Snow Particle Analyzer for Simultaneous Measurements of Snow Density and Morphology

Jiaqi Li1,2, Michele Guala1,3, and Jiarong Hong1,2

1Saint Anthony Falls Laboratory, University of Minnesota, Minneapolis, MN, USA, 2Department of Mechanical Engineering, University of Minnesota, Minneapolis, MN, USA, 3Department of Civil, Environmental, and Geo-Engineering, University of Minnesota, Minneapolis, MN, USA

Abstract The detailed characterization of snow particles is critical for understanding the snow settling behavior and modeling the ground snow accumulation for various applications such as prevention of avalanches and snowmelt-caused floods, etc. In this study, we present a snow particle analyzer for simultaneous measurements of various properties of fresh falling snow, including their size, shape, type, and density. The analyzer consists of a digital inline holography module for imaging falling snow particles in a sample volume of 88 cm^3 and a high-precision scale to measure the weight of the same particles in a synchronized fashion. The holographic images are processed in real-time using a machine learning model and post-processing to determine snow particle size, shape, and type. Such information is used to obtain the estimated volume, which is subsequently correlated with the weight of snow particles to estimate their density. The performance of the analyzer is assessed using monodispersed spherical glass and foam beads, irregular salt crystals, and thin disks with various shapes with known density, which shows <10% density measurement errors. In addition, the analyzer was tested in a number of field deployments under different snow and wind conditions. The system is able to achieve measurements of various snow properties at single particle resolution and statistical robustness. The analyzer was also deployed for 4 hr of operation during a snow event with changing snow and wind conditions, demonstrating its potential for long-term and real-time monitoring of the time-varying snow properties in the field.

Plain Language Summary Our study introduces a snow particle analyzer designed to simultaneously measure various properties of falling snow, including size, shape, type, and density. The analyzer uses a compact digital holography system to capture images of snow particles and a high-precision scale to weigh them. A machine learning-based software processes the images in real-time to extract snow particle properties, which are crucial for estimating the cumulative snow volume and average density. These properties are essential for the investigation of snow morphology, fall speed, accumulation rate, and related study of avalanches and snow drift. The analyzer is accurate, with less than 10% error in density measurement as assessed through laboratory tests. It has been successfully deployed under various snow conditions and provides continuous, real-time monitoring of changing snow properties, even within the same snowfall event. This information is vital for improving models of snow settling and weather forecast. Compared to existing methods, the snow particle analyzer measures frozen hydrometeors in a larger range of sizes and offers faster, more accurate volume estimation. In addition to snow, the system could be applied to other geophysical processes where the measured particle properties are important, such as monitoring mineral dust, embers, sediments, volcanic ashes, and pollens.

1. Introduction

Snow density and morphology (i.e., size, shape, and classification) exhibit significant variability under different meteorological conditions (Heymsfield, 1972; C. Li et al., 2021a; Magono & Lee, 1966). It is therefore critical to make simultaneous and accurate measurements of hydrometeor size, shape, and density near the ground, and incorporate them in the modeling of snow particles' fall velocity. All the above variables are important to better forecast the snow accumulation rate and to estimate the snow water equivalent (SWE) of falling snow for hydrology and water conservation studies (Clark et al., 2011), for prediction and prevention of snow hazards (e.g., avalanches, Steinkogler et al., 2014, and snow drift over transportation infrastructures, Ogura et al., 2002), and more broadly for studying the evolution of the snowpack and the long-term impact of snow cover on floods and climate (Cohen & Rind, 1991; Marks et al., 1998). Specifically, the rate of snow accumulation on the ground...
and its spatial variability largely depend on the terminal velocity of falling snow particles, which has been observed to vary significantly in space and time over both synoptic and micro-meteorological scales (Garrett & Yuter, 2014; Heymsfield, 1972; C. Li et al., 2021a). Even within the same snowfall event, the observed settling velocity can exhibit variations of up to 1 m/s (e.g., Figure 5 from C. Li et al., 2021a). Density and morphology of fresh falling snow are also important parameters to determine the properties of layered snowpack such as the snow depth (Jonas et al., 2009; Sturm et al., 2010), forcing on the ground, as well as conductive and radiative thermal properties (Haussener et al., 2012; Sturm et al., 1997). These properties are essential for predicting and preventing snow hazards such as avalanches (Steinkogler et al., 2014) and transportation accidents (Ogura et al., 2002). Furthermore, the thermal properties (i.e., conductivity, reflectance, and transmittance of snowpack) are expected to impact the local climate (Cohen & Rind, 1991) and snowmelt-caused floods (Marks et al., 1998).

The terminal velocity of snow is a required modeling input to link the precipitation forecast with predicted accumulation on the ground. Lehning et al. (2008) introduced the concept of “preferential deposition” to describe the spatial variability of snow precipitation and deposition. Their study, which used the Advanced Regional Prediction System model for fine-scale modeling of the wind field over steep and complex terrain, emphasized the role of atmospheric turbulence in creating inhomogeneous snow distribution, which is crucial for understanding snow accumulation patterns. Comola et al. (2019) further investigated the processes and scales that govern the preferential deposition of snow over hills. Their study, which used Large Eddy Simulations to simulate the turbulent atmospheric flow, investigated thoroughly the particle deposition in turbulence considering the coupled effects of particle inertia, flow advection, and gravity. These studies establish fundamental links between fall speed, snow accumulation, and large-scale turbulence driven by terrain complexity. However, the snow particle distribution and kinematics are affected by a wide range of turbulent scales, all the way to Kolmogorov, depending on the hydrometeors’ inertial and drag properties. Both the distribution and kinematics exhibit strong variability, and suffer from significant measurement uncertainties, due to the wide range of snow particle size, density, and morphology. In C. Li et al. (2021a), J. Li et al. (2021b), and Nemes et al. (2017), inertial properties of snow particles have been indirectly estimated using the distribution of the snow particle Lagrangian acceleration. Since the work of Bec et al. (2006), it was observed that fluid parcels, that is, passive tracers, respond to fluid acceleration much more dynamically than heavier particles and thus exhibit thicker tails in the acceleration probability density function. The particle inertial properties are quantified by the response time \( \tau_p \), that is, by the time it takes to respond to a variation in fluid velocity, which depends on the particle density, size, and drag coefficient. In the simpler case of a spherical shape, at very low Reynolds numbers, where Stokes drag is applicable, there exists an analytical formulation with the drag coefficient inversely proportional to the particle Reynolds number (Clift et al., 2005). Conversely, more complex particles, settling at high Reynolds number, such as snow particles, experience non-linear drag, and their settling velocity \( W_s = \tau_p g \) and response time remain unknown (\( g \) is the gravitational acceleration). For snow, even in the absence of turbulence, disentangling the density and size effects on \( W_s \) from the drag coefficient is challenging because of the variability in snow morphology, in the particle orientation with respect to the settling direction, and in the associated frontal area facing the settling direction (see for instance Tagliavini et al., 2021, 2022). Therefore, snow settling prediction must rely on two possible modeling avenues: first, an empirical, indirect estimate of \( \tau_p \) from particle acceleration (e.g., Nemes et al., 2017), assuming turbulence effects can be included through the dimensionless Stokes number \( St = \tau_p / \tau_q \) (where \( \tau_q \) is the Kolmogorov time scale); second, a direct estimate of \( \tau_p \) based on measurements of snow density and morphology and assumptions on the drag coefficient. In order to explore the latter method, the specific shape and weight of snow particles must be provided to estimate the correct frontal area and particle equivalent diameter, thus enabling the distinction among spherical particles (graupeIs and small particles), cylinders (needles), porous disks (plates and dendritic crystals), and porous aggregates of complex shape (e.g., of dendrites or plates). Hence, in addition to image-based methods for estimating snow settling speed in the field (C. Li et al., 2021a; J. Li et al., 2021b; Nemes et al., 2017), it is important to deploy instrumentation designed to estimate snow particle size, shape, and density.

Presently, the majority of snow analysis tools are designed to measure either snow density or morphology, but not both simultaneously. Measurement techniques commonly used in the field typically focus on assessing the density of accumulated snowpack. Examples of such techniques include snow wedge cutters (Conger & McClung, 2009; Proksch et al., 2016), snow tubes (Hribik et al., 2012; Zhang et al., 2017), snow forks (Elder et al., 2019), and micro-CT (computer tomography) scans (Elder et al., 2019; Kaempfer & Schneebeli, 2007). Notably, snow wedge cutters and snow tubes employ gravimetric measurements for snowpack density characterization, while snow forks use a semi-empirical relationship between the measured dielectric constant and
snowpack density. On the other hand, micro-CT scans were initially used by Kaempfer and Schneebeli (2007) to explore snow metamorphism under various isothermal conditions and its impact on density variation. Although micro-CT scans provide a nominal resolution down to 10 μm, suitable for investigating individual snow grains, the technique falls short in capturing the small cavities within these grains necessary for accurate estimation of individual grains. It is important to note that the density of a snowpack, while originated from the density of individual snow grains, is influenced by various factors such as packing density and interstitial spaces within the snowpack. Seasonal snow metamorphism, caused by compression of overlying snow, sublimation, condensation processes, and wind actions, also significantly influences snowpack density (Colbeck, 1982; Lehning et al., 2002 among others). This complexity points to the fact that snowpack density may not directly relate to the density of individual snow particles, which contributes to their fall speed and inertial properties. To better understand the density of freshly fallen snow, researchers have employed field snow collection and laboratory size-density measurements, as demonstrated by Locatelli and Hobb (1974). Their work established correlations between size, mass, and fall speed, as well as explored the effects of riming and aggregation on snow particle mass and fall speed. However, despite the advances made, the effectiveness of their measurement technique is compromised by the need for human intervention, the constraint of limited sample sizes, and the burden of a lengthy and labor-intensive process.

For the measurement of snow morphology, image-based techniques have been designed and employed, such as the hydrometeor velocity and shape detector (HVSD), snowflake video imager (SVI, and later precipitation imaging package [PIP]), and the multi-angle snowflake cameras (MASC). Barthazy et al. (2004) developed the HVSD for the measurement of snow shape and fall speed using two line-scan cameras. However, it is designed for hydrometers with a diameter >1 mm, and the limited resolution (0.15 mm) leads to large uncertainties in size measurement for sub-millimeter particles. Newman et al. (2009) introduced the SVI and later upgraded it to the PIP as part of the National Aeronautics and Space Administration’s (NASA’s) Global Precipitation Measurement Mission. The PIP achieves measurement of falling snow at 380 frames per second (FPS) temporal resolution and 0.1 mm spatial resolution in a 64 × 48 mm field of view (FOV). It has been successfully deployed for the assessment of microphysical and bulk properties of falling snow in several studies (e.g., Pettersen et al., 2020; Tiira et al., 2016; von Lerber et al., 2017). The MASC system utilizes three cameras, with the resolution ranging from 9 to 37 μm, viewing from different angles to obtain the 3D features of snowflakes (Garrett et al., 2012). It is also equipped with near-infrared motion detectors for snow fall speed measurements. This system has become a commercial tool for the quantification of snow particle size, their 3D features, and settling velocity. It has been applied for characterizing the size and shape of snow aggregates (Jiang et al., 2019) and analysis of the Arctic precipitation (Fitch & Garrett, 2022). In general, such a multi-camera system is susceptible to the small change in the camera relative location due to system drift, which may require periodic re-calibration, limiting its implementation for long-term particle analysis in harsh field environments (e.g., snowfall events with high wind speed).

To simultaneously measure the density and morphology of fresh falling snow, researchers have employed aircraft equipped with imaging probes for size and shape measurements and counterflow virtual impactor (CVI) for snow water content measurements (Heymsfield et al., 2004). The imaging probes are line-scan cameras capturing the 2D projection of the snow particles, and the CVI measures the vapor content of the evaporated snow particles captured by it. The imaging probes can measure snow particle sizes as small as 33 μm, and the CVI can measure the weight of water droplets or ice crystals larger than 8 μm in diameter. In their method, the snow particle size-dependent concentration is assumed to be a gamma distribution, and the particles are approximated as simple spheres enclosing them, which can potentially lead to large uncertainties. Moreover, the equipment for measuring snow particle size (imaging probe) and mass (CVI) work asynchronously (i.e., they do not necessarily measure the same snow particles). More recently, Singh et al. (2021) developed a Differential Emissivity Imaging Disdrometer (DEID) consisting of a thermal camera and a metal hotplate for measuring the mass, type, and density of hydrometeors. They utilized the large thermal emissivity difference between the hydrometeors (water) and the hotplate (metal) to measure the spatial dimension of the hydrometeors and converted the heat loss from the hotplate to evaporate them to mass. They tested the system in the lab and field (Rees et al., 2021), demonstrating that this disdrometer is insensitive to varying environmental conditions. However, the spherical approximation of the hydrometeor volume may lead to significant uncertainties for density measurements.

To address the limitations of the abovementioned snow analysis approaches, in this paper, we design and fabricate a snow particle analyzer by integrating digital inline holography (DIH) with a high-precision scale for simultaneous measurements of the density and morphology of falling snow particles near the ground. DIH has emerged as
a compact tool for measurements of the 3D flow field and particle transport since the beginning of this century (Katz & Sheng, 2010). It employs a coherent light source to illuminate a sample volume and capture the fringe patterns generated by the interference between the scattered signals from the sample and the unscattered portion of the illumination light source (referred to as holograms hereafter). The holograms contain information on the size, shape, and 3D position (longitudinal and lateral) of the particles in the sample volume. Such information can be extracted through conventional holographic reconstruction algorithms (e.g., Fraunhofer, Fresnel-Kirchhoff, or Rayleigh-Sommerfeld) or machine learning based on algorithms introduced recently by Shao, Mallery, and Hong (2020) and Shao, Mallery, Kumar, and Hong (2020). DIH has been widely applied for measuring mineral dust particles (Gaudfrin et al., 2020), cloud particles (e.g., cloud droplets, ice crystals; Fugal et al., 2004; Larsen et al., 2018), microorganisms (e.g., plankton Guo et al., 2021, and microcystis aeruginosa You et al., 2020), and drosophila (Kumar et al., 2016). Field measurements of snow particles with a large range of sizes and shapes using DIH have also been successfully conducted with a simple and low-cost setup (C. Li et al., 2021a; J. Li et al., 2021b; Nemes et al., 2017). However, the previous system only measures the size of snow particles with no quantification of snow particle shapes and types as well as their masses for density calculation. In addition, it operates at a low sampling rate, and its hologram processing and snow particle extraction algorithm require largely manual processing, which significantly limits its ability to generate large data sets of snow particle holograms and for long hours of operation in the field. Our current work will be an extension of these past efforts by introducing a new generation of DIH-based snow particle analyzer, which employs highly efficient automated data processing and incorporates high-precision weight measurements for snow density estimate.

In Section 2, we introduce the design of the proposed snow particle analyzer, encompassing both hardware and data processing software. Section 3.1 evaluates the performance of the analyzer using glass beads and salt crystals, while Section 3.2 discusses the assessment with real snow particles. The analyzer's capabilities during actual snow events are demonstrated in Section 4, followed by an extended discussion on its potential for measuring single-particle density in Section 5. Finally, Section 6 provides a summary and further discussion.

2. System Design

2.1. Hardware Design

As shown in Figure 1, the snow particle analyzer is comprised of a DIH system for imaging, a high-precision scale for weight measurement, a laptop for synchronizing and controlling the data acquisition and processing of the DIH system and the scale, and additional components including power supply, shielding and support. Except for the laptop, all the other components are enclosed in a wooden box with the dimension of 24 × 24 × 37 cm.

The DIH system employs a 532 nm continuous diode laser, a small concave lens (5-mm diameter, 5-mm focal length) as the beam expander, a collimating lens (bi-convex lens with 50.8-mm diameter and 75-mm focal length), a condenser lens (aspherical condenser lens with 50.8-mm diameter and 32-mm focal length), an imaging lens (Fujinon CF25HA-1 25 mm lens) that provides 0.5x magnification, and a complementary metal-oxide-semiconductor camera (Teledyne FLIR, Blackfly S USB3 mono, model: BFS-U3-123S6M-C). During image capturing, the camera sensor uses an active area of 2,048 × 1,500 pixel² after decimation by a factor of 2 in both width and height, operating at the frame rate of 50 FPS and an exposure time of 240 μs. Correspondingly, the spatial
and temporal resolutions of our DIH system are 14.3 μm/pixel and 0.02 s, respectively, with a sample volume of 2.93 × 2.15 (FOV) × 14 (depth of field) ≈ 88 cm$^3$. The current temporal resolution may limit our observation when particle settling velocity increases beyond 1.5 m/s, as there is a higher probability of missing a snow particle in the statistical description of its morphology, size, or density within the observation volume. Moreover, we acknowledge that measuring snow particles with such an exposure time results in some degree of image blurring. However, our estimates suggest that this blurring is minimal for sub-millimeter particles, limited to only a few pixels. Even though the fall speed increases with the particle size, we are able to keep the blurring to a small percentage, around 2%, of the particle size for particles larger than 1 mm. We can further decrease image blurring by decreasing the camera exposure time to a maximum of 10 μs while utilizing a higher-powered laser.

The high-precision scale (Vibra HT Series from Intelligent Weighing Technology) with a 0.1 mg resolution, a 200 g capacity, and a 10 Hz sampling rate is installed under the DIH system. A transparent snow sample collector is placed on the scale with the opening leveled with the upper side of the sample volume to make sure all snow particles captured by the imaging system fall into the collector to be weighed. The whole integrated system is enclosed in a wooden box for insulation and waterproofing. The top opening is adjustable with a maximum size of 4.5 × 14 cm. Such an adjustable opening in our design reduces the concentration of snow particles in the sampling volume, minimizing the chance of particle occlusion during heavy snowfall. Two shields are 3D-printed to protect the extended part of the DIH system. The power supplies for the laser and the scale are secured inside the box. A tripod adapter at the bottom enables easy deployment in the field. Both the camera and the high-precision scale are connected to a laptop through USB3 cables, which uses a custom-designed data acquisition software based on Python to control the synchronization and data acquisition of the camera and the scale.

The precision of our scale, at 0.1 mg, does have limitations in accurately characterizing individual particles with a mass below this limit. However, we are primarily concerned with the characterization of snow to improve settling velocity prediction, which requires an average density rather than a single particle density. Our resolution is sufficient to measure particle accumulation in the collector and estimate their density over periods of time shorter than micro-meteorological time scales governing appreciable statistical variations in snow morphology, for example, as those considered in Figure 9.

2.2. Data Processing Method

The data processing is divided into five steps, including hologram enhancement, snow particle detection and classification, snow particle segmentation, size and shape measurement, and density quantification, as shown in Figure 2. The collected holograms are first enhanced to remove the static background and other noises. Then, the enhanced holograms are fed into a trained machine learning model for snow particle detection. Classification is applied in parallel with the detection based on the snow particle morphology to better estimate the volume of snow particles from the dimensions of their segmented 2D projections. The volume and snow particle type are finally correlated with the weight measurement from the high-precision scale for density quantification.

A moving window background subtraction technique is applied for hologram enhancement. This method takes into account particles that adhere to the container wall and updates the background continuously. A machine-learning-based approach is employed for the detection and classification of snow particles. We apply...
Table 1
Classification and Corresponding Volume Estimation of Snow Particles

| Snow type | Code | Thickness (μm) | Volume |
|-----------|------|----------------|--------|
| Aggregate | I    | NA             | $\sum \frac{1}{n} \pi d_{eq}^3 N_i$ |
| Dendrite  | P2   | $T = 2.801d_{maj}^{0.377}$ | $\frac{1}{6} \pi d_{maj}^3 T$ |
| Graupel   | R    | NA             | $\frac{1}{6} \pi d_{eq}^3$ |
| Plate     | P1   | $T = 2.506d_{maj}^{0.398}$ | $\frac{1}{6} \pi d_{maj}^3 T$ |
| Needle    | N/C  | NA             | $\frac{1}{6} \pi d_{maj}^3$ |
| Small particle | G | NA             | $\frac{1}{6} \pi d_{maj}^3$ |

Note: The codes are assigned based on Magono and Lee (1966).

The detected snow particles are reconstructed to the focal plane, and threshold-based segmentation is applied to binarize the snow holograms. We conduct region-based measurements to obtain the size and shape of the detected snow particles. Our system is designed to operate at a frame rate of 50 FPS, which allows us to binarize the snow holograms and for even faster processing speed. As shown in Table 1, the snow particles are classified into six categories with assigned codes based on Magono & Lee (1966): aggregate/irregular (I), dendrite (P2), graupel/rime (R), plate (P), needle/column (N/C), small particles/germ (G). Sample holograms for each type of snow particle are presented in Figure 3. A total of 2,500 snow particles (each in a 256 × 256 pixel² image) are hand-picked and manually classified as the training data set. Each 16 snow particles are randomly selected to form a 1,024 × 1,024 pixel² combined image, and a total of 520 images are generated for training. The images are annotated using the software Roboflow (Roboflow Inc., https://roboflow.com/) with a bounding box for each snow particle and its type. Data augmentation is applied to the raw images to enrich the data set by rotating the images by 90°, changing the exposure between ±30%, blurring up to 7 pixels, and adding salt and pepper noise to up to 5% of the pixels. We train the model for 800 epochs, and the snow particle detection rate reaches 99%, with an average classification accuracy of 95%.

The volume of each snow particle is then estimated based on equations in Table 1. For aggregates, due to the complex shape, we first segment out the individual snow crystals (referred to as monomers in Dunnavan et al., 2019) that form the aggregates using the watershed function in MATLAB and treat each monomer as a spheroid with the diameter as the equivalent diameter ($d_{eq}$) of the 2D projection of the segment (see Appendix A and Figure A1). The volume is thus estimated as the sum of the volume of the monomers. For graupels and small particles, we estimate the volume as a whole spheroid considering the simpler geometry following the convention in literature (Heymsfield et al., 2004; Singh et al., 2021). While for dendrites, plates, and needles, as one dimension of these particles is much smaller than the other dimensions (for needles, the dimension of the cross-section is smaller than the length; and for plates and dendrites, their thickness is much smaller), their volumes are estimated based on the cylindrical shape assumption. The major axis ($d_{maj}$) is used as the diameter for dendrites and plates, and their thickness ($T$) is obtained from empirical equations (Auer & Veal, 1970). Needles, on the other hand, have the minor axis ($d_{min}$) as their diameter and the major axis ($d_{maj}$) as their length. Our current methodology for estimating snow particle volume, as described above, employs the best available techniques, given the inherent complexity of snow particle shapes and the single 2D projection provided by holograms. However, the precision of these estimates could potentially be enhanced by additional use of machine learning, beyond the snow type classification implemented here. Yet, employing machine learning to retrieve the full 3D particle morphology is currently challenged by the lack of accurate ground truth volume
measurements and by the absence of projections from other orientations (Han et al., 2019). Despite these challenges, we acknowledge the potential of machine learning in this context and consider it a promising direction for future research.

The volume of individual snow particle from each frame of hologram, estimated accounting for specific snow morphologies, is then correlated with the weight signal from the high precision scale. As the volume measurement from holograms and the weight measurement are synchronized, we then divide between increments of weight and volume during selected sampling periods to obtain the density. The duration of the sampling period is selected considering the particle fall speed, scale response time, and wind-induced fluctuations. The minimal sampling duration for snow particle density measurements is adjusted based on wind speed and snowfall intensity: under calm wind conditions (0–2 m/s), a 1-s interval is sufficient to image and weigh a few particles and, under moderate snow concentration, match the single particle image to an increment in weight. However, for wind speeds of 2–4 m/s, a 30-s interval is used to smooth out weight signal fluctuations caused by wind-induced pressure changes. We thus obtained a robust estimate of the average density of all the snow particles captured during the sampling period by summing up the volume of these particles while the weight increment is linearly obtained from the temporal signal. Moreover, the average density of multiple snow particles collected through an extended period can also be estimated as the slope of the linear fitting between the time-synchronized weight and volume signals (see example in the inset plot in Figure 2).

Figure 3. Sample holograms and corresponding illustrations for each type of snow particles: (a) aggregate (I); (b) dendrite (P2); (c) graupel (R); (d) plate (P1); (e) needle (N/C); (f) small particle (G).
3. System Assessment

3.1. Assessment With Glass Beads, Foam Beads, Salt Particles, and Thin Disks

We first assess the performance of our snow particle analyzer in the laboratory using glass beads, foam beads (spherical shape), salt crystal particles (irregular shape), and thin disks of various shapes to quantify the uncertainties related to the size and density measurement. The calibration of the system is conducted by measuring the size and density of individual glass beads and compare with the reference density of $2.5 \times 10^3$ kg/m$^3$ (Weast, 1981). The glass beads show a relatively uniform size of $d = 1.36 \pm 0.06$ mm (Figure 4a). Figure 4b shows the step increment of the volume and weight signals of each glass bead. We tested 20 individual glass beads, and the resulting average density is $2.52 \pm 0.13 \times 10^3$ kg/m$^3$, showing 5% uncertainty in the density measurement. This uncertainty arises from a combination of factors, including the precision of the weighing mechanism, variations in volume estimation due to the beads’ shape not being perfectly spherical, and fluctuations in the weight signal.

To assess the accuracy of our density estimation for particles appearing at different locations in the sample volume, we further test the system by dropping the glass beads at four different distances with respect to the camera imaging plane. Note that we also drop multiple glass beads at the same time to assess the ability of our system to handle high concentration cases. In this manner, the system is not able to accurately differentiate the weight signal of the individual particle, which is inevitable for occasions with high snow concentration. Thus, only the average density of the particles in the sample volume can be obtained. The average densities for each test are: $\rho_1 = 2.55 \times 10^3$ kg/m$^3$, $\rho_2 = 2.44 \times 10^3$ kg/m$^3$, $\rho_3 = 2.58 \times 10^3$ kg/m$^3$, and $\rho_4 = 2.50 \times 10^3$ kg/m$^3$, all within the 5% uncertainty range. Thus, we confirm the density measurement is insensitive to the relative distance of the particles to the camera.

We then use light-weight foam beads, which are spheres with diameters range from 2.6 to 3.8 mm and exhibit a ratio of minor to major axes of $0.97 \pm 0.02$, for evaluating the ability of the system to measure particles with low density (i.e., aggregates). We calibrated the average density of the foam beads filled in a plastic test tube by measuring their total volume by injecting water into the enclosed test tube. The resulting ground truth density was found to be $\rho_{gt} = 24.3$ kg/m$^3$. The same procedures used for the glass beads were applied to assess the system with foam beads and we were able to obtain measurements with results within a 10% uncertainty range relative to the ground truth density measured. Given the low density of foam beads, which is similar to the lower limit for snow particles, it is reasonable to expect a larger degree of uncertainty.

Subsequently, irregular salt particles are employed to further assess the performance of our snow particle analyzer for density, size, and shape measurements of particles with more complex geometries (i.e., graupels, aggregates). Figure 5a shows sample enhanced holograms of salt particles. Due to the complex shape, we estimate the particle volume using $V = \frac{1}{6} \pi d_{eq}^3$, where $d_{eq}$ is the equivalent diameter of the 2D projection of imaged salt particles. In Figure 5b, the average density is calculated as a function of the number of measured particles from the accumulated weight and volume using the equation $\bar{\rho}(n) = \sum_{i=1}^{n} m_i / \sum_{i=1}^{n} V_i$. Our density measurement initially fluctuates but gradually converges to a value of $2.07 \times 10^3$ kg/m$^3$ when the number of salt particles used for density
calculation increases above 12. The measured value is within 5% of the reference value of salty crystal density of $2.17 \times 10^3$ kg/m$^3$ (Haynes et al., 2016). Note that the actual time to reach convergence can vary due to the particle concentration and overall mass being weighed.

Finally, we conduct experiments with thin disks and artificial dendritic snow particles to assess the robustness of our volume estimation methodology, particularly for the dendrites and plates. The specifications of the tested circular disks and two distinct types of artificial dendritic snow particles are summarized in Table 2. Sample images and holograms are illustrated in Figure 6. These thin disks, composed of polyethylene terephthalate (PET, $\rho_{\text{PET}} = 1,380$ kg/m$^3$), are individually dropped into the snow particle analyzer. The same circular disks were also utilized by Tinklenberg et al. (2023) to study the settling of thin plates. Consistent to the established procedures outlined in Section 2.2 for the density measurement, we first detect and segment the particles, followed by a measurement of their region properties. We then proceed to estimate the volume, applying the assumption of a disk shape for all particle types, using the formula

$$A = \frac{1}{4} \pi d_{\text{maj}}^2 T$$

where $T$ in this context refers to the nominal thickness of these disk particles, as provided by the vendor's specifications and confirmed through caliper measurements of multiple disks stacked tightly together. The potential to measure the disk thickness using DIH imaging has been preliminarily tested, and its ramifications on the density estimates will be discussed in Section 5.2. We define the disk bulk density in alignment with the method propounded by Heymsfield (1972):

$$\rho_{\text{bulk}} = \left( \frac{A_{\text{crystal}}}{A_{\text{total}}} \right) \rho_{\text{PET}} = \frac{m}{V},$$

where $A_{\text{crystal}}$ represents the particle's maximum projected area, and $A_{\text{total}}$ signifies the area of the circle enclosing the maximum projection. For the circular disk, this area ratio stands at one. For the small dendrite and the large dendrite, we compute this ratio as 0.562 and 0.455, respectively, thereby deriving the bulk density summarized in Table 2.

These measurements, based on the disk's known thickness, reveal a discrepancy in density within 5% for the circular disk, and up to 10% for the dendrites. These findings align closely with the above tests involving spherical glass beads, foam beads, and salt particles. We attribute the slightly elevated uncertainties for the dendrites to the inherent ambiguities in major axis measurements, which are influenced by their varied orientation and the substantial void surrounding the edge of the enclosing ellipse.

### Table 2: Measured and Nominal Properties of the Three Types of Disks

| Particle type       | $m$ (mg) | $d_{\text{maj}}$ (mm) | $T$ (μm) | $\rho_{\text{max}}$ (kg/m$^3$) | $\rho_{\text{bulk}}$ (kg/m$^3$) |
|---------------------|----------|------------------------|----------|-------------------------------|---------------------------------|
| Circular disk       | 0.70     | 3.6 ± 0.13             | 50       | 1,376 ± 45                    | 1,380                           |
| Small dendrite      | 1.33     | 6.7 ± 0.49             | 50       | 760 ± 62                      | 776                             |
| Large dendrite      | 3.04     | 8.8 ± 0.27             | 75       | 675 ± 42                      | 628                             |

#### 3.2. Assessment With Snow Particles of Different Types

The snow particle analyzer is then assessed using snow particle hologram data sets collected during field deployments. Three data sets with different dominating types of snow particles, that is, aggregates, graupels, and dendrites, are selected for the density calibration. These data sets are...
selected from multiple deployments of the snow particle analyzer (17 April 2022 data set 1 for dendritic aggregates, 22 January 2022 data set 1 for dendrites and data set 3 for graupels, as shown in Table B1) at the Eolos field station in Rosemount, MN (44°43′36.4794″N, 93°2′51.72″W). The sample holograms from these data sets are shown in Figures 7a–7c, respectively, illustrating the clear difference in morphology across the three types of snow particles. To account for the wind-induced fluctuations of the weight signal from the scale, we use

Figure 6. Depicting various samples and their holograms. (a) Showcases the tested thin disk, small dendrite, and large dendrite; (b)–(d) Sample holograms of the thin disks (b), small dendrite (c), and large dendrite (d) showing different orientations.

Figure 7. Sample holograms of (a) aggregates, (b) graupels, and (c) dendrites; (d) linear fitting of the weight and volume measurements for the average density estimate.
linear fitting between the weight and volume time series to obtain the slope as the average density as demonstrated in Figure 7d. The results indicate that the dendrites have the highest density while the aggregates are mostly porous and thus yield the lowest density. The percentages of the dominant types are 89%, 94%, and 85%, respectively for the aggregate-, graupel-, and dendrite-dominating data set. To obtain a more accurate average density for each type of snow particle, we consider the impurities (other types of snow) within each data set and solve a set of equations $\sum_i \rho_i V_i / V = \bar{\rho}$, where $\rho_i$ is the $i$th type of snow particles, $V_i$ is the corresponding volume, $V$ is the total volume increment throughout each data set, and $\bar{\rho}$ is the average density obtained from the linear fitting. To reduce the number of unknowns, and to combine snow particles based on the volumetric estimates, dendrites and plates are grouped as one type, and graupels are grouped together with small particles (needles are neglected as there are less than 1% detected in all data sets, as the conditions that favor their formation were not present in our field deployments). We acknowledge that the density population in Figure 7 is slightly influenced by the presence of plate crystals, which constitute 15% of the dendrite-dominant data set together with other types. We opted to group dendrites and plates together in our volume estimation methodology as the volume calculations for both use a similar disk geometry (thin cylinder), which means that their influence on density estimates is similar. To improve the accuracy of density estimates and morphology classification, further research is needed to more accurately represent the branching structure of dendrites. Moreover, we have not yet obtained a plate-dominant data set for a more systematic investigation of the density difference between dendrites and plates.

The average density calculated for dendrite aggregates is $82 \pm 9$ kg/m$^3$, and it is comparable to the 20–150 kg/m$^3$ density range from Ishizaka et al. (2016). We attribute this relatively lower density to the larger size and higher porosity of the aggregates in comparison to other examined types. We derive the average density for graupels to be $140 \pm 10$ kg/m$^3$. The measurement is in agreement with the density ($\sim 120$ kg/m$^3$) measured by Ishizaka (1993) through microscopic imaging in the lab. These graupels have a relatively low average density, indicating porosity within the particles. Dendrites are estimated with a smaller volume (thin plate-like particle), with only air gaps between the icy branches. Thus, the dendrites have the largest density of $577 \pm 13$ kg/m$^3$, among the three types. Heymsfield (1972) summarized empirical equations for estimating the dendrite snow density as $\rho[d/cm^3] = 0.588d^{-0.377}$ With the size measured for the dendrites, we can obtain the average dendrite density in theory as 550 kg/m$^3$, comparable to the measured density. It is important to note that the volume estimation methods for dendrites and dendrite aggregates are different, which can lead to large differences in the estimated densities. For dendrites, we estimate their volume based on a disk shape, while for aggregates, we estimate the volume of the constituent monomers assuming each one with a spherical shape. Our volume estimation method is designed to better describe the inertial and aerodynamic properties of these particles, aiming to more accurately measure the particle response time and estimate their still air terminal velocity. The density measurement uncertainties can be attributed to the errors involved in the 3D volume estimation, snow type classification, and the linear fitting method used to obtain the average density. Specifically, our 3D volume estimation shows 5% uncertainty based on the laboratory calibration using irregular salt particles and up to 4.9% uncertainty in volume considering the misclassification of snow type.

4. System Demonstration

The performance of our snow analyzer is evaluated through a multi-hour field deployment, during which the snow analyzer is shown to provide a detailed characterization of the variation of snow particle properties over time. The deployment was conducted on 22 January 2022, between 18:00 and 23:00 local time, at the Eolos field station in Rosemount, MN. The field station is equipped with a meteorological tower for atmospheric flow quantification. Four sonic anemometers, each with a 20 Hz sampling rate (CSAT3 from Campbell Scientific), are placed at heights of 10, 30, 80, and 129 m on this tower. Moreover, six cup-and-vane anemometers, which sample at a 1 Hz rate, are installed at elevations of 7, 27, 52, 77, 102, and 126 m on the same meteorological tower. The field station and the instrumentation are described in more detail in Heisel et al. (2018), Hong et al. (2014), and Toloui et al. (2014). The top plot in Figure 8 shows the streamwise wind speed and turbulent intensity variation over time. The blue dashed boxes indicate the three 9-min sampling periods during which the snow particle analyzer was acquiring data. Under 50 FPS, a total of 24,000 holograms are captured for each sampling period. The wind speed increases at around 20:00 local time and stays at about 2 m/s after 20:30. Turbulent intensity first increases and drops at around 20:00, then grows again after 20:15 and holds at the highest level from 20:50 till the
end. Although the wind changes during the deployment, temperature and relative humidity keep the same level at around −13°C and 84%, respectively.

The snow type and size distribution across the three sampling periods change drastically, as shown by the six small plots in Figure 8. Note that the snow particle diameter $D$ is defined as $d_{\text{eq}}$ for aggregates, graupels, and small particles, as $d_{\text{maj}}$ for dendrites and plates, and as length $L$ for needles. Dendrites and plates dominate the snow particle types for sampling period 1, with a more uniform distribution in size across the three periods. The number of dendrites and plates decreases during sampling period 2, with a wider size distribution, indicating larger aggregates. Sampling period 3 has mostly graupels and few aggregates, with no particles with a diameter larger than 4 mm.

Specific time variations of the snow density and size are presented in Figure 9. As discussed in Section 2, we apply a 30-s moving averaging window to the time series of the particle size and density estimates for the three distinct sampling periods considering the wind-induced fluctuations of the weight signal. The average density decreases during sampling period 1 and climbs up during sampling period 2. During sampling period 3, the fluctuation magnitude of average density is shown to be much larger, due to more substantial variability in snow morphology, with larger density peaks representing short periods with smaller and denser particles. Note that empirical equations from Brandes et al. (2007), Locatelli and Hobbs (1974), and Heymsfield (1972), and reference therein, suggest that the density of snow particles exhibits a negative correlation with their size, supporting...
our measurements here (comparing the temporal trends of \( \langle \rho \rangle_{30\, \text{s}} \) and \( \langle D \rangle_{30\, \text{s}} \), in Figures 9a–9d, and 9b–9e, while it is less clear in Figures 9c–9f).

The mean snow size (\( \bar{D} \)), density (\( \bar{\rho} \)), volume fraction (\( \phi_v \)), together with the mean wind speed (\( \bar{U} \)), root mean square of fluctuating velocity (\( u_{\text{rms}} \)), turbulent intensity (TI), RH, and temperature (\( \bar{T} \)) during the three sampling periods are listed in Table 3 for comparison. Note that the volume fraction is obtained by the equation \( \phi_v = \frac{V_{\text{total}}}{N_{\text{img}} V_S} \), where \( V_{\text{total}} \) is the volume of all snow particles detected during the sampling period, \( N_{\text{img}} \) is the number of images captured, and \( V_S \) is the sample volume of the DIH system. The volume fraction estimated for the current snow event is comparable to those from C. Li et al. (2021a), J. Li et al. (2021b), and Nemes et al. (2017).

In comparison to the other two sampling periods, the snow particles from sampling period 1 have a relatively large size and the most significant density due to the presence of many dendrites and plates. The ground temperature of around −13.5°C was measured by the sensor accompanying the cup-and-vane anemometer at a height of 7 m. While we acknowledge that cloud temperature is more directly relevant to the formation of snow crystals, we do not have the means to measure it directly at our field site. Therefore, we made an estimation of the cloud temperature to be similar value based on the ground temperature and the observed temperature profile (showing less than 0.5°C difference) in the weakly stable atmospheric boundary layers up to the top sensor height of 129 m. This temperature suggests the formation of primarily dendrite- and plate-like crystals in the clouds (Magono & Lee, 1966). As the snow volume fraction, wind speed, and turbulent intensity increase, snow particles have a higher chance of clustering, colliding, and forming larger aggregates when they fall from the clouds to the ground during sampling period 2 (Dunnavan et al., 2019; Fujiyoshi & Wakahama, 1985; C. Li et al., 2021a). The reduction in the number of dendrites and plates with large densities, as well as the growing percentage of large size aggregated particles, lead to the smaller snow density during sampling period 2 as compared to that

| Sampling period | \( \bar{D} \) (mm) | \( \bar{\rho} \) (kg/m\(^3\)) | \( \phi_v \times 10^{-3} \) | \( \bar{U} \) (m/s) | \( u_{\text{rms}} \) (m/s) | TI | RH (%) | \( \bar{T} \) (°C) |
|----------------|------------------|------------------|----------------|----------------|----------------|---|-------|-----------|
| 1              | 0.77 ± 0.46      | 234 ± 24         | 15             | 0.86           | 0.17           | 0.19 | 84.4  | −13.1     |
| 2              | 0.80 ± 0.57      | 91 ± 16          | 28             | 1.99           | 0.54           | 0.29 | 85.0  | −13.4     |
| 3              | 0.43 ± 0.23      | 200 ± 38         | 22             | 1.98           | 0.57           | 0.28 | 84.6  | −13.0     |
during sampling period 1. During sampling period 3, near the end of the snow event, the concentration of snow in the atmosphere decreases as indicated by the drop of snow volume fraction, leading to a lower snow particle collision rate. Thus, the number of aggregates is at its lowest, and the majority of the snow particles observed are small graupels formed through the process of deposition of water vapor and riming (coating of supercooled water droplets on ice crystals) as the crystals fall from the clouds to the ground (Harimaya, 1988). As the mean particle size decreases drastically from sampling period 2 to 3, along with the reduction in the number of aggregates characterized by smaller density, the mean snow particle density increases from 91 to 200 kg/m³.

5. Individual Snow Particle Analysis

5.1. Individual Snow Particle Weight and Density

In addition to the measurement of average density and statistics of snow particles from a sequence of holograms, the snow analyzer is also capable of quantifying the density of individual snow particles. This analysis is particularly feasible under specific micrometeorological conditions, namely low wind speed (0–2 m/s) and moderate snow concentration. These conditions allow for accurate weight measurements and ensure that there are enough samples of individual snow particles for analysis. Individual particles are filtered out from the collected snow holograms by the following criteria: (a) only one particle is present in the current frame; (b) no other particles appear during the period ±0.5 s from the current frame considering the response time of the scale. To obtain the weight of the particles, we analyze the time series data from our scale, looking for an identifiable increment larger than 0.1 mg, which is above the minimum measurement range of our scale, within 0.5 s after the snow particle being captured by the DIH system. By carefully selecting particles that meet these criteria, we ensure that any inverse dependence of particle density on size is a genuine observation and not an artifact of measurement error.

In Figure 10a, we show the time series of the weight signal associated with the corresponding imaged snow particle. Classification is also applied to the individual snow particles for better volume estimation.

Our measurement result is shown in Figure 10b, with particles covering a large size range (from 0.5 to 6.5 mm). Individual needles are not observed after filtering due to the rare occurrence within the presented data sets. Overall, our findings concur with earlier measurements of individual snow particles (Brandes et al., 2007; Heymsfield, 1972, 1978; Locatelli & Hobbs, 1974; Magono & Nakamura, 1965), demonstrating a negative correlation between size and density. Specifically, as shown in Figure 10c, dendrites (P2) from snow particle analyzer measurements align with the density empirical equation \( \rho_{[g/cm^3]} = 0.588d^{-0.377}_{[mm]} \) from Figure 5 of Heymsfield (1972) with 34% average deviation defined as: \[ \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\rho_{\text{meas}, i} - \rho_{\text{calc}}(D_i)}{\rho_{\text{calc}}(D_i)} \right| \], where \( \rho_{\text{meas}} \) is the measured density of the \( i \)th dendrite, and \( \rho_{\text{calc}}(D) \) is the calculated density using its diameter from the empirical equation.

The measurements of dendrite aggregates cover the same range of masses and maximum dimensions as those from Locatelli and Hobbs (1974), and this also holds true for graupels. Consequently, the mass-diameter power law dependencies derived from Locatelli and Hobbs (1974) do not exhibit significant differences for particles with mass smaller or larger than 0.1 mg. This suggests that our field instrumentation, despite its limited mass resolution, may still be suitable for the task. We recognize that the graupels from our measurements are not classified into subgroups and encompass a broader range of densities compared to those from Locatelli and Hobbs (1974). Thus, the observed density variation can be attributed to the limited ability of our imaging system to differentiate graupels with varying porosities and degrees of riming.

The above analysis suggests that the snow classification and the associated density estimation are reasonably accurate at the single particle scale, and not only statistically for snowfalls characterized by a dominant morphological type. The individual snow density analysis can provide us with the necessary information to understand the impact of individual snow density and morphology on its settling behavior. With experimentally validated, size-specific, statistical correlations between snow particle size and density, we can estimate the density of specific snow particles using only imaged-based methods with no need for simultaneous weight measurements. Such correlations would allow us to extend the scenarios in which we can deploy our system for studying snow particle aerodynamic properties and improve snow settling predictions, for example, under high snow concentration, where only the average snow density of particles with different sizes and shapes can be obtained, or under strong wind where weight measurements are challenging. Snow morphological types that remain challenging to identify and characterize are the graupels due to the variability in the riming process observed in nature.
5.2. Discussion on Dendrite Density Evaluation

The primary aim of our study is to better understand the aerodynamic behavior of snow particles, particularly their drag coefficient, particle response time, and terminal fall speed. To this end, we define the density of a snow particle as a bulk density, which plays a crucial role in achieving our research objectives. In estimating the volume and density of dendritic snow crystals as mentioned in Section 2.2, we have adopted an approach informed by the findings of Tagliavini et al. (2021). These findings suggest that dendrites exhibit kinematics similar to circular disks. Consequently, we estimate the volume of these dendrites based on the assumption of a disk shape. This approach allows us to account for the spaces between the fractal branches of the dendrite, which we consider as porosity within the snow particle. Our methodology aligns with the extensive discussions by Heymsfield (1972) and the early measurements of Nakaya & Terada (1935), where the thin disk analogy was first used.

The density of dendrites is thus estimated based on their major axes. For the dendrite thickness, we referenced the comprehensive lab microscope measurements conducted by Auer and Veal (1970) on over 1,500 natural ice crystals. Their empirical equations of crystal diameter and thickness, spanning a broad range of sizes, have proven to be a valuable reference. Notably, the temperature range under which they obtained the dendrites (−13~−17°C) aligns with our measurements, further validating our methodology. However, we acknowledge that the use of the empirical equation could introduce potential uncertainties in the volume estimation of dendrites. Specifically, higher resolution holograms and associated training sets may reduce this uncertainty, by providing the YOLOv5 machine learning model with the ability to subclassify graupel based on their internal ice structure composition.

(Figure 10f)
Auer & Veal's data shows a gap for diameters from 0.5 to 1.5 mm, a range within which a significant portion of our measured dendrite crystals fall. Furthermore, for dendrites with a diameter of around 2 mm, the thickness was observed to vary from 40 to 80 μm. These factors could lead to a discrepancy of up to twofold in volume estimation, and consequently, in density estimation.

Our DIH system provides a potential in measuring the thickness of dendrite particles. To access such a capability, we conduct additional analysis. Our analysis of the PET artificial dendrite particle images yields a minimal thickness of 84 μm, compared to the ground truth of 50 μm. Further analysis of the observed (real) dendrite snow particles yielded a minimum thickness of 120 μm for a dendrite diameter (major axis) of 1.3 mm. This measured thickness is approximately twice as large as the thickness of 42 μm predicted by the empirical equation by Auer and Veal (1970). The resulting effect on the density of dendrites is significant: DIH alone may underestimate the density due to overestimated crystal thickness, while the volume formulation based on Auer and Veal (1970) may lead to an overestimate in the density due to unexpected riming or other uncertainties in the original data set. While we recognize the considerable challenges in the thickness measurement from DIH, it is important to note that the observed discrepancies could be attributed to various factors, such as the orientation of the imaged particles and potential accretion and riming on the dendrites. The challenges in these measurements underscore the complexity of the task at hand. Looking forward, we believe that there are ways to enhance the accuracy of our plate thickness measurements. One promising approach is to increase the frame rate of our system. By doing so, we would be able to capture holograms of the same particle with multiple orientations. This would increase the probability of obtaining a more accurate representation of the true thickness of the dendrite particles. Another possibility is to increase the camera spatial resolution and increase the accuracy of thickness measurements.

6. Conclusions and Discussion

In this study, we present a snow particle analyzer for simultaneous measurements of various properties of fresh falling snow, including their size, shape, type, and density. The analyzer consists of a DIH system for imaging falling snow particles in a sample volume of 88 cm³ and a high-precision scale to measure the weight of these same particles in a synchronized fashion. The DIH system is able to capture snow particles with size ranging from 0.03 to 15 mm, based on the camera pixel resolution and FOV. The holographic images are processed in real-time using a customized YOLOv5 machine learning model to determine snow particle size, shape, and type. Such information is used to classify the snow precipitation and correctly estimate the volume, which is subsequently correlated with the weight of snow particles measured by the scale to obtain their density. The performance of the analyzer is assessed using monodispersed spherical glass and foam beads, irregular salt crystals, as well as thin solid and porous (dendrite-like) disks with known density, which shows <10% density measurement errors despite the uncertainties involved in the particle volume estimate. In addition, the analyzer has been tested in a number of field deployments under different snow and wind conditions. The integration of machine learning-based data processing allows us to autonomously detect and classify the imaged snow particles based on their morphology, and statistically estimate particle properties such as size, shape, and density. Under different snowfall events, we are able provide the size distribution and geometric properties of frozen hydrometeors, as well as their time-average density. When deployed during a 4-hr snow event under changing snow and wind conditions, the analyzer demonstrated its ability to monitor in real time the time-varying snow properties in the field.

The system was also tested to estimate high-resolution particle morphology and weight, down to the single-particle scale. Despite limitations due to scale precision, wind sensitivity, and snow particle concentration, we were able to conduct preliminary investigations of snow-type specific correlations, such as size and density, based on individual particle data. These findings were then compared to seminal studies in the literature (Heymsfield, 1972, 1978; Locatelli & Hobbs, 1974). Acquiring such information is crucial for enhancing the modeling of terminal velocity of falling snow, predicting ground snow accumulation, and determining snowpack porosity, density, and thermal properties. Moreover, it plays a vital role in estimating SWE for hydrological studies.

Compared to the precipitation imaging package and multi-angle snow camera, our snow particle analyzer offers a larger depth of focus (effectively a larger sample volume) for measuring snow particles. Our system also provides...
more accurate volume estimation based on the classified snow type, with machine learning-based image processing enabling a much higher processing speed in comparison to the DEID. However, the improvements in depth of field and sample volume come at the expense of reduced contrast within the particle boundaries, which varies based on the particle position within the sample volume. This limitation hinders our ability to distinguish certain details of the rimed ice structure within graupels, which is unfortunate as this structure accounts for the considerable density variability observed in nature.

There are still several improvements that can be made to our design. First of all, the minimal duration of the sampling period to obtain stable density measurement is limited by factors such as the response time of the high-precision scale, the time lag due to particle falling, and wind-induced fluctuations. We can potentially use a high-precision load cell that has a faster response to the weight changes and improve the mounting of the collector on the scale to reduce this minimal duration. In addition, with high wind speed, the weight of snow particles may not clearly emerge from the large wind-induced temporal fluctuations. It would be problematic if the snow and wind conditions change within a short time scale over which the wind-induced weight fluctuations cannot be averaged out. Shields around the snow particle analyzer would be necessary to minimize such fluctuations in the weight signals. Second, snow terminal velocity is an important variable for predicting snow accumulation, which is not measured in our current system due to the confined sample volume. A new design that allows for simultaneous measurement of settling velocity and morphology with a larger imaging area (up to 6 × 6 cm), as shown in Gopalan et al. (2008), and potentially even larger than 10 × 10 cm in theory, as reported by Ekimov (2019) in a potentially undisturbed vertical channel can resolve this issue. Thus, correlations among settling velocity, morphology, and density could be obtained with combined data from the current and new systems. Third, the setup is currently not designed for remote operation or for being left unsupervised in the field for multiple snowfall events. The collected data is stored on local drives, which takes up a large portion of the storage space, but enables us to accumulate a comprehensive database of various snow particle types over multiple field deployments. By scanning through this enriched database, we can enhance the robustness and accuracy of our machine-learning-based detection and classification model. With a more robust and accurate model, we can pave the way for real-time data processing alongside data acquisition. This advancement would enable the system to selectively save image crops of detected snow particles or specific variables that describe their morphology. Consequently, this would reduce the storage requirements and allow the system to operate over extended periods. Beyond optimizing data-saving and storage, achieving long-term measurements over several days requires comprehensive enhancements to our snow particle analyzer. This includes a redesign of the snow collector, including the integration of a self-cleaning mechanism, a data logger, and a robust protective system akin to those in wind and temperature measurement instruments. These improvements will equip our system for extended field deployments during significant snowfall events. Finally, it is worth noting that the technology developed in this study for snow measurements holds potential for broader applications. Specifically, it can be adapted to analyze other particles involved in geophysical processes where size, shape, type, and density are important, such as mineral dust, embers, sediments, volcanic ashes, and pollens, etc.

Appendix A: Volume Estimation for Snow Aggregates

Due to the uniform geometry of graupels and small particles (close to a sphere), as well as disk, dendrites, and needles (close to a cylinder), we can estimate their volume easily using one or more of the measured parameters, that is, major axis length, minor axis length, and equivalent diameter. However, snow aggregates can have more complex and irregular geometries, as shown in Figures A1a and A1c. Thus, the simple spherical assumption would lead to large uncertainties in volume estimation, especially for the ones with a large aspect ratio (i.e., major axis over minor axis). As the snow aggregates are composite of several snow particles (monomer), we apply image segmentation (watershed function in MATLAB) to obtain those monomers and treat each monomer as a spheroid. The volume of the snow aggregate is estimated to be the sum of the volumes of each monomer ($V_{eq, tot} = \sum_{i=1}^{N} \frac{1}{6} \pi d_{eq, i}^3$). By comparing the volume estimated by this method to the volume estimated assuming a single sphere ($V_{eq} = \frac{1}{6} \pi d_{eq}^3$), we find a systematic overestimation of $V_{eq}$ (Figure A1c). We believe that the volume estimates after segmentation are more accurate than the volume estimates assuming a single sphere.
Appendix B: Field Equipment and Field Condition Summary

As shown in Figure B1, our snow particle analyzer is deployed at the field station with a 20-m distance to the meteorological tower for quantification of the field atmospheric and field conditions. The field conditions have been summarized in Table B1.
Table B1
Summary of the Field Deployments Conducted, Including the Duration of the Data Sets, Mean Temperature, Mean Relative Humidity, Snow Particle Size Range, Dominant Snow Type, Mean Snow Density, Mean Wind Speed, and Turbulent Intensity

| Date          | Duration (min) | \(\bar{T}\) (°C) | RH (%) | \(D_{\text{max}} \sim D_{\text{min}}\) (mm) | Dominant type | \(\bar{p}\) (kg/m\(^3\)) | \(\bar{U}\) (m/s) | TI |
|---------------|----------------|------------------|--------|--------------------------------------------|--------------|-----------------|----------------|----|
| 22 January 2022 | 9              | −13.1            | 84.4   | 0.26 \sim 6.5                              | P1 and P2    | 234             | 0.86           | 0.19|
| 22 January 2022 | 9              | −13.4            | 85.0   | 0.24 \sim 8.4                              | I and R      | 91              | 1.99           | 0.29|
| 22 January 2022 | 9              | −13.0            | 84.6   | 0.25 \sim 3.8                              | R and G      | 200             | 1.98           | 0.28|
| 17 April 2022  | 45             | 0.4              | 96.4   | 0.16 \sim 18                               | I and P1     | 76              | 1.78           | 0.19|
| 17 April 2022  | 45             | 0.3              | 97.2   | 0.17 \sim 9.5                              | I and P1     | 82              | 2.31           | 0.17|

Conflict of Interest
The authors declare no conflicts of interest relevant to this study.

Data Availability Statement
The snow classification data used for the machine learning model training is available at https://hdl.handle.net/11299/241878 (J. Li et al., 2022).

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