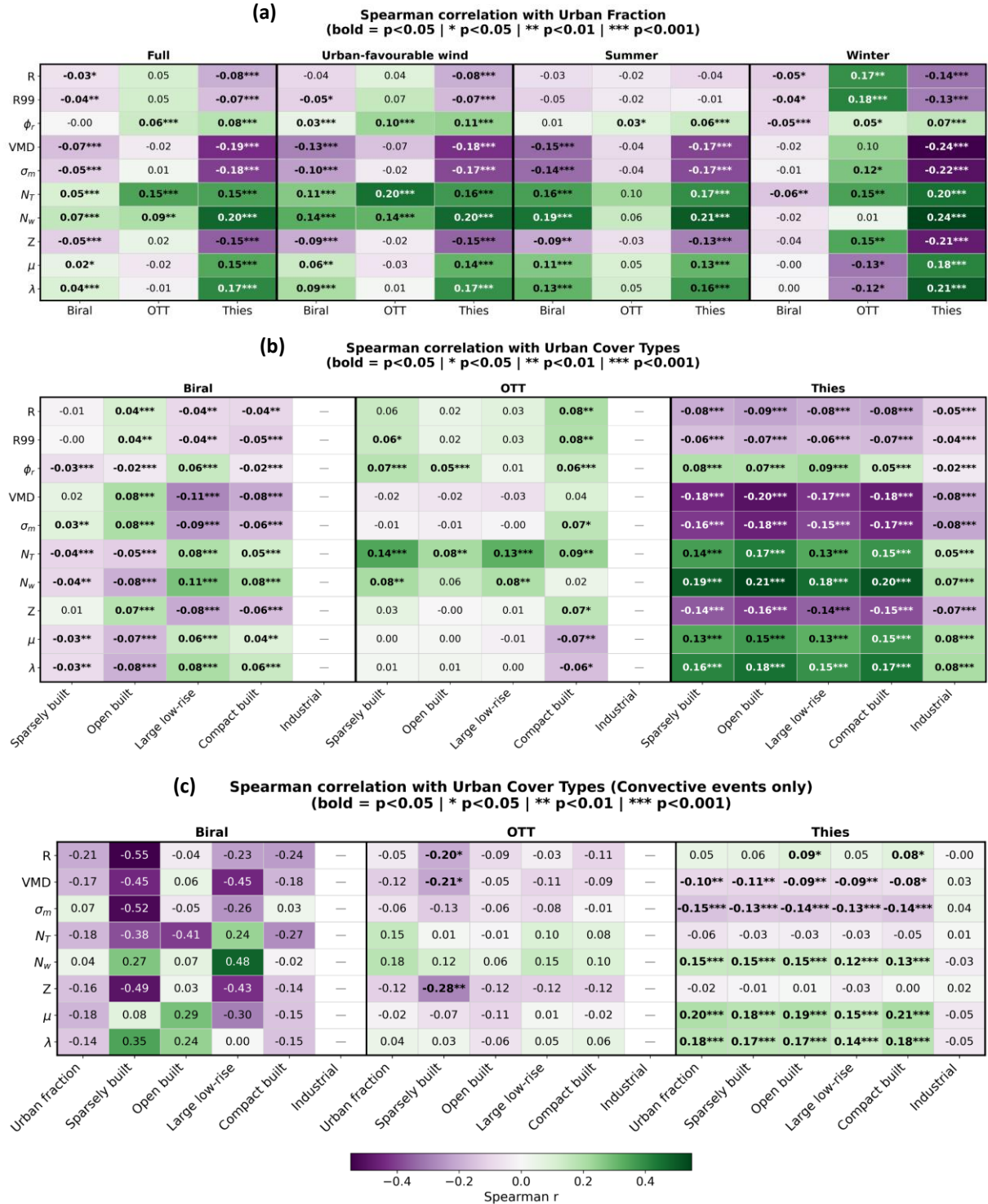
Stratifying the data by wind or temporal conditions does not fundamentally change these relationships. Under urban-favourable wind speed conditions (low wind speeds for Biral, high wind speeds for OTT and Thies), correlations strengthen slightly but the signal remains largely unchanged (Table 7a). A significant increase in rain fraction is, however, observed for all locations ($p < 0.001$). During summer, no significant relationship is found between urban fraction and rainfall intensity, although drop sizes remain lower downwind of Brussels and Liège. When looking at winter data, the strongest signals emerge for Ghent and Liège, albeit with opposite signs. Rainfall intensity is increased (decreased) downwind of Ghent (Liège) ($p < 0.01$). For Thies, higher urban fractions are also associated with decreased VMD and increased N_w . Winter rains are slightly more frequent downwind of Ghent and Liège, but downwind of Brussels, they are less common. For Biral, the effects during winter remain overall weak.

Analysing individual urban land cover types provides additional context. For Biral, dense urban classes (compact built and large low-rise) are associated with lower rainfall intensity and smaller drop sizes, whereas more open urban classes (sparsely built and open built) show the opposite tendency (Table 7b). The signal is more similar across the different urban cover types in Ghent and Liège. For Ghent, compact urban areas show the strongest positive association with rainfall intensity, drop size and concentration. For Liège, both compact and open urban types are associated with reduced intensity and drop size, but increased drop concentration and rainfall frequency. Industrial areas show weak or no consistent relationships.

When only considering convective events, the results remain inconsistent between sites. Both OTT and Thies show a tendency towards smaller drop sizes and lower N_w in urban sectors, but rainfall intensity decreases downwind of Ghent and increases downwind of Liège (Table 7c). This is in contrast with the full dataset analysis, which found increased rainfall intensity downwind of Ghent and decreased intensity downwind of Liège. However, most of the relationships are not significant for OTT, indicating limited robust signals for convective cases.

Table 7:

Heatmaps of the Spearman correlations between rainfall variables and urbanisation: (a) urban fraction, (b) urban cover types for all data and (c) only for convective events. Significant correlations ($p < 0.05$) are shown in bold. Asterisks indicate the level of significance. Industrial area is absent for Biral and OTT and is kept blank. Subplot (a) shows correlations with the full dataset and after filtering for urban-favourable wind speeds (lower-than-mean wind for Biral; higher-than-mean for OTT and Thies (Appendix 6)), summer rainfall and winter rainfall.



4.4 Air pollution effects

4.4.1 Spatial and temporal context of air pollution

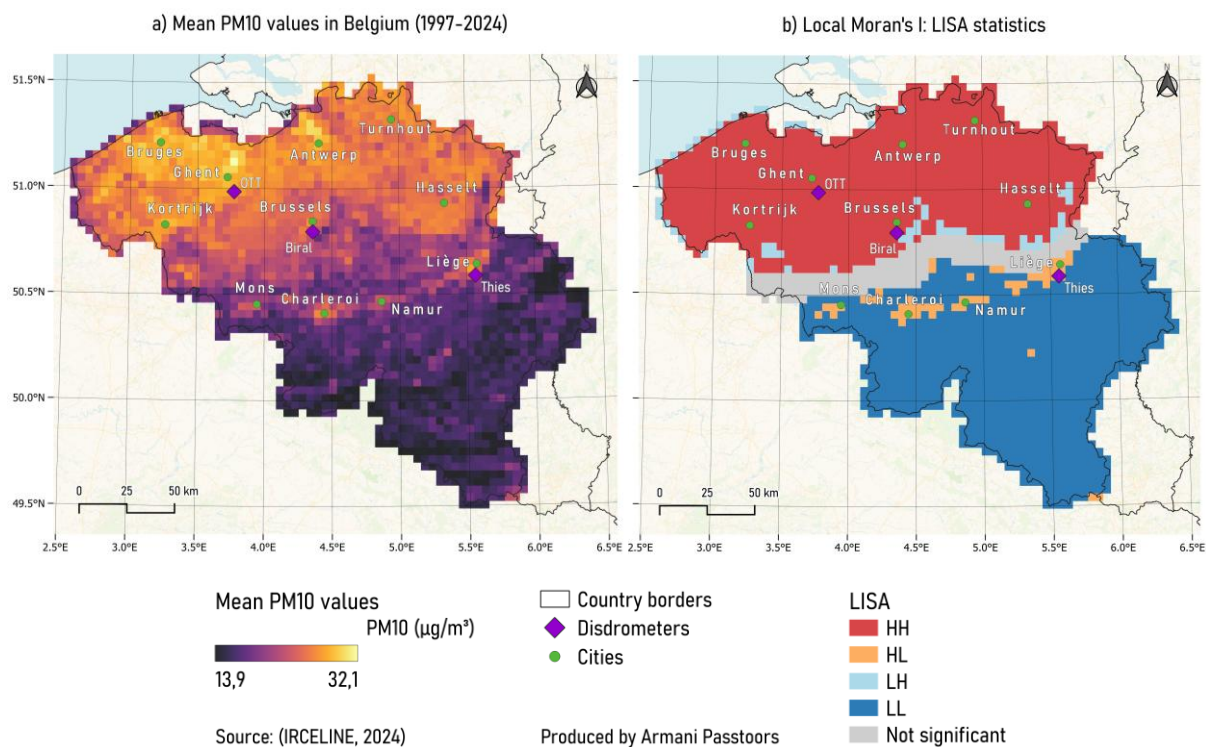
Air pollution in this study is represented by concentrations of particulate matter, which is divided into two metrics: PM_{10} and $PM_{2.5}$. The concentrations show strong spatial and temporal variability across Belgium.

Spatially, PM_{10} concentrations are highest in the northwestern part of the country and lowest in the Ardennes region in the southeast, with local differences up to 50% (Fig. 29a). This gradient broadly aligns with topography, with lower elevations corresponding to higher concentrations. Local anomalies are superimposed on these large-scale patterns and are often related to land use (urbanisation or vegetation). Elevated concentrations occur near industrial areas, such as the port regions of Antwerp and Ghent, while lower concentrations are associated with forested regions, such as the Sonian Forest near Brussels.

Spatial autocorrelation analysis using Local Moran's I confirms these patterns (Fig. 29b). A large hotspot of high PM_{10} values is identified over Flanders, while Wallonia forms a large cold spot. Within Wallonia, the Meuse and Sambre valleys stand out as localised hotspots. The three disdrometers are all located in distinct regions regarding pollution context: OTT lies within a major hotspot, Biral near a local low anomaly associated with forest cover, and Thies within a local high anomaly near Liège.

Figure 29:

Maps of (a) mean PM_{10} values in Belgium as well as (b) the results of local spatial analysis (HH: high-high; HL: high-low; LH: low-high; LL: low-low; see Section 3.4.5 for definitions). The spatial weights matrix has a distance threshold of 25 km. Results for $PM_{2.5}$ show similar spatial patterns and are omitted for brevity.



Temporally, particulate matter concentrations show a strong long-term decline across Belgium. PM10 concentrations have decreased substantially since 1997, dropping by approximately 60–70% within 27 years (Fig. 30). This decline is well described by a linear trend at all sites. The steepest decrease is observed at Sart-Tilman (Thies) with a slope of $-0.90 \mu\text{g m}^{-3} \text{ year}^{-1}$, while the weakest decline occurs at Uccle, with $-0.77 \mu\text{g m}^{-3} \text{ year}^{-1}$. Concentrations at Merelbeke-Melle remain consistently higher than at the other two sites throughout the period, followed by Uccle and Sart-Tilman, with the difference between the latter two increasing slightly over time.

PM_{2.5} concentrations exhibit a similar temporal evolution, with a reduction of approximately 50–60% since 2008 (Fig. 30). Concentrations at Merelbeke-Melle and Uccle are comparable, whereas Sart-Tilman consistently records lower values. The strongest decline is observed at Uccle ($-0.78 \mu\text{g m}^{-3} \text{ year}^{-1}$), which is similar to its PM₁₀ trend. Since PM_{2.5} is a subset of PM₁₀, a comparable slope suggests a large contribution of small particles in Uccle. Conversely, larger differences between PM₁₀ and PM_{2.5} trends at Merelbeke-Melle and Sart-Tilman indicate a relatively greater contribution of coarse particles to PM₁₀ decline at those sites.

Changes in the distribution of PM₁₀ values further illustrate this decline (Fig. 31). During the period 1997–2010, Uccle and Sart-Tilman show broadly similar distributions, although Sart-Tilman exhibits a less pronounced high-value tail. Merelbeke-Melle stands out with higher mean and extreme concentrations. In the more recent period (2011–2024), distributions at all sites become less skewed and shift towards lower values, with pronounced

peaks between 5 and 15 $\mu\text{g m}^{-3}$. This shift is also visible through percentile changes, as the 90th percentile of the recent period is close to or below the 67th percentile of the earlier period while the 67th percentile of the recent period falls below the 33rd percentile of the earlier period at all sites. $\text{PM}_{2.5}$ shows a comparable shift between 2008–2015 and 2016–2024, although the reduction in percentile values is less pronounced than for PM_{10} . In the most recent period, concentrations cluster at low values, with the 0–4 $\mu\text{g m}^{-3}$ being most frequent at Sart-Tilman (Fig. 31).

Figure 30

Graph of yearly mean PM_{10} (upper) and $\text{PM}_{2.5}$ (lower) values for the grid cells wherein the disdrometers lie. Blue, orange and green lines represent data from the Biral, OTT and Thies disdrometer, respectively. The temporal evolution is fitted with linear regression using OLS, with the results (equation and R^2) annotated in the bottom left.

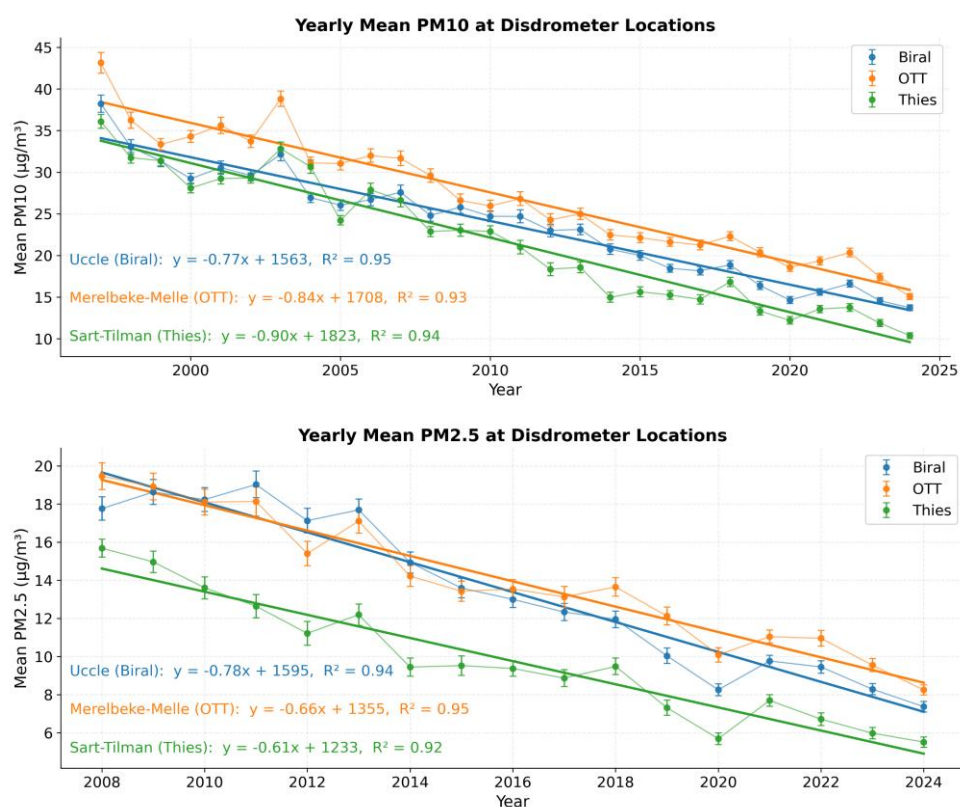
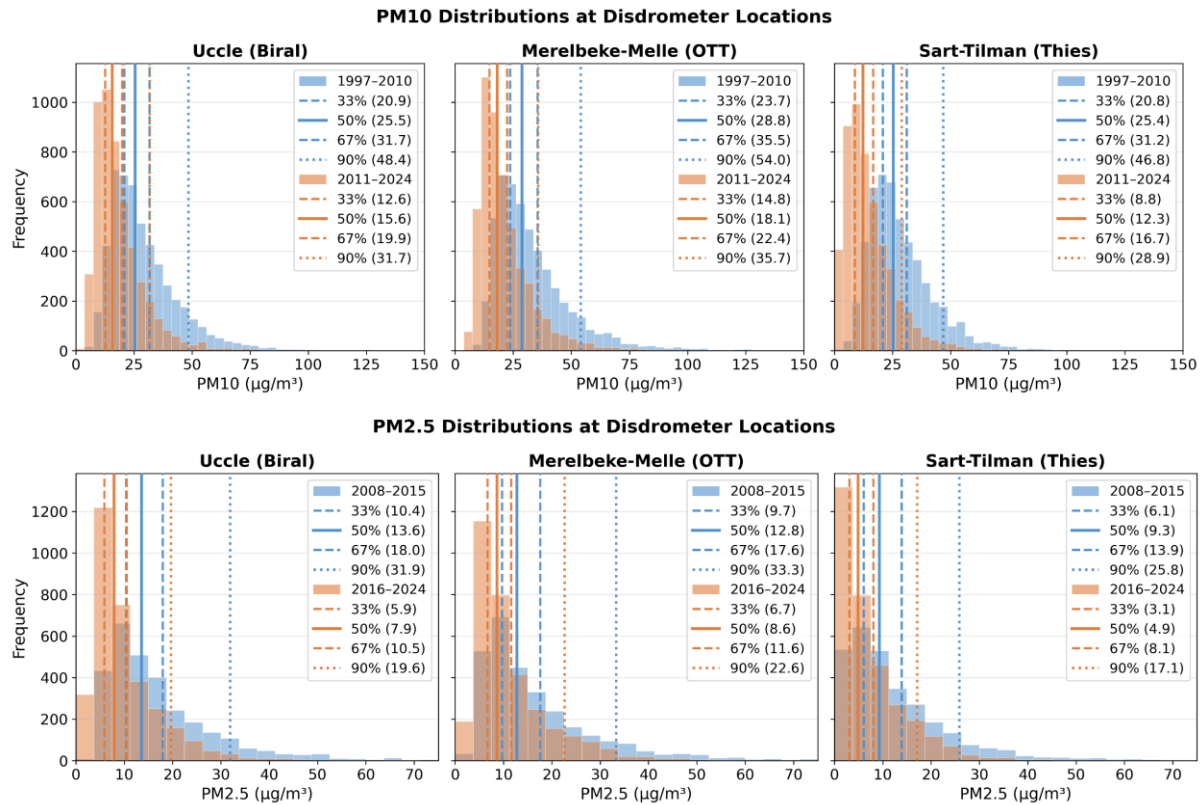


Figure 31

Histograms of PM_{10} (upper) and $PM_{2.5}$ (lower) distributions in different decades (PM_{10} : 1997-2010 (blue), 2011-2024 (orange); $PM_{2.5}$: 2008-2015 (blue), 2016-2024 (orange)) at the disdrometer locations. Values of percentiles are given in parentheses.



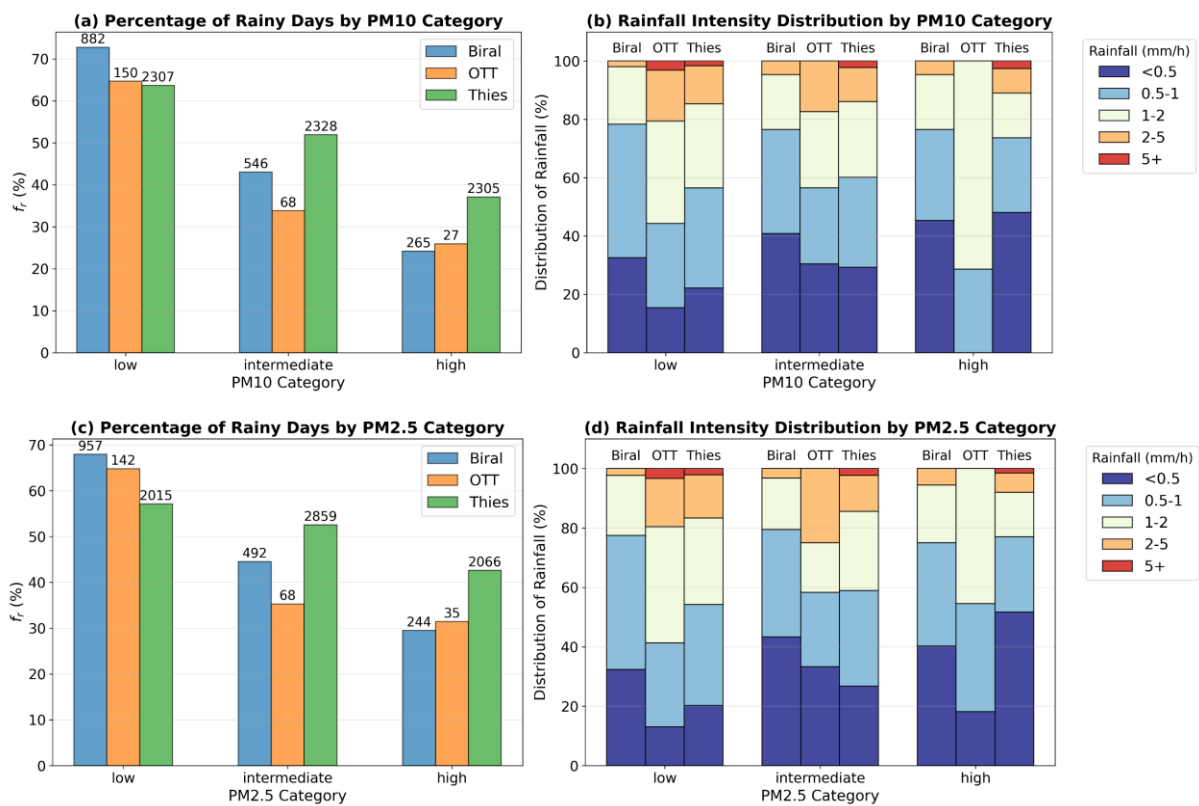
4.4.2 PM -rainfall relationships at daily scale

Rainfall data from the disdrometers are aggregated to daily data and linked to daily mean PM concentrations. Each day was classified into low, intermediate or high pollution categories based on tercile values. The tercile values were calculated for the same periods for all disdrometers (PM_{10} : 2006 – 2024, $PM_{2.5}$: 2008 – 2024), meaning that, given the linear decrease in PM concentrations (Fig. 30), low PM days are relatively more prominent for Biral and OTT than for Thies. Across all three sites, higher PM levels are associated with lower rainfall occurrence (Fig. 32a, c), with rain frequency decreasing systematically from low to high PM categories. Changes in rainfall intensity are more variable. Low-intensity rainfall ($< 0.5 \text{ mm h}^{-1}$) becomes more frequent at higher PM concentrations, although this pattern is less clear for the highest PM category of OTT due to limited sample size (Fig. 32b, d). For Biral, the fraction of rainfall below 1 mm h^{-1} remains relatively constant at

approximately 75%, despite a slight increase in the lowest intensity class. For Thies, high-intensity rainfall (> 5 mm) becomes slightly more frequent in higher PM₁₀ categories, but not in PM_{2.5} categories. The opposite tendency is observed for OTT, with decreasing high-intensity rainfall for increasing PM concentrations.

Figure 32:

Bar plots of (a, c) rain frequency and (b, d) rainfall intensity for each PM₁₀ (a, b) and PM_{2.5} (c, d) category. Sample sizes are shown on top of the bars for subplots (a) and (c). Subplots (b) and (d) show stacked bars of the relative occurrence of different rain rates summing to 100%.

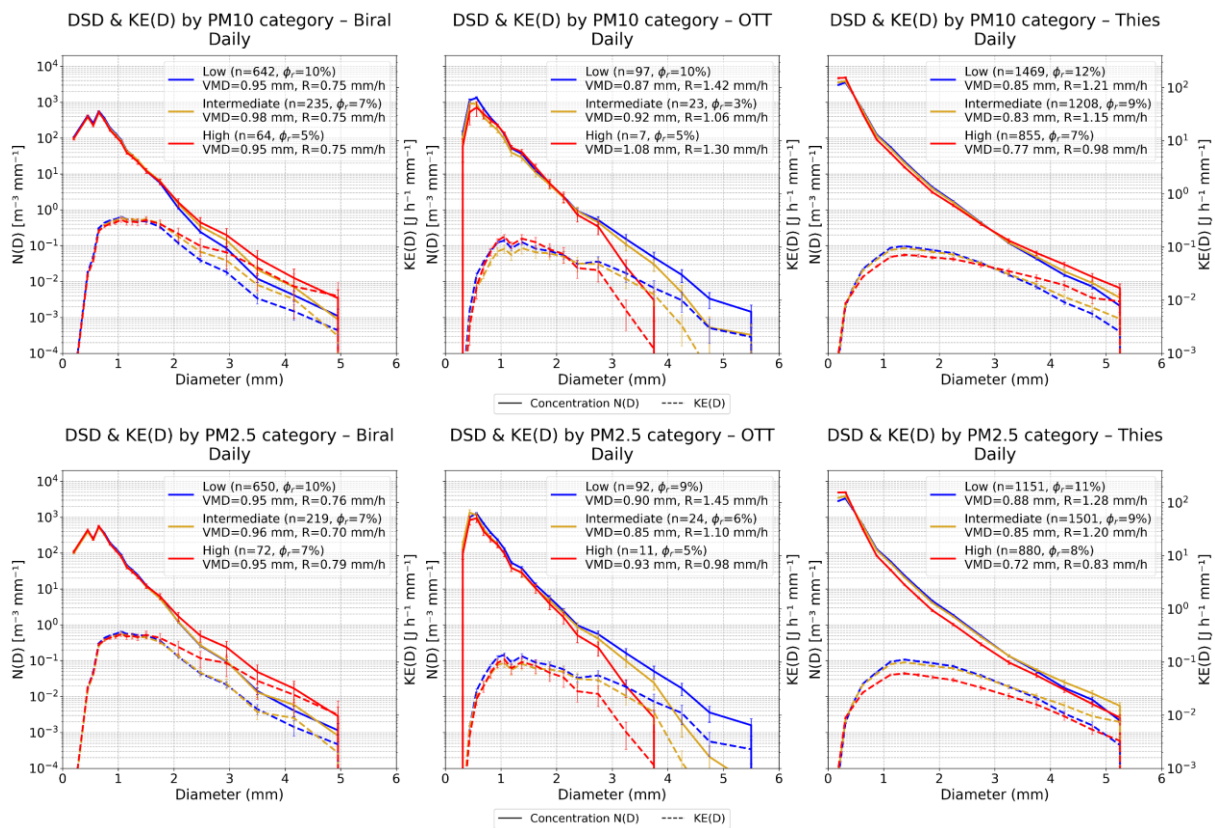


Air pollution also seems to influence DSDs, but the signal is inconsistent across the three disdrometers. For Thies, peak concentrations increase with PM level, while the opposite is true for OTT (Fig. 33). For Biral, no clear change in peak concentrations is observed. Concentration of drops in the 0.5–2 mm range, which contribute the most to rainfall kinetic energy, generally decreases with increasing PM. This trend is most pronounced for Thies; however, OTT does not exhibit this pattern for PM₁₀. Behaviour of the large-drop tail differs between sites: Biral shows increasing concentrations and kinetic energy for large drops with higher PM, while OTT shows a decrease. For Thies, the tail becomes more pronounced for high PM₁₀, but less pronounced for PM_{2.5}.

The impact on the mean drop sizes and rainfall rate also varies by site. VMD and rainfall rate remain approximately constant for Biral. For OTT, the mean VMD increases slightly while rainfall rate decreases with increasing PM, whereas both decrease for Thies. In contrast, the rainfall fraction ϕ_r (% time raining) decreases consistently across all sites, indicating shorter duration of rainfall during highly polluted days.

Figure 33:

Mean concentrations (solid line) and rainfall kinetic energy spectrum (dashed line) per $PM_{2.5}$ (upper row) and PM_{10} (lower row) category for daily averages. Blue, orange and red lines represent low, intermediate and high PM categories, respectively. The legend shows sample size (n), rainfall fraction (ϕ_r), mean VMD and mean rainfall rate (R). Error bars indicate SEM.

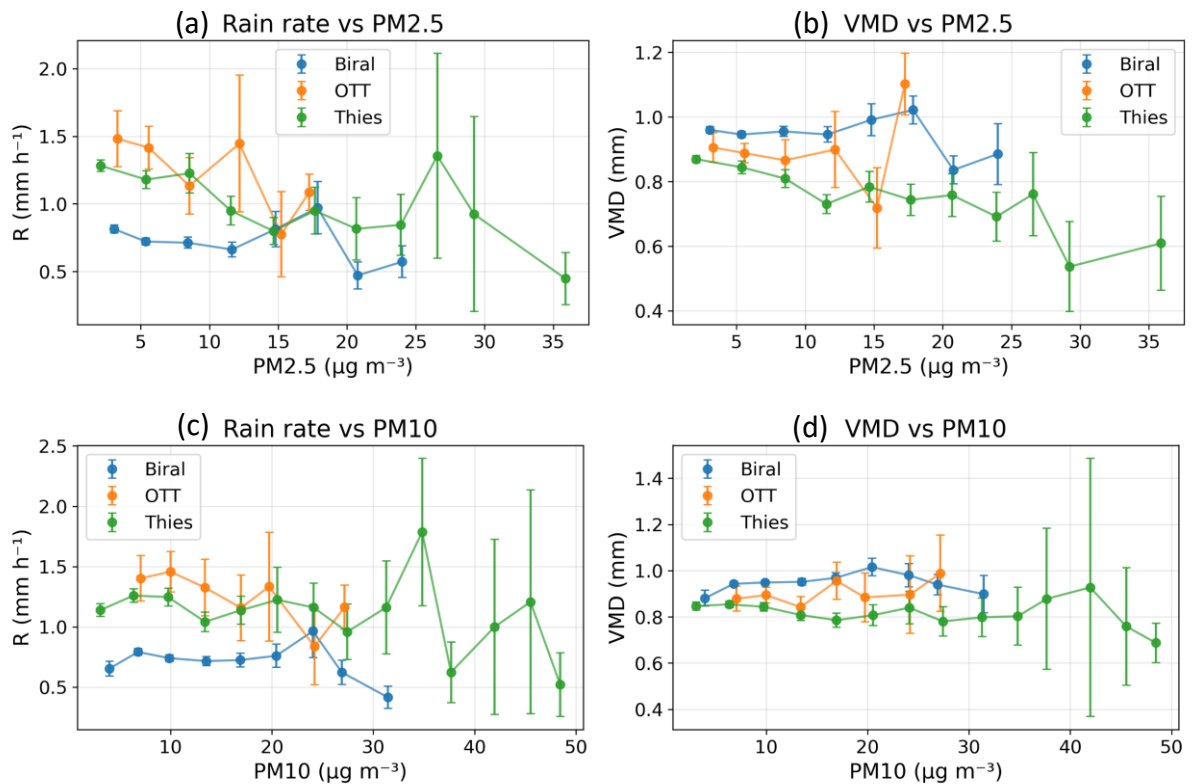


Relationships between PM concentration and rainfall variables show systematic trends (Fig. 34). Rainfall rate tends to decrease approximately linearly with increasing PM_{2.5}, although variability increases at higher concentrations (Fig. 34a). For PM₁₀, the onset of the decrease is delayed, with a slight increase observed below $10 \mu g m^{-3}$, before declining at higher concentrations (Fig. 34c). No consistent relationship is found between PM

and VMD for Biral and OTT, while a clear decrease in VMD with increasing PM is observed for Thies, especially for $PM_{2.5}$.

Figure 34:

Relationships between (a) rainfall rate and $PM_{2.5}$, (b) VMD and $PM_{2.5}$, (c) rainfall rate and PM_{10} , and (d) VMD and PM_{10} . Error bars indicate SEM. Blue, orange and green lines represent the Biral, OTT and Thies disdrometer, respectively.



Overall, highly polluted days are characterised by reduced rainfall occurrence, with frequencies 15–50% lower than on low pollution days, and weaker extremes, with R99 values reduced by 40–60% (Table 8). Rainfall duration is also shorter, as reflected in lower rainfall fractions. Effects on drop size and concentration are less consistent across instruments, with only Thies recording significantly smaller drops during highly polluted days. Kinetic energy and liquid water content decrease substantially for Biral and Thies. The change in total drop concentration shows no consistent pattern. With few exceptions, $PM_{2.5}$ and PM_{10} produce similar signals.

Table 8:

Median differences (%) between the highest and lowest PM category (high PM – low PM) for daily rainfall. The even and uneven numbered columns show $PM_{2.5}$ and PM_{10} correlations respectively. Sample size (n) is depicted below each column. Asterisks indicate the significance of the Kruskal-Wallis test.

	Biral		OTT		Thies	
R	-17.76**	-18.92**	-24.17	9.08	-47.92***	-39.86***
R99	-37.50***	-40.31***	-42.32*	-4.21**	-61.72***	-58.63***
ϕ_r	-44.74***	-70.73***	-12.73*	-21.93***	-42.55***	-57.84***
f_r	-38.41***	-48.64***	-33.36***	-38.74***	-14.53***	-26.58***
VMD	-1.04	-0.24	-1.20	27.43	-23.18***	-17.10***
σ_m	0.71	0.05	28.83	51.58	-29.71***	-24.93***
n_T	-3.50**	-12.31**	-31.81*	-32.43***	3.32	-1.05
N_T	-3.57*	-12.04***	-22.27	-46.36**	19.15***	11.11*
LWC	-9.57*	-14.60*	-26.31	-6.81	-30.20***	-25.97***
KER	-27.01*	-35.15*	-29.13	58.70	-66.55***	-58.93***
Z	-4.64	-8.46	-2.39	21.47	-25.01***	-19.65***
N_w	-1.36	-8.79**	-8.18	-37.38*	29.79***	22.19***
μ	0.90	6.40	-20.80	-27.46	87.84***	81.98***
λ	1.44	-0.04	-33.36	-40.67	64.95***	52.87***
	PM2.5 (n = 1693)	PM10 (n = 1693)	PM2.5 (n = 245)	PM10 (n = 245)	PM2.5 (n = 6210)	PM10 (n = 6940)

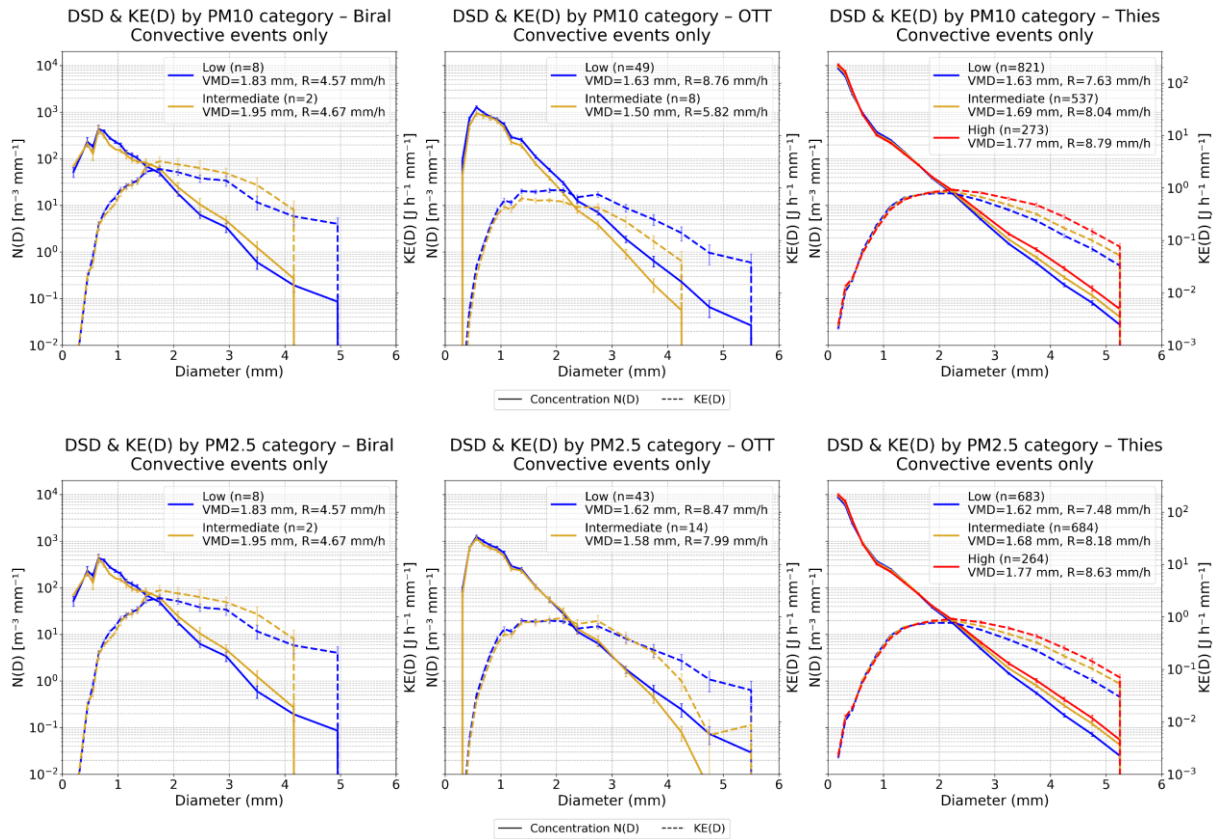
Median difference (%)

4.4.3 PM–rainfall relationships during convective events

When restricting the analysis to convective events, a consistent pattern emerges. For both $PM_{2.5}$ and PM_{10} , higher PM concentrations are associated with increases in mean drop size and rainfall intensity at the Biral and Thies locations (Fig. 35). These changes are primarily driven by differences in the large-drop tail of the DSD. Concentrations of drops larger than 2 mm increase systematically with PM level, leading to higher rainfall kinetic energy, while concentrations of smaller drops (< 2 mm) remain largely unchanged. Although this pattern is not observed by OTT, the results are less robust given the limited number of samples.

Figure 35:

Average concentrations (solid line) and rainfall kinetic energy spectrum (dashed line) per $PM_{2.5}$ (upper row) and PM_{10} (lower row) category for convective events. Blue, orange and red lines represent low, intermediate and high PM categories, respectively. The legend shows sample size (n), rainfall fraction (ϕ_r), mean VMD and mean rainfall rate (R). Error bars indicate SEM.



Statistical analysis confirms these trends. At Sart-Tilman (Thies), which has the largest sample size, higher PM categories are associated with increased volume-weighted mean diameter (VMD; $p < 0.001$) and greater drop size variation (σ_m ; $p < 0.001$) (Table 9). Rainfall kinetic energy is approximately 18% higher in the highest PM category compared to the lowest. At the same time, the normalised intercept parameter decreases significantly ($p < 0.001$). The combined increase in VMD and decrease in N_w results in a systematic shift towards the lower-right region of the VMD- $\log_{10}(N_w)$ space at higher PM concentrations for all instruments (Fig. 36), with the exception of PM_{10} for OTT. At Merelbeke-Melle (OTT), no significant relations could be detected, probably owing to the smaller sample size. For Uccle (Biral), no robust statistics can be derived due to the limited number of convective events.

Table 9:

Median differences (%) between the highest and lowest PM category (high PM – low PM) for convective events. The even and uneven numbered columns show $PM_{2.5}$ and PM_{10} correlations, respectively. Sample size (n) is depicted below each column. Asterisks indicate the significance of the Kruskal-Wallis test. Differences for convective events measured by Biral are incalculable due to the limited sample size. See Appendix 7 for 95% confidence intervals.

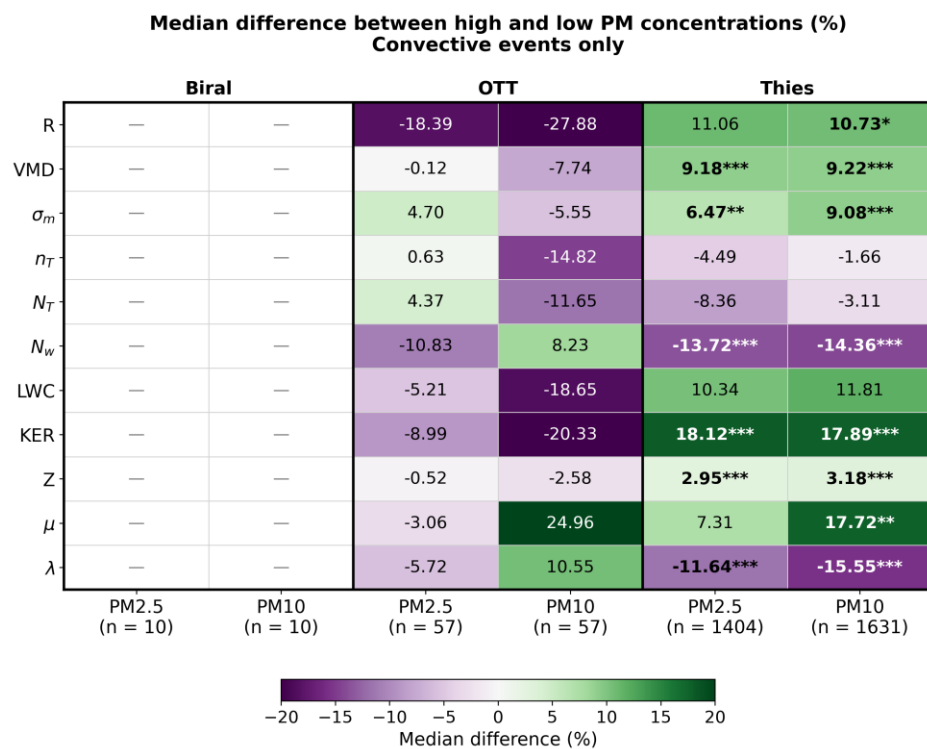
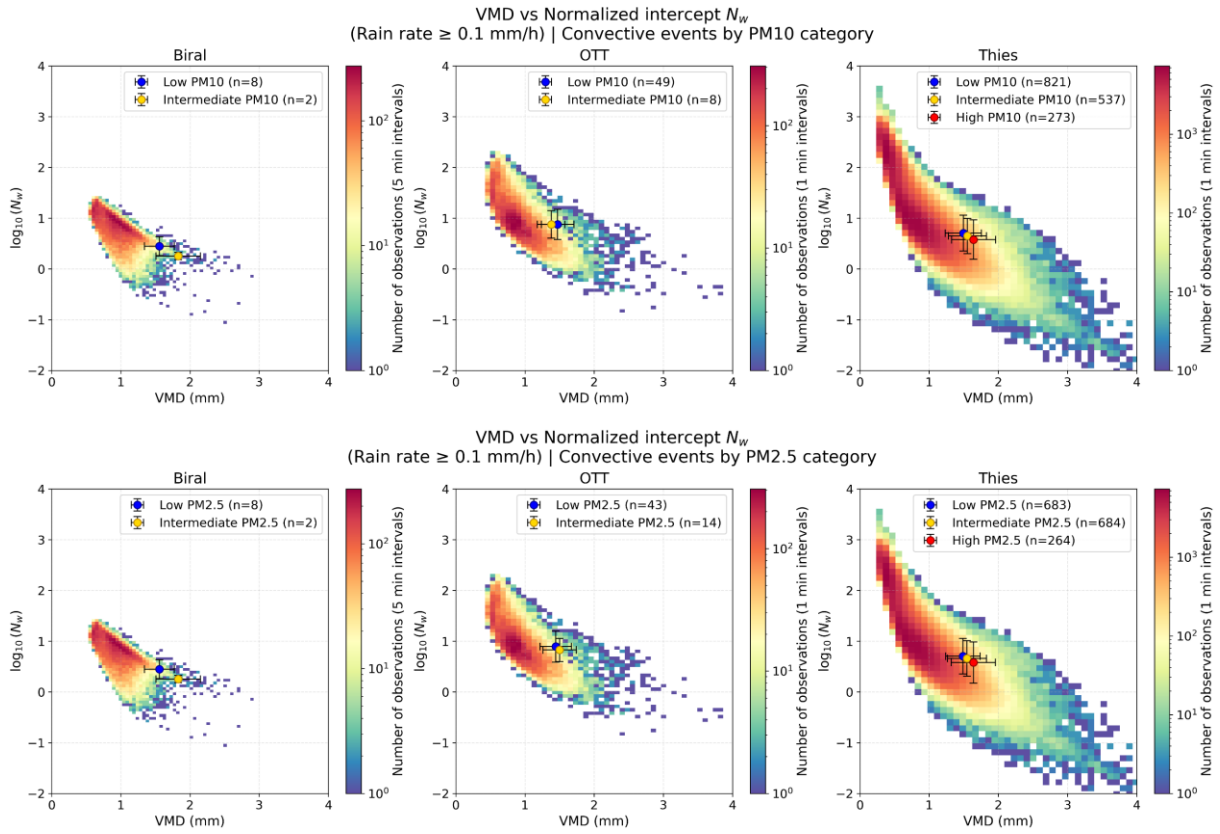


Figure 36:

Disdrometer rainfall periods in VMD- $\log_{10}(N_w)$ space, overlaid with the mean value within each PM_{10} (upper) and $PM_{2.5}$ (lower) category. Error bars indicate standard deviation. Blue, orange and red dots represent low, intermediate and high PM categories, respectively. Sample size per category is shown in the legend.



4.4.4 Confounding factors

Particulate matter concentrations are correlated with meteorological conditions such as wind speed and air pressure, which may confound the observed relationships between PM and rainfall. To better isolate the PM signal, Spearman partial correlations were computed while controlling for wind speed and mean sea level pressure (MSLP).

At the daily scale, these partial correlations indicate a consistent, though weak, relationship between PM and rainfall characteristics (Table 10). For Uccle (Biral) and Sart-Tilman (Thies), higher PM concentrations, particularly $PM_{2.5}$ are associated with lower rainfall rates ($p < 0.01$), liquid water content (LWC; $p < 0.01$) and kinetic energy rate (KER; $p < 0.01$). For Thies, higher PM is also associated with smaller drop sizes ($p < 0.001$). However, correlation coefficients remain low (generally < 0.2), indicating that PM explains only a limited fraction of the variability. Relationships involving drop concentration metrics are less consistent. For Biral, PM_{10} shows negative correlations with total drop count, total concentration and N_w , whereas for Thies, PM (especially $PM_{2.5}$) shows positive correlations with these variables. No clear or significant relationships are found for OTT, largely due to the smaller sample size.

For convective events, relationships are more pronounced for PM_{10} than for $PM_{2.5}$ (Table 10). For Thies, higher PM_{10} concentrations are associated with larger drop sizes ($p < 0.001$) and increased variability ($p < 0.001$), accompanied by a significant decrease in N_w ($p < 0.05$) and in the gamma distribution parameters μ and λ ($p < 0.001$). For OTT, correlations with PM_{10} are also stronger than for $PM_{2.5}$, although only the increase in μ is statistically significant.

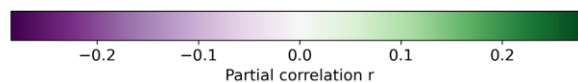
Table 10:

Spearman partial correlation between PM concentrations and various rainfall variables. For each instrument (four columns), the first two columns refer to daily mean rainfall data, while the last two columns refer to convective events. The even and uneven numbered columns show $PM_{2.5}$ and PM_{10} correlations respectively. Numbers represent the Spearman correlation coefficient (r). Numbers in bold are significant ($p < 0.05$) and asterisks indicate the level of significance. Correlations for convective events measured by Biral are incalculable due to the limited sample size.

Partial correlations between PM and rainfall variables controlled for wind speed and pressure												
	Biral				OTT				Thies			
	Daily mean		Convective events		Daily mean		Convective events		Daily mean		Convective events	
	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10
R	-0.10**	-0.08*	—	—	-0.05	-0.02	0.03	0.15	-0.16***	-0.11***	0.04	0.03
R99	-0.14***	-0.16***	—	—	-0.14	-0.13	—	—	-0.12***	-0.12***	—	—
VMD	-0.05	0.06	—	—	0.10	0.16	-0.12	-0.14	-0.18***	-0.08**	0.07	0.15***
σ_m	0.00	0.06	—	—	0.09	0.13	-0.17	-0.26	-0.13***	-0.07*	0.11**	0.16***
n_T	-0.00	-0.09**	—	—	-0.23*	-0.28**	0.11	0.25	0.09**	0.01	0.04	0.03
N_T	0.01	-0.12***	—	—	-0.17	-0.26**	0.12	0.22	0.14***	0.06*	0.03	0.05
N_w	0.01	-0.12***	—	—	-0.14	-0.22*	0.11	0.25	0.17***	0.05	-0.01	-0.09*
LWC	-0.10**	-0.08*	—	—	-0.10	-0.09	0.08	0.20	-0.12***	-0.09**	0.04	0.02
KER	-0.10**	-0.05	—	—	-0.01	0.04	0.02	0.11	-0.18***	-0.11***	0.05	0.08
Z	-0.09**	-0.05	—	—	-0.01	0.04	-0.05	-0.00	-0.16***	-0.11***	0.08	0.12**
μ	-0.07*	-0.06	—	—	-0.10	-0.10	0.20	0.29*	0.06*	0.06	-0.09*	-0.16***
λ	-0.02	-0.06	—	—	-0.12	-0.14	0.17	0.25	0.12***	0.07*	-0.09*	-0.17***

-0.2-0.1000.10.2

Partial correlation r



5. DISCUSSION

5.1 Disdrometer performance

5.1.1 *Biral VPF-730*

The Biral disdrometer shows systematic inconsistencies between reported rainfall intensities and those derived from the measured DSDs. Agreement is generally acceptable at low intensities, but discrepancies increase markedly with rain rate, with DSD-based rain rates increasingly underestimating reported values. The large spread in these deviations indicates that the mismatch cannot be resolved through a simple correction and likely reflects a combination of measurement uncertainty and internal processing. The manufacturer applies an empirical calibration to accumulated precipitation, but the details of this procedure remain unclear. In this study, a geometric correction was applied to account for the lower detection probability of large drops. However, the forward scattering principle differs fundamentally from the optical approach, which may introduce additional uncertainties regarding particle detection that are not rectified with this correction.

Comparison with rain gauge data further highlights these limitations. The Biral instrument tends to underestimate rainfall intensity relative to the gauge, consistent with the underrepresentation of large drops. This bias is exacerbated by the applied quality control, which omits observations with large deviations between reported and DSD-derived rain rates. While necessary to ensure data consistency, this filtering disproportionately removes high-intensity events, leading to a strong underrepresentation of extreme rainfall and convective conditions.

Furthermore, the methodology to calculate rain rates from the DSDs has proven unsuccessful in reproducing reported rain rates for Biral. As the reported calibration factor represents a bulk adjustment, its application would not have resolved the variability of deviations in DSD-derived variables. Greater insight into the instrument's internal processing could help reduce uncertainty and better align results with reported values. It should also be noted that the Biral VPF-730 is primarily used as a nephelometer for fog and low cloud detection and visibility applications, rather than for detailed characterisation of DSDs (Pohl *et al.*, 2021; Ye Kai *et al.*, 2019). This might mean that the instrument is less optimised for this purpose. To the best of the author's knowledge, no research on precipitation has yet been conducted using this instrument.

5.1.2 OTT Hydromet Parsivel²

The OTT disdrometer provides the most consistent and physically reliable measurements among the three instruments. Both internal validation and comparison with rain gauge data show strong agreement, with minimal bias across rainfall intensities. In contrast to Biral and Thies, no systematic underestimation of high rain rates is observed. External validation confirms this performance, with relatively low errors and a stable representation of rainfall statistics. However, the comparison also illustrates inherent limitations in point-scale measurements. The probability of detection is moderate (61%), meaning that a substantial fraction of rainfall events recorded by the rain gauge are not detected by the disdrometer, and vice versa. Such discrepancies are well documented and reflect small-scale spatial variability and sampling differences rather than instrument errors (Jaffrain, 2012). Additional sources of uncertainty include evaporation and turbulent effects, which preferentially affect small drops and can lead to differences between instruments even at very short distances (Tilg *et al.*, 2020). While optical disdrometers are often reported to overestimate rainfall relative to gauges (Vuerich *et al.*, 2009), the deviations found in this study correspond well to findings from Chinchella *et al.* (2026).

Overall, OTT provides the most robust dataset for microphysical analysis, with deviations that are largely explainable by known observational uncertainties rather than systematic instrument bias.

5.1.3 Thies Clima LPM

The Thies disdrometer benefits from a long and continuous data record, which ensures large sample sizes even after temporal aggregation. Internal validation shows generally good agreement between reported and DSD-derived rain rates, although deviations increase linearly with intensity. Most differences remain within 25%, indicating acceptable performance for a wide range of conditions. Quality control effectively removes unrealistic values, particularly cases with anomalously low calculated rain rates. In contrast, external validation with the rain gauge reveals weaker agreement. Although both instruments capture similar overall rainfall patterns and cumulative totals, exact comparisons yield low correlations. This discrepancy cannot be explained by a simple time shift, as applying a constant lag does not significantly improve the results. Several explanations are plausible. A timing inconsistency in either dataset could introduce misalignment, especially over a long observation period. Alternatively, the spatial separation between the instruments (approximately 400 m) may introduce variability due to local turbulence or small-scale heterogeneity in rainfall. However, the relatively low number of coincident rainy hours compared to the Biral dataset suggests that temporal misalignment is the

more likely explanation. The fact that aggregation to hourly resolution does not substantially improve the correlation further supports this interpretation.

Despite these limitations, the Thies dataset remains valuable due to its length and statistical robustness. However, caution is required when interpreting absolute rainfall intensities and concentrations, particularly given the known sensitivity of the instrument to small drops and the potential for timing inconsistencies in the validation data.

5.2 DSD structure and microphysical interpretation

5.2.1 Average DSD structure

The three disdrometers show broadly similar mean DSD shapes, but differ strongly in the representation of small drops. Whereas Biral and OTT are characterised by mean shapes that resemble a gamma distribution, concentrations of small drops are substantially higher for Thies, thus more resembling a negative exponential distribution. The magnitude of this difference is large, with the smallest diameter bin reaching concentrations up to 40 times higher for Thies. Part of this contrast could reflect physical processes. The Thies site is located in a more complex topographic setting, where orographic uplift can enhance the supply of small droplets and promote drop breakup through turbulence and updrafts (Kim *et al.*, 2022; Prat *et al.*, 2012; Singh *et al.*, 2024). This effect is larger for higher altitude differences, although it is already visible for low altitudes in the Alps (Napoli *et al.*, 2019). Since rainfall frequencies at Sart-Tilman (Thies) are notably higher when wind originates from directions perpendicular to the slope (west to northwest), this may indicate a possible contribution of orographic effects. However, the relatively modest elevation difference (approximately 180 m) suggests that terrain effects alone cannot explain the magnitude of the observed differences. Instrumental effects are therefore likely dominant. The Thies LPM is known to overcount small drops due to a higher sensitivity and measurement uncertainties such as splash and edge effects (Guyot *et al.*, 2019). The role of instrument effects is further suggested when looking at DSDs by rainfall intensity. For both Biral and OTT, higher rainfall intensities are associated with broader DSDs and lower peak concentrations, corresponding to more pronounced collision-coalescence. In contrast, Thies shows increasing peak concentrations with rain rate, which does not align with expected microphysical behaviour. At the opposite end of the spectrum, Biral appears to underestimate large drops relative to the other instruments. This is probably a sampling bias, as its large-drop concentrations align well with the average values from other instruments at the same rainfall intensities (Appendix 8). Since many

high-intensity observations have been filtered out for Biral, the mean DSD will thus reflect lower intensity rainfall. As a result, absolute concentrations are not directly comparable between instruments, and interpretation is therefore focused on relative trends rather than magnitudes.

5.2.2 *Microphysical relationships*

The observed relationships between bulk rainfall variables provide insight into equilibrium microphysical states. For OTT, several relationships converge towards values consistent with a negative exponential distribution. In particular, the VMD/AMD ratio approaches approximately 1.3 at high rain rates, which is close to the theoretical value of $4/3$ for an exponential DSD (Smith, 2003). This behaviour is supported by the Z–R relation ($Z = 176R^{1.59}$), which closely matches the classical Marshall–Palmer (1948) relation ($Z = 200R^{1.60}$), indicating physically consistent results.

Biral and Thies deviate from this behaviour. Biral shows a lower VMD/AMD ratio (approximately 1.2), implying a narrower distribution with a positive shape parameter. Its Z–R relation ($Z = 244R^{1.47}$) suggests a shift towards larger drops and lower concentrations, which is typically associated with convective rainfall. This appears inconsistent with the relatively low large-drop concentrations in the mean DSD, but can be explained by the underrepresentation of high-intensity events due to quality control filtering. Thies, on the other hand, exhibits a much higher VMD/AMD ratio (approximately 2.0), corresponding to a negative shape parameter. While this could indicate a steep distribution dominated by small drops, negative values are often linked to measurement errors (Alcoba *et al.*, 2022). This is consistent with the overrepresentation of small drops and the comparatively low KE–R exponent, both pointing to an exaggerated contribution of small drops across intensities. Furthermore, the Z–R relation ($Z = 154R^{1.68}$) of Thies indicates a shift towards more stratiform-like rain compared to the theoretical relation.

5.2.3 *Rainfall regimes*

The separation between convective and stratiform rainfall is physically coherent across all instruments. Convective events are associated with larger drops, higher intensities, and lower N_w , and occupy a distinct region in VMD– $\log_{10}(N_w)$ space compared to stratiform events. However, the representation of convective events differs between instruments. For Biral, the number of convective events is clearly underestimated due to the removal of high-intensity observations and the longer sampling interval. As a result, the remaining convective cases are

biased towards events with larger drops and lower variability, potentially overemphasizing ice-driven processes. This limits the representativeness of the convective sample at this site.

The μ - Λ relationship provides additional insight into DSD evolution and the stability of its shape. For convective events, Thies shows the strongest correlation, suggesting a consistent relation between shape and slope parameters. OTT exhibits a steep increase of Λ with μ , indicating rapid narrowing of the distribution, which may reflect enhanced breakup processes at higher μ . Biral shows a weaker and inverse relationship, indicating that the parameters are not consistently linked, possibly influenced by sampling limitations. For stratiform events, Biral and OTT both show strong and consistent μ - Λ relationships, indicating stable microphysical conditions. Thies, however, displays a weaker and more scattered relationship, with indications of multiple branches. This may reflect a mixture of microphysical regimes or increased sensitivity to measurement noise.

5.2.4 *Gamma parameter implications*

The behaviour of the gamma distribution parameters μ and Λ is partly linked to their formulation. When derived using the method of moments (MM), both parameters share a common denominator. Consequently, these parameters tend to behave similarly: when AMD increases relatively more than VMD, the difference between the two decreases, which leads to an increase in μ and Λ . When the difference between AMD and VMD increases, μ and Λ both decrease, unless AMD stays larger than three-quarters of VMD, in which case μ increases while Λ decreases, though this is less common.

When both parameters decrease, this suggests a higher variability of large drops, associated with higher mean drop sizes (G. Zhang *et al.*, 2003). The total concentration also increases, as a lower μ causes stronger peak concentrations of small drops. The opposite is true when both parameters increase.

5.3 Temporal variability of rainfall microphysics

In general, temporal effects on rainfall characteristics and DSDs align well with patterns found in the literature. At the diurnal scale, afternoon rain tends to be more intense, with larger drops and higher variability. This is caused by solar surface heating, leading to boundary layer development and enhanced instability, promoting convective activity during the day (Yu *et al.*, 2010). These characteristics are associated with broader DSDs, reflected in lower μ and Λ values. Nighttime rainfall, in contrast, is generally weaker and more uniform.

Differences between rainfall during morning or evening are minimal. Though the signal is consistent across all instruments, differences in magnitude, particularly for concentration-related variables, likely reflect instrument sensitivity and measurement technique rather than physical variability.

Seasonal analysis highlights pronounced differences between summer and winter. Summer is dominated by convective regimes, driven by thermodynamically induced instability, updrafts and surface energy, leading to more variable rain with increased drop sizes, intensity, kinetic energy and LWC (Tilg *et al.*, 2020). However, systematic differences between the sites suggest distinct microphysical regimes. Summer precipitation over Brussels and Liège is associated with a decrease in normalised drop concentration, consistent with a continental convective regime in which ice processes dominate (Bringi *et al.*, 2003). In contrast, Ghent exhibits an increase in normalised concentration during summer convective conditions, indicative of a more marine-influenced regime with enhanced warm-rain processes such as collision-coalescence. Winter rain, on the other hand, is characterised by stratiform precipitation with smaller drops and lower intensities, but with higher rain fractions. Drop concentrations tend to be higher, suggesting dominant drop growth through vapour deposition (Peinó *et al.*, 2024). Autumn and spring exhibit similar mean rainfall characteristics.

The timing of rainfall regimes is consistent with these patterns. Convective events occur most frequently in the afternoon and during summer, reflecting periods of high solar radiation and maximum instability. Stratiform events lack a clear diurnal pattern, owing to the synoptic origin of this regime (Jaffrain, 2012). Seasonally, they occur mostly during the winter, when convective events reach a minimum.

5.4 Urban impacts on rainfall microphysics

The three measurement sites lie in a notably different urban and environmental context, which strongly impacts the interpretation of urban effects. Brussels is characterised by a large and dense urban footprint, Ghent by a compact but spatially limited urban core, and Liège by a more diffuse and elongated urban structure. The surrounding non-urban areas also differ substantially, with extensive forest cover near Brussels, predominantly cropland near Ghent, and more complex, hilly terrain near Liège. These contrasts imply that any urban signal is subject to site-specific background conditions, making direct comparison between sites difficult.

The urban wind direction analysis does not reveal a consistent enhancement of rainfall intensity or drop size downwind of urban areas, as is commonly reported in the literature. Instead, all three sites show a tendency

towards increased drop concentrations downwind of urban sectors, while mean drop sizes and rainfall intensities either decrease (Brussels and Liège) or remain largely unchanged (Ghent). However, rainfall occurrence generally increases near or downwind of urban areas. This suggests that the cities may increase rainfall initiation, potentially through thermal convection from the UHI effect, surface roughness and turbulence (J.-Y. Han *et al.*, 2014; Torelló-Sentelles *et al.*, 2025). Furthermore, the observed decrease in rain rate and mean drop size might be caused by aerosol-induced rainfall suppression. Although urban effects generally cause enhanced rainfall intensity and larger drops over or downwind of cities, stratiform rainfall has been found to exhibit increased drop concentrations and reduced mean drop sizes in urban environments (Ma *et al.*, 2019).

The directional dependence of rainfall characteristics often appears stronger than the influence of urban fraction, indicating that large-scale wind patterns likely dominate and confound local urban effects. Additionally, the Ghent site is more sensitive to marine influences, since the urban sectors largely overlap with north-westerly winds originating from the North Sea, located less than 50 km away. Sea effects are known to favour urban rain islands by increasing moisture supply (Sui *et al.*, 2025), which might be an explanation for the lack of rainfall intensity suppression reported by OTT. Additionally, marine air masses contain coarse sea-salt aerosols acting as giant CCN, which promote warm-rain processes and partially counteract urban aerosol suppression effects. At the Liège site, local topography associated with the Meuse valley and surrounding hilly terrain may affect rainfall patterns as well, since leeward hilltops generally receive less rainfall than adjacent valleys.

Stratifying the data by season, wind speed, rainfall regime, or cover type does not significantly alter these conclusions. Urban-related signals remain weak and inconsistent, although they become slightly stronger under urban-favourable wind conditions. Interestingly, the clearest signals emerge during winter rather than summer, contrary to most studies, as UHI-driven convective enhancement is often strongest in summer. This may indicate that mechanically induced convection from surface roughness plays an important role, as this is most pronounced in winter (Daniels *et al.*, 2016; Ding *et al.*, 2025). Similarly, the analysis of convective events does not reveal robust urban enhancement, despite such effects generally being strongest for convective precipitation.

Several methodological constraints further limit the interpretation of the results. The Ghent disdrometer is located approximately 8.85 km from the city centre, and only a small number of wind sectors represent strongly urbanised conditions. These sectors largely overlap with north-westerly winds influenced by the North Sea, introducing marine effects that cannot be disentangled from urban effects. At the Liège site, the maximum urban fraction is substantially lower than at the other sites, reducing the contrast between urban and non-urban

sectors. At the Brussels site, quality control procedures remove a considerable fraction of high-intensity rainfall periods, effectively excluding many convective events. Consequently, any potential urban influence on high-intensity rainfall, such as convective precipitation, is likely underrepresented. Furthermore, since all urban sites are situated roughly north of the disdrometers, correlations with urban fraction (Table 7) may reflect wind-direction-dependent rainfall variability, rather than urban effects themselves. As easterly winds are typically drier than westerly winds, variations in rainfall occurrence associated with large-scale circulation patterns could be falsely attributed to urban influence.

In summary, these results indicate that urban influences on rainfall microphysics in Belgium are difficult to isolate from larger-scale meteorological variability and local site characteristics. The absence of a consistent signal across sites suggests that urban effects are either weak relative to background variability or highly dependent on local context.

5.5 Air pollution impacts on rainfall microphysics

5.5.1 Analysis of daily means and convective events

The spatial air pollution context of the three sites differs significantly, depending on emission and dispersion conditions. Merelbeke-Melle is located within a pronounced hotspot of particulate matter, due to its proximity to large emission sources (from nearby urban areas and highways), combined with relatively efficient dispersion owing to the low topographic variation. Uccle is influenced by emissions from Brussels but is partially buffered by the surrounding forested area. Sart-Tilman is located near a local pollution hotspot in the Meuse valley, where dispersion is more constrained by topography.

Across all sites, particulate matter concentrations show a strong long-term decline, which is the result of European and regional emission control regulations (Fierens *et al.*, 2016). This temporal trend has direct implications for the analysis. Because pollution categories are defined using fixed terciles over long time periods, datasets with shorter temporal coverage are biased towards lower pollution conditions. This is particularly relevant for the OTT dataset, where high pollution conditions are underrepresented, reducing statistical robustness for that category.

At the daily scale, a consistent relationship emerges between higher particulate matter concentrations and suppressed rainfall. This is expressed through lower rainfall frequencies, lower mean and extreme rainfall intensities, and shorter rainfall durations. While this pattern is robust across sites, it is unlikely to reflect a purely causal aerosol effect. Instead, it most likely reflects the influence of confounding meteorological conditions that enhance pollutant accumulation and suppress precipitation. High-pressure areas, for instance, are associated with low boundary layer height and suppressed precipitation, limiting the dispersion and removal of air pollution via wet scavenging (C. He *et al.*, 2024). Low wind speeds, on the other hand, inhibit the dispersion of pollutants, leading to higher concentrations (Yang *et al.*, 2022).

Changes in drop size distributions at the daily scale are less consistent. A general decrease in concentrations of intermediate-sized drops (0.5–2 mm) with increasing pollution can be linked to reduced collision-coalescence efficiency in more polluted clouds. However, responses of larger drops differ between sites and between PM metrics, indicating substantial uncertainty. This inconsistency is likely influenced by both measurement uncertainty and the use of surface particulate matter as a proxy for cloud-relevant aerosol concentrations. Although ground-based PM₁₀ and PM_{2.5} measurements are commonly used as indicators for atmospheric aerosol concentrations, their accuracy varies by region and season, and can be influenced by factors like relative humidity (He *et al.*, 2021; Mozafari, 2017; Petržala & Kocifaj, 2026).

A more detailed look at the PM–rainfall relationships shows that both rainfall intensity and VMD vary approximately linearly with increasing particulate matter concentrations. This contrasts with the non-linear or “boomerang-like” relationships reported in previous studies, where rainfall intensity initially increases with aerosol loading before decreasing at higher concentrations (Andreae *et al.*, 2004; Zang *et al.*, 2023). The absence of such behaviour in this study may reflect the dominant influence of confounding meteorological conditions, which can mask non-linear aerosol effects.

In contrast to the daily-scale results, convective events exhibit a more coherent and physically interpretable response. Higher particulate matter concentrations are associated with increased rainfall intensity and larger drop sizes. These changes are primarily driven by an enhanced contribution of large drops and increased rainfall kinetic energy. This behaviour is consistent with the aerosol invigoration hypothesis, whereby delayed warm rain processes allow more condensate to be lifted to higher altitudes, enhancing ice-phase processes and ultimately leading to more intense precipitation (Rosenfeld *et al.*, 2008). The observed shift towards higher VMD and lower N_w further supports this interpretation. However, confounding factors such as pressure may also play a role: high

pressure is generally associated with suppressed rainfall and drier conditions, due to a stable atmosphere and large-scale subsidence (Mahlobo *et al.*, 2024). On the other hand, a temperature inversion can lead to the buildup of convective available potential energy (CAPE), thus leading to more intense rainfall when the buildup exceeds the inversion strength (Tuckman *et al.*, 2023). The overall dry atmosphere also heightens the vapour pressure deficit, promoting the evaporation of small drops, which increases VMD for subsequent rainfall (Q. Yang *et al.*, 2022). Furthermore, high wind speeds generally stimulate collisional breakup, thus increasing concentrations of small drops. As aerosol concentrations are usually higher under calm conditions, mean drop sizes might be larger because of the lack of wind.

It should be noted that convective events are relatively rare, and sample sizes are limited, especially for Biral and OTT. Moreover, daily PM concentrations are used to characterise events that occur on much shorter timescales, introducing a temporal mismatch that may weaken relationships.

5.5.2 PM attribution analysis after accounting for confounding factors

After controlling for wind speed and pressure, the relationship between particulate matter and rainfall becomes weaker but remains detectable. The low correlation coefficients indicate that particulate matter explains only a small fraction of the variability in rainfall characteristics. A slight decrease in rainfall intensity with increasing PM persists, particularly for PM_{2.5}. A significant negative correlation with mean drop size is also observed for Thies. This might reflect the aerosol indirect suppression effect, which is responsible for reducing rain formation in warm clouds. At the same time, relationships involving drop concentration metrics remain inconsistent between instruments, suggesting that part of the signal reflects measurement differences rather than physical processes.

For convective events, the analysis accounting for confounding factors still indicates a tendency towards larger drops and lower N_w at higher PM concentrations, highlighting the shift towards more pronounced ice processes. However, the signal is much more pronounced for PM₁₀ than for PM_{2.5}. This may point to a role of larger particles acting as giant cloud condensation nuclei, which can accelerate droplet growth and alter precipitation processes. Research underlines that giant CCN can enhance precipitation initiation in warm clouds (Posselt & Lohmann, 2008), effectively counteracting the aerosol suppression effect, which may explain why suppression of daily mean rainfall rates was only observed for PM_{2.5} and not for PM₁₀. However, their role in mixed-phase cloud processes is less clear and may even stabilise clouds by enhancing sublimation of ice crystals (Ji *et al.*, 2025).

The absence of consistent support from the literature means that a straightforward interpretation of these results is difficult.

5.6 Further research

Several aspects of this study could be improved in further research. First, a better understanding of instrument-specific biases is needed, particularly for forward scattering instruments such as Biral, to ensure robust DSD-derived variables. Second, the analysis of urban effects would benefit from multiple disdrometers positioned in different directions relative to urban centres. This would help separate local urban influences from large-scale wind direction patterns. Moreover, detailed case studies could be employed to further investigate the ambiguous urban influence on convective events found in this study. Third, the air pollution analysis could be strengthened by using remotely sensed aerosol data instead of surface PM concentrations, allowing a more accurate representation of atmospheric aerosols as well as a distinction between aerosol types. Finally, repeating the analyses after several additional years of observations would increase the robustness of the results, particularly for the OTT dataset, which currently covers a relatively short time period. In addition to improving the robustness of the analyses, these recommendations would also support a more direct microphysical interpretation of the observed relationships, which remain largely suggestive and indirect in this study.

6. CONCLUSION

This thesis investigated how urbanisation and air pollution influence precipitation microphysics and drop size distributions (DSDs) in Belgium using high-resolution observations from three disdrometers located near Brussels, Ghent and Liège. In addition to assessing these environmental drivers, the study characterised the general microphysical properties of rainfall in Belgium and their variability across precipitation regimes and temporal scales.

The comparison between instruments revealed substantial differences in performance and derived DSD structures. The OTT Parsivel² shows the best overall agreement with the nearby rain gauge and theoretical values, such as a Z-R relationship resembling the Marshall-Palmer relation. While the laser-optical disdrometers near Ghent (OTT Parsivel²) and Liège (Thies LPM) showed satisfactory consistency, the forward-scatter disdrometer in Brussels (Biral VPF-730) exhibited larger discrepancies, leading to an underrepresentation of high-intensity rainfall periods. The Thies disdrometer tends to overestimate small drops, leading to an exponential-shaped mean DSD that is likely an instrumental artefact rather than a physical signal. For both Biral and OTT, the mean DSDs are well described by a gamma distribution.

The analysis of DSD variability depends strongly on rainfall intensity, regime and temporal scale. As rainfall intensity increases, the volume-weighted mean diameter converges towards approximately 2.2-2.6 mm, suggesting a stabilisation of drop growth processes at high intensities. Convective events, characterised by larger drops and higher rainfall intensities, occur more frequently in summer and during the afternoon, consistent with enhanced thermal instability. However, site-specific differences suggest distinct convective microphysical regimes. Reduced concentrations in Brussels and Liège indicate a more continental character, likely associated with stronger ice processes, whereas Ghent exhibits higher concentrations, consistent with a more maritime character and a larger contribution of warm-rain processes. Conversely, stratiform rainfall dominates in winter and at night and is associated with smaller drops and higher concentrations, reflecting more uniform precipitation.

With respect to urban effects, no robust or consistent downwind urban signal of rainfall is detected in the DSDs. Nevertheless, several weak trends emerge. Rainfall occurrence increases slightly downstream of cities, which may reflect enhanced mechanical convergence associated with the increased surface roughness of cities. Total drop concentrations also tend to increase, potentially indicating aerosol-induced suppression of raindrop

growth. At the same time, rainfall intensity decreases downwind of Brussels and Liège, but not of Ghent. The absence of this reduction near Ghent may be influenced by the proximity of the sea, which supplies additional moisture and partly compensates for the urban reduction in intensity. Overall, given the weak relations, it appears that local urban influences are largely obscured by large-scale circulation patterns.

Air pollution effects show a clearer, but regime-dependent signal on precipitation. On a daily scale, higher particulate matter concentrations are associated with reduced rainfall intensity, smaller drop sizes (particularly a reduction in medium-sized drops) and lower rainfall frequency. This most likely reflects meteorological conditions such as high pressure and weak winds, which are conducive to pollution accumulation and rainfall suppression. During convective events, however, higher particulate matter concentrations are associated with larger drops, lower total concentrations and increased kinetic energy. After controlling for confounding meteorological variables such as pressure and wind speed, a persistent signal remains. On daily scales, the suppression is most significant for $PM_{2.5}$, consistent with reduced collision-coalescence efficiency due to the small particles. On the other hand, convective enhancement is more strongly correlated with PM_{10} , highlighting the potential importance of large particles in stimulating rainfall under unstable conditions.

7. REFERENCES

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7.2 Datasets

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