



Patterns of Solid Precipitation Particle Size and Velocity Distribution from Long-term Observations in North Japan

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Abstract. This study conducted long-term observations using a volume scanning video disdrometer at five sites
15 representative of the two contrasting climates in Japanese snow-covered areas to identify generalized patterns of solid
precipitation particle size and velocity distributions (PSVDs). A novel framework combining the expectation-maximization
(EM) algorithm and self-organizing maps successfully approximated complex distributions composed of multiple particle
types through the superposition of generalized child distributions. This approach effectively eliminates the need for
subjectively preconfiguring the number of child elements and mitigates the overfitting problem in standard EM algorithms.
20 The child distributions were broadly classified into four groups: (S) a small and slow distribution serving as a fundamental
component commonly present in all observed PSVDs; (A1) a large and slow distribution primarily corresponding to
aggregated plate-type crystals; (A2) an intermediate distribution between A1 and G primarily corresponding to aggregated
column-type crystals or their combinations with plate-type crystals; and (G) small and fast distributions corresponding to
riming crystals. While the pattern consisting solely of S with low particle concentrations was the most frequent across all
25 sites, superposition patterns of S+A1 and S+A2 (or solely A2) were the next most prevalent. These patterns were site-
specific: S+A1 patterns predominated at sites facing the Sea of Japan, where precipitation is primarily driven by the winter
monsoon, whereas S+A2 (or solely A2) patterns were more frequent at inland sites dominated by extratropical cyclones. As
a generalizable framework, the findings of this study could potentially refine bulk microphysical schemes.

1 Introduction

30 Precipitation particle size and velocity distribution (PSVD) is one of the most fundamental descriptors of microphysical
and precipitation processes. The PSVD allows for the derivation of precipitation particle concentration, precipitation rate,
size distribution, velocity distribution, and radar reflectivity, by integrating the distribution and by calculating its moments.



The PSVD also reflects precipitation particle types such as liquid, mixed-phase, graupel, and aggregates of solid particles, as well as their degree of riming (Bernauer et al., 2016; Ishizaka et al., 2013; Locatelli and Hobbs, 1974; Nakai et al., 2022).

35 This nature is furthermore utilized to estimate snowfall depth (Ishizaka et al., 2016; Takami et al., 2022). A bulk microphysical scheme, generally implemented in numerical meteorological models, forecasts precipitation amounts by assuming several categories of particle types and a corresponding PSVD for each, typically represented by a parametric Gamma distribution for diameter and a power law for velocity (Liu et al., 2023; Tomita, 2008). However, this assumption introduces large uncertainty into the calculation of precipitation amounts (Gilmore et al., 2004), which may be particularly
40 problematic when forecasting snowfall, because the wide variety of snow particles leads to high variability in both size and velocity (Grazioli et al., 2022; Locatelli and Hobbs, 1974). Hence, a statistically robust and parametric PSVD based on a long-term observation is required to reduce the uncertainty in the snowfall amount forecasting.

Japanese snowfall is mainly given by winter monsoon and extratropical cyclones. The winter monsoonal wind, carrying cold and dry airmass, blows from Eurasia onto the Sea of Japan, where the sea surface is relatively warm. Consequently,
45 many convective clouds are produced, are advected to the coastal Japanese region facing the Sea of Japan, and produce large amounts of snowfall. Field observations using hydrometer videosondes showed a variety of solid precipitation particles such as graupel, heavily rimed particles, and unrimed crystals, depending on the developing stage of convective clouds and updraft intensity (Murakami et al., 1994). Several visual observations on the ground reported that graupel and densely rimed aggregates frequently occurred during winter monsoonal conditions in Japan, although unrimed or lightly rimed crystals also
50 fall from widely spreading clouds (Nakamura, 2022; Yamaguchi et al., 2019). This winter monsoonal snowfall often occurs just after the passage of an extratropical cyclone and continues for more than a few days. On the other hand, solid precipitation particles in approaching extratropical cyclones may differ from those observed during winter monsoonal conditions, probably because of different precipitation systems. In New York, side-planes and bullets grow in cold temperatures ($< -10^{\circ}\text{C}$) with light riming are occurred within the outer comma head to the north and northeast of the
55 cyclone, associated with the warm conveyor belt (Colle et al., 2014). In Japan, many unrimed crystals are often observed during the approach of extratropical cyclones, which causes snow avalanche hazards (Matsushita, 2021; Nakamura, 2022; Yamaguchi et al., 2019). These previous studies indicate that the PSVD patterns may depend on whether they are associated with convective or stratiform precipitation during cyclone passage and the winter monsoon. Thus, their climatological patterns may be location dependent, differing between areas facing the Sea of Japan and inland. In fact, although based on
60 rainfall observations in China, the results show that size distributions tend to be narrower for stratiform than for convective precipitation (Niu et al., 2010), suggesting that the difference in precipitation type, along with geographical factors, is one of the dominant factors in characterizing size distributions (Wang et al., 2025). However, the PSVD patterns from snowfalls have not been identified yet. King et al. (2024) found three empirical orthogonal modes that potentially characterize precipitation intensity, snow particle density, and the slope of the size distribution; however, comprehensive patterns
65 incorporating particle velocity distributions were not addressed.



There are mainly two reasons why PSVD patterns and their location dependencies have not been fully investigated using long-term observations. One is a cost associated with instrumentation. This is because disdrometers such as Laser Precipitation Monitor (LPM; Angulo-Martínez et al., 2018) and PARSIVEL (Löffler-Mang and Joss, 2000) are expensive to install across multiple sites. For long-term observations, maintenance costs are also significant factor. Moreover, measurable range for size by LPM and PARSIVEL is insufficient for solid precipitation; for instance, the maximum size measurable by LPM is only 8 mm. Another reason is the issue of mixed distributions—specifically, multimodal distributions resulting from the coexistence of multiple types of precipitation particles, which is sometimes observed in nature (Brandes et al., 2007; Yuter et al., 2006). Although resampling with a very short time interval, such as one minute, can partly mitigate this problem, it leads to an insufficient sample size to obtain an accurate probability distribution (Smith et al., 2009). Consequently, this limits the targets to heavy snowfall cases and prevents the identification of general PSVD patterns over a long-term period. Although nonparametric analyses such as principal component analysis (PCA) may circumvent the issues associated with multimodal distributions (King et al., 2024), they do not provide a parametric representation, making them difficult to integrate into numerical atmospheric models. Moreover, our preliminary experiments indicated that PCA failed to capture a significant variety of PSVD patterns.

To address the aforementioned mixed distribution and cost problems, we have developed a low-cost disdrometer and a widely applicable algorithm for obtaining parametric PSVDs from disdrometer data. The Volume Scanning Video Disdrometer (VSVD) is a specialized instrument designed specifically to measure solid precipitation (Katsuyama and Inatsu, 2021). Its measurement range is sufficiently broad for solid precipitation, extending up to 30 mm, and it offers performance comparable to the Two-Dimensional Video Disdrometer (Kruger and Krajewski, 2002), while remaining cost-effective enough for multi-site deployments. Katsuyama and Inatsu (2020) obtained parametric PSVDs following a mixed joint probability density function (PDF) using an Expectation Maximization (EM) algorithm, which enabled the estimation of the constituent components of the PSVDs regardless of whether the data contained multiple types of precipitation particles. Furthermore, the estimated PSVDs were grouped into graupel and snow categories using a self-organizing map (SOM), an unsupervised machine learning method (Kondo et al., 2024).

This study performed long-term observations with VSVDs at five widely distributed sites in Northern Japan, capturing snowfalls produced by both the winter monsoon and the passage of extratropical cyclones. The observation period varied by site, reaching a maximum of nine years. The observed original PSVDs, which potentially consisted of multiple particle types, were first approximated as the superposition of several child elements using the EM algorithm. Following Kondo et al. (2024), the SOM classified these child elements into a few typical patterns; however, the method was partially updated to accommodate a wider variety of PSVD categories. Finally, we investigated these typical PSVD patterns and their location dependencies.

This paper is organized as follows. Section 2 provides a brief description of the VSVD, the details of the combined EM algorithm and SOM framework, and the other data used to evaluate the framework and its relationship with synoptic meteorological conditions. In Sect. 3, we first present the PSVD patterns commonly observed across all sites as identified by



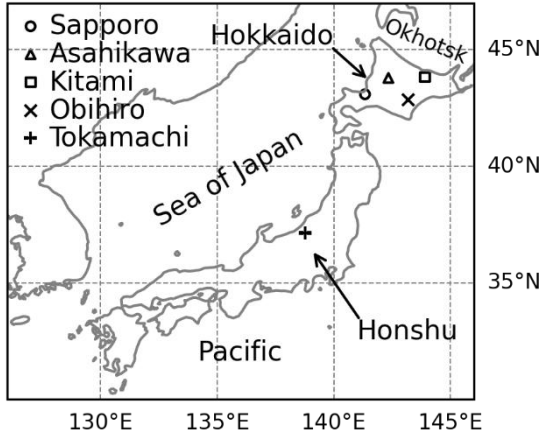
100 the EM algorithm and SOM framework. These identified patterns are furthermore compared with visual observations to determine their relationship with actual particle types. Then, through a case study of a passing cyclone, we demonstrate how the framework represents the temporal variations of PSVDs. Subsequently, site-specific PSVD patterns are discussed. In Sect. 4, we provide interpretations of the obtained PSVD patterns while considering the limitations of the framework, and suggest potential applications for future research. Finally, the conclusions of this study are summarized in Sect. 5.

105 **2 Data and method**

2.1 VSVD observation

This study utilized a VSVD (Katsuyama and Inatsu, 2021) to observe the PSVD during winter. The VSVD is a volume scan-type disdrometer designed to directly measure the particle number concentration rate within specific velocity and size ranges per unit volume. This approach offers the advantage of obtaining an accurate particle size distribution regardless of
110 the accuracy of the velocity measurement (Katsuyama and Inatsu, 2021). The disdrometer consists mainly of a single image camera that captures afterimages of falling particles generated by reflected and scattered visible light, processing these images into particle velocity and size data using a simple algorithm. Since it employs a standard visible light camera, the disdrometer is limited to measuring solid precipitation only; however, this allows the entire system to remain highly cost-effective. A simultaneous field observation comparing the VSVD and 2DVD during winter demonstrated comparable
115 particle diameter distributions, at least within the range of 0.5–13 mm. However, due to limitations in camera specifications and image processing, particles smaller than 0.5 mm and those with velocities slower than 0.5 m s^{-1} were excluded from this study. For further details on the VSVD, see Katsuyama and Inatsu (2021).

We installed VSVDs at five sites, widely distributed in northern Japan to the extent possible: Sapporo, Asahikawa, Kitami, Obihiro, and Tokamachi (Fig. 1). The Sapporo and Asahikawa sites are located in Hokkaido and face the Sea of
120 Japan, where snowfall is driven by both winter monsoon conditions and the passage of extratropical cyclones within a cold environment; however, monsoonal snowfall is more frequent. The climatological air temperature and precipitation for December–February (DJF) are $-2.3 \text{ }^{\circ}\text{C}$ and 319.0 mm in Sapporo, and $-5.7 \text{ }^{\circ}\text{C}$ and 222.4 mm in Asahikawa, respectively (JMA, 2026). Similarly, the Tokamachi site faces the Sea of Japan in Honshu, exhibiting heavy snowfall primarily under winter monsoon conditions associated with relatively warmer temperatures, with DJF climatological values of $0.8 \text{ }^{\circ}\text{C}$ and
125 1052.9 mm (Takeuchi et al., 2019). In contrast, the Kitami and Obihiro sites are located on the side opposite to the Sea of Japan in Hokkaido, where the environment is less influenced by marine effects (i.e. more inland) and snowfall is predominantly caused by cyclones. These sites are characterized by lower precipitation and colder air temperatures, with DJF climatologies of $-5.5 \text{ }^{\circ}\text{C}$ and 124.3 mm in Obihiro and $-6.8 \text{ }^{\circ}\text{C}$ and 121.2 mm in Kitami (JMA, 2026).



130 **Figure 1: Installation locations of the Volume Scanning Video Disdrometers (VSVDs).**

The data periods for the VSVD observations were from December to March in following year for the 2016–2024 winters at Sapporo, 2016–2022 winters at Asahikawa, Kitami, and Obihiro, and 2021–2024 winters at Tokamachi. Notably, in some winters, the periods were shortened due to schedule constraints or unexpected troubles (see Supplement S1 for exact periods). All sites were located in flat and open fields and the disdrometers were surrounded by wind-breaking nets. The installation height was sufficiently high to avoid burial by snowpack. The Asahikawa site was relocated by 800 m in 2019 due to an agreement of land administrator. The Kitami site was relocated by 500 m in 2017. Utility power was available at Sapporo, Kitami, and Tokamachi sites, where observation continued 24 hours a day without unexpected interruptions. However, the Asahikawa and Obihiro sites relied solely on solar power, resulting in occasional interruptions due to power shortages. Summaries and photos for installation specifications are available in Supplement S1.

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2.2 PSVD approximation

The observed PSVDs, which potentially consisted of multiple particle types, were approximated as the sum of several child elements following the procedure described by Katsuyama and Inatsu (2020). To achieve this approximation, the data were first aggregated hourly (within a window of ± 30 minutes centered on each hour); we then selected only those samples where the total number of particles exceeded 100 and the missing ratio was less than 10 % per hour. The observed PSVDs were approximated using K child elements, assuming that the diameter (D , mm) follows a gamma distribution and the velocity (V , m s^{-1}) for each diameter follows a normal distribution, combined as a mixture of their joint distributions:

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$$\begin{aligned}
 N(V, D) &= \sum_{k=1}^K N_k(V, D) \\
 &= N_{\text{tot}} \sum_{k=1}^K \omega_k \text{Normal}(V | a_k D^{b_k}, \sigma_k^2) \cdot \text{Gamma}(D | \mu_k, \lambda_k)
 \end{aligned} \tag{1}$$



, where ω , σ^2 , μ , and λ are a mixing fraction, variance of normal distribution, and shape and slope parameters of gamma distribution, respectively. The mixing fractions satisfy $\sum_{k=1}^K \omega_k = 1$. The mean velocity for each diameter in the normal distribution is assumed to follow a power law: $\bar{V}(D) = aD^b$. Here, N_{tot} denotes the total number concentration of precipitation particles (m^{-3}). Consequently, the number concentration represented by the k -th child element can be expressed as $\omega_k N_{\text{tot}}$. An expectation-maximization (EM) algorithm (Dempster et al., 1977) was employed to estimate the optimal parameter set for each child element. It is worth noting that this approximation is applicable even to hourly data, whereas most previous studies have analyzed data aggregated over windows of several minutes to avoid the issue of multiple particle type mixtures. For further details on the procedure, see Katsuyama and Inatsu (2020).

The EM algorithm requires the parameter K , the number of child elements, to be specified in advance. We set $K = 1$ for datasets with fewer than 1,000 particles, as the EM algorithm often fails to optimize when K is large relative to a small sample size (Katsuyama and Inatsu, 2020). For datasets exceeding 1,000 particles, we sequentially tested the EM algorithm from $K = 8$ down to $K = 1$, selecting the result with the maximum K for which every element satisfied $0 < b_k < 1$ and $(\mu_k + 1)/\lambda_k^2 > 0.01$ (i.e. variance of diameter larger than 0.01 mm^2). Although a large K can sometimes lead to overfitting—producing child elements that are highly similar to one another (Katsuyama and Inatsu, 2020)—this study intentionally maximized K as much as possible. Subsequently, the SOM was employed to reduce an excessively large K by regrouping these similar elements (Sect. 2.3).

2.3 SOM classification

Following the approach of Kondo et al. (2024), this study utilized SOM to classify the child PSVD elements obtained via the EM algorithm. The SOM is an unsupervised machine learning method based on neural networks that classifies vector data into several generalized patterns (Kohonen, 2013); it has been widely applied to tasks such as the identification of atmospheric circulation patterns (Kawazoe et al., 2020; Nishiyama et al., 2007). We first constructed a 6×6 matrix where each node was initialized with a random n -dimensional vector, matching the dimensionality of the input data. This matrix and its elements are referred to as the SOM map and SOM nodes, respectively. The SOM map learns the generalized patterns of input vectors through the following steps: (1) randomly selecting a single vector from the input dataset, (2) selecting the closest SOM node to this vector based on the Euclidean distance, (3) updating this node and its neighbors to be more similar to the selected vector, and repeating these steps iteratively. In step (3), the i -th node was updated as follows (Nishiyama et al., 2007):

$$m_i(t+1) = m_i(t) + \frac{\alpha_0(T-t)}{T} \exp\left(-\frac{\|\mathbf{r}_c - \mathbf{r}_{t+1}\|^2}{2s^2(t)}\right) \quad (2)$$

$$s(t) = 1 + \frac{(s(t)-1)(T-t)}{T} \quad (3)$$



, where T is the total number of iterations and $\|\mathbf{r}_c - \mathbf{r}_{t+1}\|$ is the Euclidean distance between the closest node ($\mathbf{r}_c$) and the input vector ($\mathbf{r}_{t+1}$). This study adopted $\alpha_0 = 0.2$ and $s(0) = 2$ based on preliminary sensitivity tests (Supplement S2). T was set to 10 times the total number of input data samples.

The input dataset for the learning process was constructed using all child PSVD elements obtained via the EM algorithm across all observation sites and periods. Each child PSVD element was treated as an independent sample, regardless of its site or observation time. The total sample size was 36,343 (i.e. $T = 363430$). Prior to the SOM analysis, each PSVD element was vectorized by binning the diameter into 0.6 mm increments (up to 15 mm) and the velocity into 0.3 m s⁻¹ increments (up to 5 m s⁻¹), resulting in a total of 400 bins, which defined the dimensionality of the input vector. To highlight the diversity of the PSVD patterns, each input vector was weighted by particle mass and normalized immediately before the SOM learning step:

$$r_j = N_k(V_j, D_j) \cdot M(V_j, D_j) / C \quad (4)$$

, where j is the bin index. $N_k(V_j, D_j)$ represents the number concentration rate for the velocity and diameter of the j -th bin within the k -th child PSVD element. $M(V_j, D_j)$ is the particle mass estimated from its velocity and diameter (Ishizaka et al., 2013), and C is a normalization constant. The input data were then randomly fed into the SOM map to generate the learned map. Following these learning steps, the SOM map produced 6×6 generalized PSVD patterns. To further reduce the number of patterns, we visually aggregated nodes with similar characteristics into several groups; these are hereafter referred to as "SOM groups."

To represent the PSVDs using the generalized patterns in the SOM map, the PSVDs at each time step and observation site were reprojected onto the trained SOM map. The reprojected PSVD for the i -th SOM node (or its corresponding SOM group) is expressed as:

$$\hat{N}_i(V_j, D_j) = \sum_{k \in U_i} N_k(V_j, D_j) \quad (5)$$

, where U denotes the PSVD element associated with the closest SOM node in terms of Euclidean distance, normalized according to Eq. (4). This process effectively reduced the number of child PSVD elements by consolidating patterns that were highly similar to one another. In other words, this approach mitigated the potential overfitting typically associated with the EM algorithm.

Thus, Eq. (5) represents the reprojected pattern of a PSVD child element, and their superposition constitutes the final form that corresponds to the original PSVD at a specific location and time. Since these superposition patterns vary across different locations and times, an additional SOM classification was performed to characterize them. The SOM map for this second analysis employed a 4×4 configuration, while all other parameters remained identical to those used in the initial SOM classification of the child PSVD elements. The input vector consisted of a fraction of the reprojected PSVD integrals for every SOM group, expressed as



$$\iint \hat{N}_i dDdV = N_{\text{tot}} \sum_{k \in U_i} \omega_k \quad (6)$$

210 for the i -th SOM group. Prior to the learning step, each element of this input vector was normalized to a range between 0 and 1.

The framework combining the EM algorithm and SOM analysis described above is summarized in the following steps: (1) approximating the original PSVD data by decomposing it into as many child elements as possible; (2) training a SOM map to represent the generalized patterns of these child elements; (3) reprojecting the child elements from step (1) onto the trained SOM map from step (2); (4) superposing these reprojected child elements to reconstruct the PSVD at each location and time; and (5) performing an additional classification of the resulting superposition patterns.

2.4 Visual snowfall particle observation

Visual observations of individual snowfall particles were conducted to identify the relationships between actual particle types and PSVD patterns identified by the SOM analysis. A total of 2,467 macro photographs were manually taken at the Tokamachi site between 2021 and 2024. Following the global classification (Kikuchi et al., 2013), these crystals were visually categorized into four groups: column (C), plate (P), combination of column and plate (CP), and riming (R). Furthermore, the degree of riming was graded from 0 to 4 (0: no riming, 1: light riming, 2: dense riming, 3: graupel-like, and 4: graupel). Crystals with riming degrees of 3 or 4 were assigned to the R group. For aggregated crystals, the individual constituent crystals were classified; therefore, the aggregation of snow crystal groups from the global classification was not adopted. Combinations of crystal groups and riming degrees are denoted as a single code (e.g., P1 represents plate crystals with a riming degree of 1). These observations were compiled into a minute-by-minute binary table indicating the presence or absence of each crystal group per minute. Subsequently, the fractional occurrence of each crystal class was calculated for one-hour intervals. It should be noted, however, that photographs were not acquired every minute throughout the entire hour—typically covering only 5–15 minutes per hour—meaning this fraction may not strictly represent the total distribution for the full hour.

Given these limitations in sampling completeness, Spearman's rank correlation was employed to examine the relationship between the actual particle classes and the SOM groups. Ranks were determined on an hourly basis for both the observed particle classes and the SOM groups, with tied ranks handled by assigning the median rank. Subsequently, the correlation coefficients and p-values were calculated for all combinations of visual observation classes and SOM groups.

2.5 Atmospheric reanalysis data

The ERA5 reanalysis (Hersbach et al., 2020) was employed to identify the relationship between the PSVD patterns and synoptic-scale atmospheric circulation patterns. The temporal resolution was one hour, with a spatial resolution of $0.25^\circ \times 0.25^\circ$ over a domain extending from 20° N – 60° N and 110° E – 160° E . The selected atmospheric variables were mean



sea level pressure (mSLP), mSLP anomalies, and air temperature anomalies at the 850 hPa level. These anomalies were
calculated as the difference from the daily averages for the period 1990–2020. To identify the relationship between synoptic-
scale atmospheric patterns and the superposition patterns of reprojected PSVDs, a composite analysis was performed. For
each SOM node, the corresponding atmospheric data were extracted for all time steps associated with that node and then
averaged to create a composite map.

3 Results

3.1 PSVD patterns classifications

Figure 2 shows the reprojected patterns of PSVD child elements estimated by the EM algorithm on the SOM map,
derived from data across all sites and times. The nodes exhibit a clear spatial gradient: the left-to-right axis represents a
transition from larger to smaller particle patterns, while the top-to-bottom axis represents a transition from faster to slower
particle patterns. Consequently, the bottom-right, left-side, and top-right nodes characterize very small and slow, large and
slow, and small and fast particles, respectively. The central nodes represent intermediate patterns. The mean parameters of
Eq. (1) estimated by the EM algorithm varied following these distributions. For instance, the λ of node #1 was very small,
indicating long-tailed diameter distribution extending toward larger size, whereas the b was very small, representing gentle
slope in the power law; this pattern was characteristic for aggregated snow crystals. Similarly, the combination of the larger
 λ and larger b of node #6 correspond to small particles with steeper slope in the power law, likely corresponding to graupel
or graupel-like snow. Therefore, we categorized the SOM nodes into four groups: (S) small and slow, (A1) large and slow,
(A2) intermediate between A1 and G, and (G) small and fast distributions (Fig. 2). This classification remained largely
consistent regardless of variations in the map size or α_0 and $s(0)$ of Eq. (2) (Supplement S2).

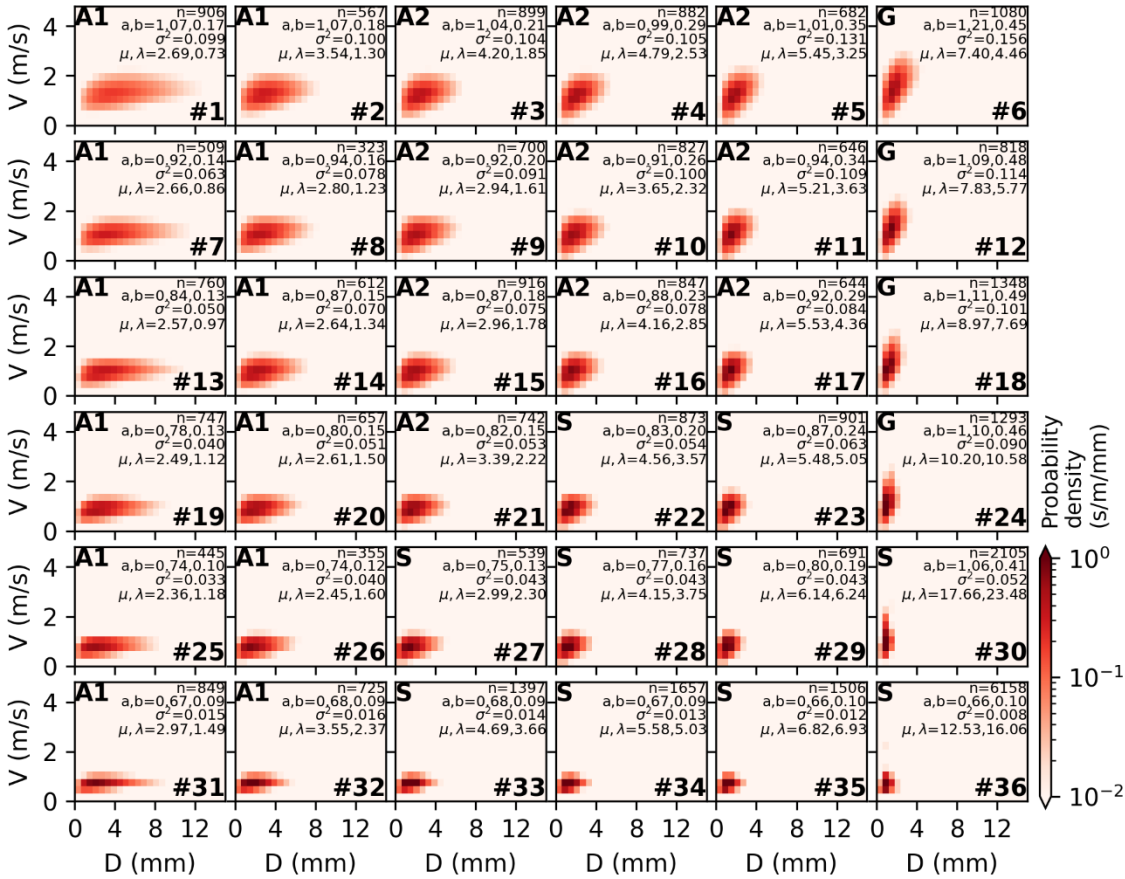


Figure 2: Reprojected patterns of particle size and velocity distribution (PSVD) child elements on the trained self-organizing map (SOM). The SOM node index and its corresponding group name are indicated at the bottom right and top left of each node, respectively. The number of samples and the mean parameters of Eq. (1) estimated by the EM algorithm for each node are shown at the top right. For all panels, the X- and Y-axes denote diameter (mm) and velocity (m s^{-1}), respectively.

The trained SOM map and derived groups were utilized to approximate the original PSVD through a superposition of the generalized patterns, as defined by Eq. (5), for each site and time step. Figure 3 shows an example of this approximation at Sapporo site at 09:00 on 2 February 2023. The original PSVD exhibited a combination of two distribution components: (1) a component with long tail extending toward larger diameters and a nearly constant velocity of 1 m s^{-1} , and (2) a component where the velocity increased with increasing diameter (Fig. 3a). This pattern was well approximated by the superposition of three generalized patterns (Fig. 3b), consisting of node #20 (37 %), node #5 (33 %), and node #32 (30 %) (Fig. 2). In terms of SOM groups, since the node #20 and #32 belong to the same SOM group (A1), the PSVD pattern was ultimately approximated as a weighted sum of the A1 pattern (67 %) and A2 pattern (33 %). Consequently, in this case, distribution components (1) and (2) correspond to patterns A1 and A2, respectively.

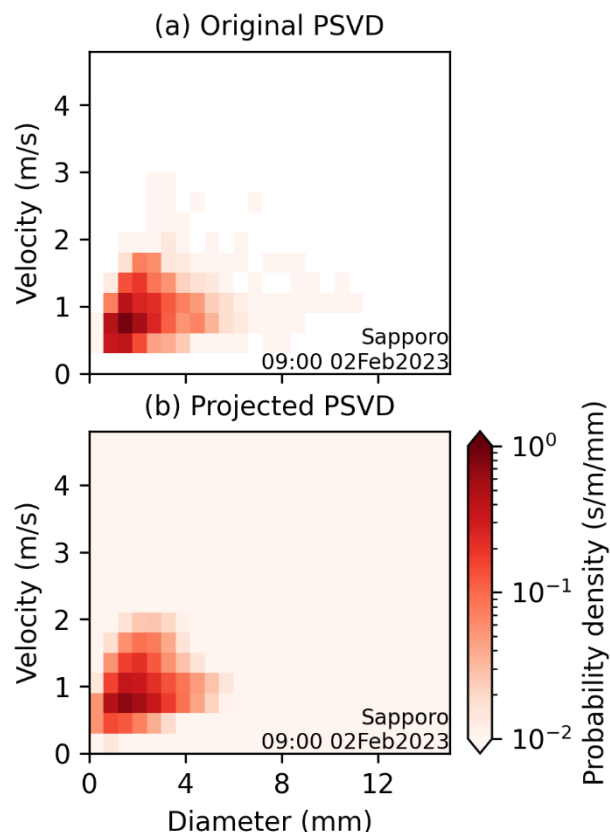


Figure 3: (a) Original PSVD observed at the Sapporo site at 09:00 on 2 February 2023 in a vectorized form, and (b) its corresponding reprojected PSVD on the SOM map.

275 The superpositions of SOM groups were further classified into $4 \times 4 = 16$ patterns using an additional SOM analysis (Fig. 4). Particle number concentrations were higher toward the top of the map, whereas the frequency (n in the figure) exhibited the opposite trend. The bottom-right node (#16) predominantly consisted of the S group with the lowest particle number concentration, representing small and slow distributions associated with weak precipitation intensity. This node had the highest occurrence, totaling 5,177 cases (14 % of all samples). Central upper nodes, including #2, #3, #6, #7, and #11, also
 280 primarily consisted of the S group but were characterized by higher particle concentrations. Nodes on the upper right side, such as #4, #8, and #12, comprised a mix of S and A1 groups, while the A2 group was dominant in the lower-left nodes (#1, #5, #9, #13, and #14). The fraction of the G group was relatively higher in nodes #10 and #15. The S group was consistently present across most nodes except for node #13, suggesting that the S group is a fundamental component of PSVDs in many cases. Conversely, the A2 group occasionally served as the dominant component, as evidenced by the 1,038 cases assigned
 285 to node #13.

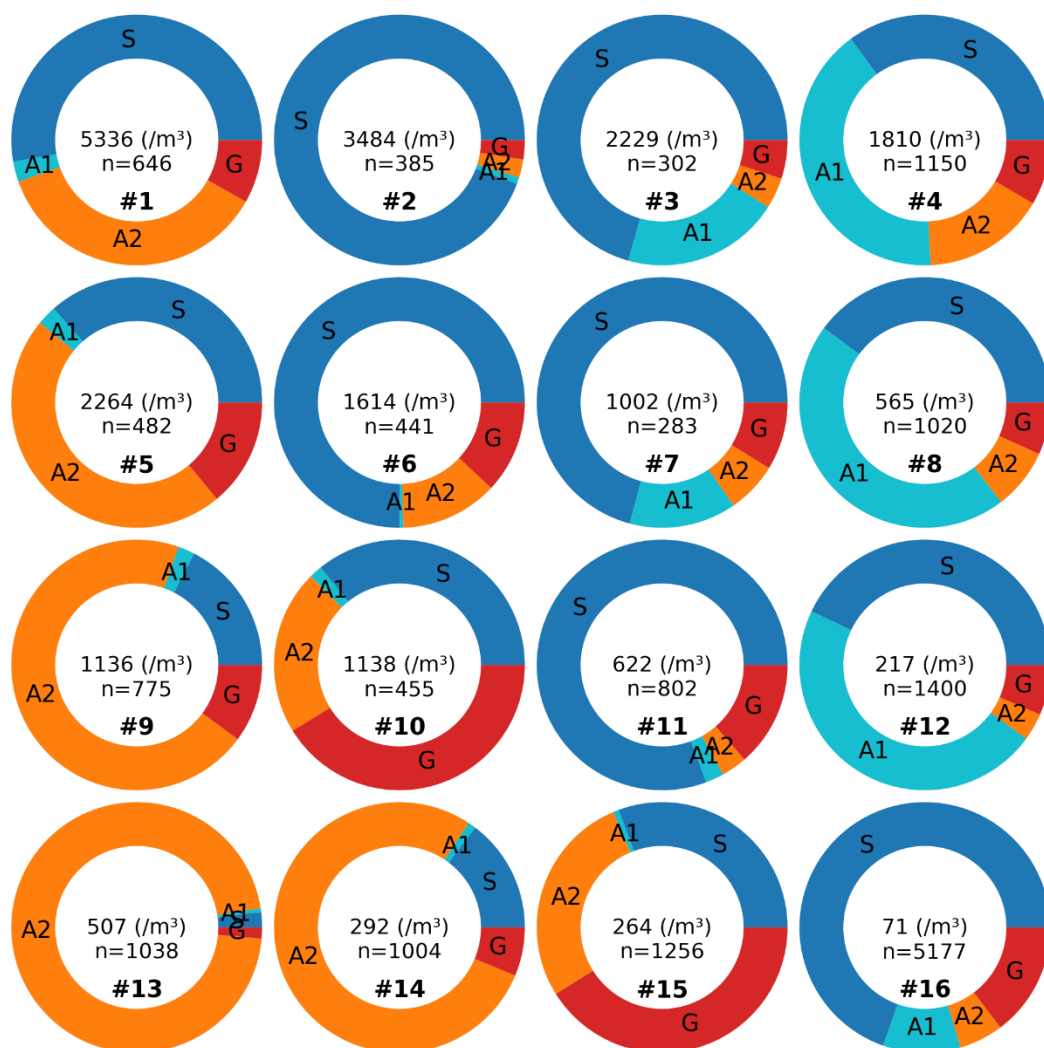


Figure 4: Trained SOM map of the superposition patterns of reprojected PSVDs shown in Fig. 2. Blue, cyan, orange, and red denote SOM groups S, A1, A2, and G, respectively. The mean precipitation particle concentration, the number of samples, and the node index are indicated at the center of each pie chart. The intensity of the background color corresponds to the mean precipitation particle concentration.

3.2 Relation to actual particle types

Spearman's correlation coefficients revealed the relationship between the relative fractions of visual observation classes and those of SOM groups (Fig. 5). The A1 group was positively correlated with the P0 and P1 classes at the 5 % significance level. Therefore, an increase in the fraction of A1 was associated with increases in P0 and P1. In contrast, the A2 group showed a positive correlation with CP0, CP1, and CP2, and a negative correlation with P0 and P1, suggesting that A2 is



more closely linked to CP-type crystals. The G group was negatively correlated with CP1. The S group showed no significant correlation with any actual particle types, further supporting the idea that it represents a fundamental component of PSVDs. Although the C2 class was included in the figure for the sake of completeness, it showed no correlation with any SOM groups, as C2 particles were not actually observed during the study.

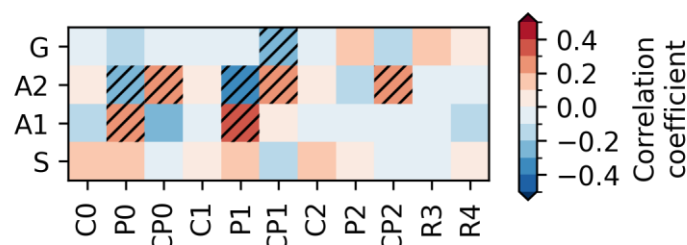
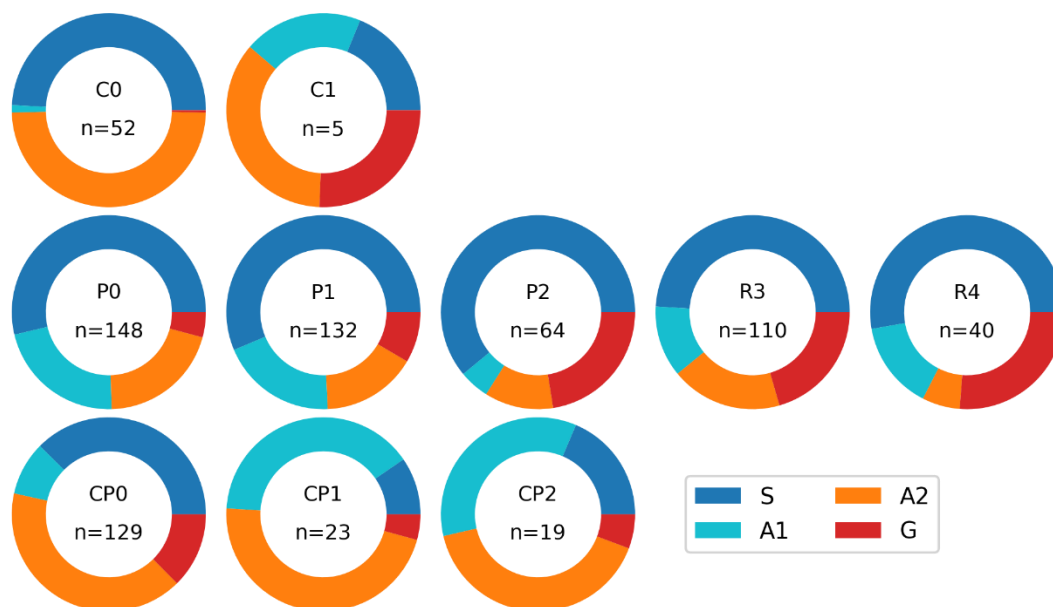


Figure 5: Spearman's correlation coefficient matrix between visual observation classes (X-axis) and SOM groups (Y-axis). Cells with correlations significant at the 5% level are indicated by hatching.

Furthermore, the reprojected PSVDs were aggregated for each visually observed particle class to create composite patterns (Fig. 6). It should be noted that since these composite PSVDs represent a mixture of multiple precipitation particle types over a one-hour interval, any single visually observed particle type is only one of several components contributing to the resulting aggregated PSVD. The composite patterns for C0 and CP0 predominantly consisted of the S and A2 groups, whereas those for P0 included an additional contribution from the A1 group. The CP1 and CP2 classes consisted of A2 and A1, despite the relatively small sample size. Along the horizontal axis, the fraction of the G group within the P class increased with the riming degree. This trend could not be evaluated for C and CP classes.

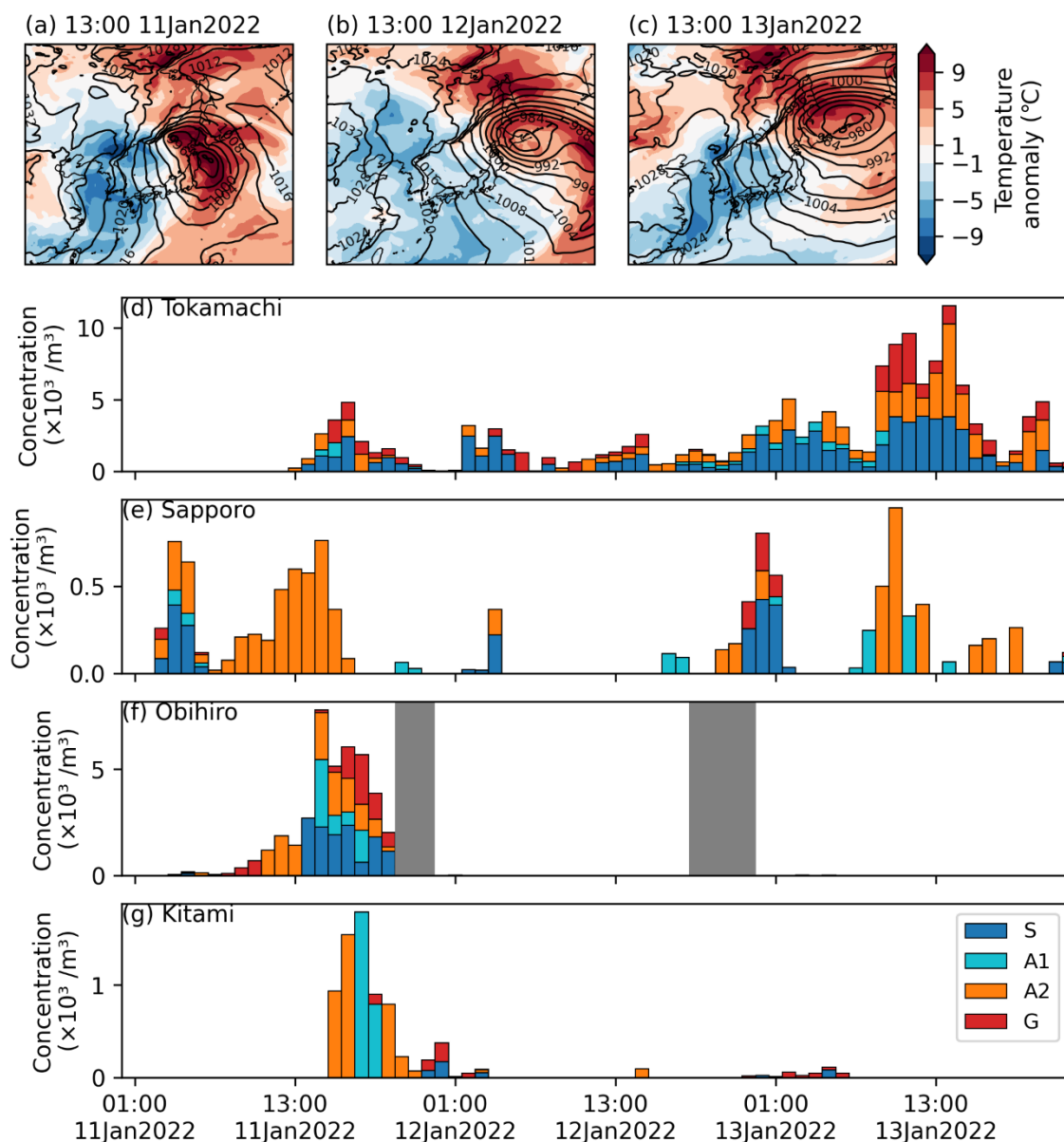


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Figure 6: Composites of the superposition patterns of reprojected PSVDs for each visually observed particle class. The panels are arranged along the vertical axis by particle type and along the horizontal axis by riming degree.

3.3 Case study

We illustrate how the temporal variations in PSVDs at each observation site are represented by the reprojected PSVD patterns during the passage of an extratropical cyclone from 11 to 13 January 2022 (Fig. 7). In this case, a developing extratropical cyclone approached Hokkaido from the southwest on 11 January, passed near Obihiro, and reached the Okhotsk Sea on 13 January (Figs. 7a–c). During this period, Tokamachi was located behind the cyclone center, representing a typical wintertime monsoonal snowfall pattern characterized by convective precipitation due to the cold air mass advection from northwest in areas facing the Sea of Japan (Figs. 7a–c). The PSVD patterns at Tokamachi exhibited significant variations: from 13:00 on 11 January to 15:00 on 12 January 2022, they primarily consisted of a mixture of S and G groups, with a maximum particle number concentration of $5,000 \text{ m}^{-3}$. Subsequently, this transitioned into a mixture of S and A2 groups from 16:00 on 12 January until 8:00 on 13 January, after which the patterns evolved into a mixture of S, A2, and G groups with a particle concentration reaching $11,000 \text{ m}^{-3}$ (Fig. 7d).



325 **Figure 7:** Mean sea level pressures (black solid contours at 4 hPa intervals) and air temperature anomaly at the 850 hPa level (shaded colors) at 13:00 on (a) 11 January, (b) 12 January, and (c) 13 January 2022. Hourly time series of the reprojected PSVDs are shown for (d) Tokamachi, (e) Sapporo, (f) Obihiro, and (g) Kitami. The gray shading indicates periods with no observation due to power failure.

330 In Hokkaido, the time series of PSVD patterns reflected the approach and passage of the cyclone. At Sapporo, precipitation from 3:00 to 17:00 on 11 January consisted of either a mixture of S and A2 groups or solely the A2 group (Fig. 7e) corresponding to the cyclone approaching (Fig. 7a). Following the passage of the cyclone around 12:00 on 12 January, the PSVD components transitioned among several patterns, including solely A1, a mixture of S and G, or solely A2 (Fig. 7e).



Interestingly, during the approach of the cyclone, Obihiro exhibited a pattern consisting solely of the A2 group from 11:00 to 13:00 on 11 January (Fig. 7f), similar to the pattern observed in Sapporo around 13:00 (Fig. 7e). Subsequently, as the cyclone center passed near Obihiro from 15:00 to 20:00 on 11 January, high particle concentrations exceeding $5,000 \text{ m}^{-3}$ in maxima occurred, comprising all SOM groups (Fig. 7f). In contrast, at Kitami, which was located slightly further from the cyclone center, lower particle concentrations of approximately $1,000 \text{ m}^{-3}$ were observed during the same period, consisting solely of A2 or A1 group components (Fig. 7g). It should be noted that the Asahikawa site was not operational during this event due to technical issues.

3.4 Site-specific long-term PSVD patterns

We analyzed the data for each observation site to investigate the long-term characteristics of the PSVD patterns at each location. While the total fractions of SOM groups aggregated over all datasets were generally similar across the sites, Sapporo was characterized by a lower fraction of the S group and a higher fraction of the A1 group (Fig. 8). The fraction of the A2 group in Asahikawa was high (0.32), similar to that observed in Sapporo; however, Asahikawa exhibited a relatively larger fraction of the S group, in contrast to its lower fraction for the A1 group (0.1). Moreover, the fraction of the G group was half that observed in Sapporo, which is in line with the findings of Kondo et al. (2024), who investigated the differences between snow and graupel in Sapporo and Asahikawa. In Kitami and Obihiro, where snowfall occurs primarily during cyclone passages, the fraction of the S group was the largest while that of the A1 group was the smallest, indicating a relatively smaller particle size compared to the other sites. At Tokamachi, where the winter monsoon produces significant snowfall, the fraction of the A2 group was the smallest among all sites, at 0.24.

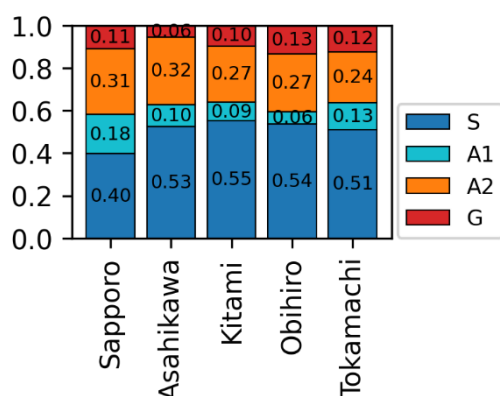


Figure 8: Fractions of SOM groups aggregated over all data at each observation site. Numerical values of the fractions are indicated inside the bars.

Although the total fractions of PSVDs were relatively similar among observation sites (Fig. 8), the frequency of each individual PSVD pattern was more site-specific. Figure 9 shows the distribution of cases assigned to the SOM nodes illustrated in Fig. 4. Common to all locations, node #16—characterized by the lowest particle concentration and a dominance



of the S group—was the most frequent PSVD pattern. In contrast, the prevalence of other nodes varied by location. In Sapporo and Asahikawa, nodes #4, #8, and #12 (a mixture of S and A1 groups) were relatively frequent. Furthermore, nodes #13, #14, and #15 also appeared frequently, indicating that PSVD patterns consisting solely of or partially including the A2 group were common. Nodes #1, #2, #5, and #6, which feature higher particle concentrations and consist primarily of the S group with partial A2 mixtures, were slightly more frequent in Asahikawa than in Sapporo. The distribution in Kitami was similar to that of Asahikawa but was more heavily concentrated at node #16. In Obihiro, node #1 was the second most frequent, while other nodes appeared sporadically. At Tokamachi, nodes #4, #8, and #12 were relatively frequent, whereas the frequency among remaining nodes was mostly uniform.

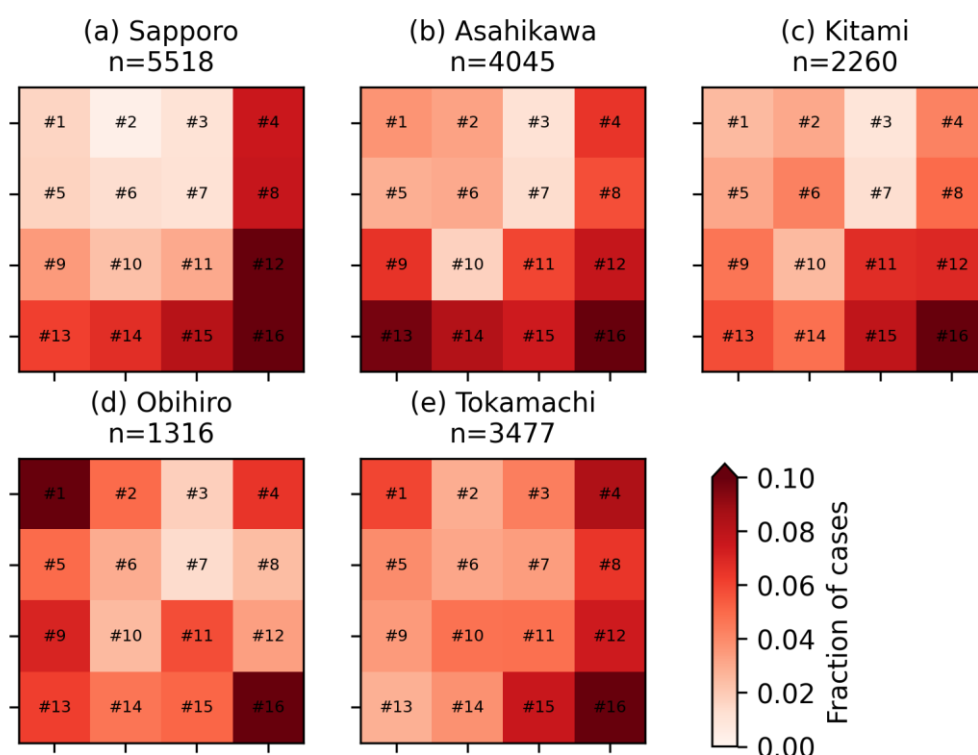


Figure 9: Distribution of cases across the SOM nodes for the superposition patterns shown in Fig. 4 at (a) Sapporo, (b) Asahikawa, (c) Kitami, (d) Obihiro, and (e) Tokamachi. The SOM node indices from Fig. 4 are indicated within each node.

To investigate the relationship between PSVD patterns and synoptic-scale atmospheric circulation patterns, a composite analysis was conducted (Figs. 10, 11). Since snowfall frequently occurs at both Sapporo and Asahikawa under both extratropical cyclone passage and winter monsoon conditions, composite maps were generated for cases at these two locations that were assigned to the SOM nodes shown in Fig. 4 (Fig. 10). For nodes #1, #5, #9, #10, #11, #13, #14, and #15, the composite maps revealed cyclones positioned around Hokkaido (Fig. 10), corresponding to PSVD patterns composed of the S, A2, and/or G groups (Fig. 4). However, the cyclone signal was relatively weak, indicating that these patterns also included numerous cases without an accompanying cyclone passage. In contrast, for the remaining nodes—which primarily



represent a mixture of the S and A1 groups—the synoptic patterns exhibited higher mSLP to the west and lower mSLP to the east, characteristic of the winter monsoon over Japan (Fig. 10). Regarding temperature anomalies, node #2, which corresponds to higher particle concentrations, exhibited lower temperatures than node #16, which corresponds to lower concentrations (Figs. 4, 10), suggesting stronger cold air mass advection from the northwest in node #2.

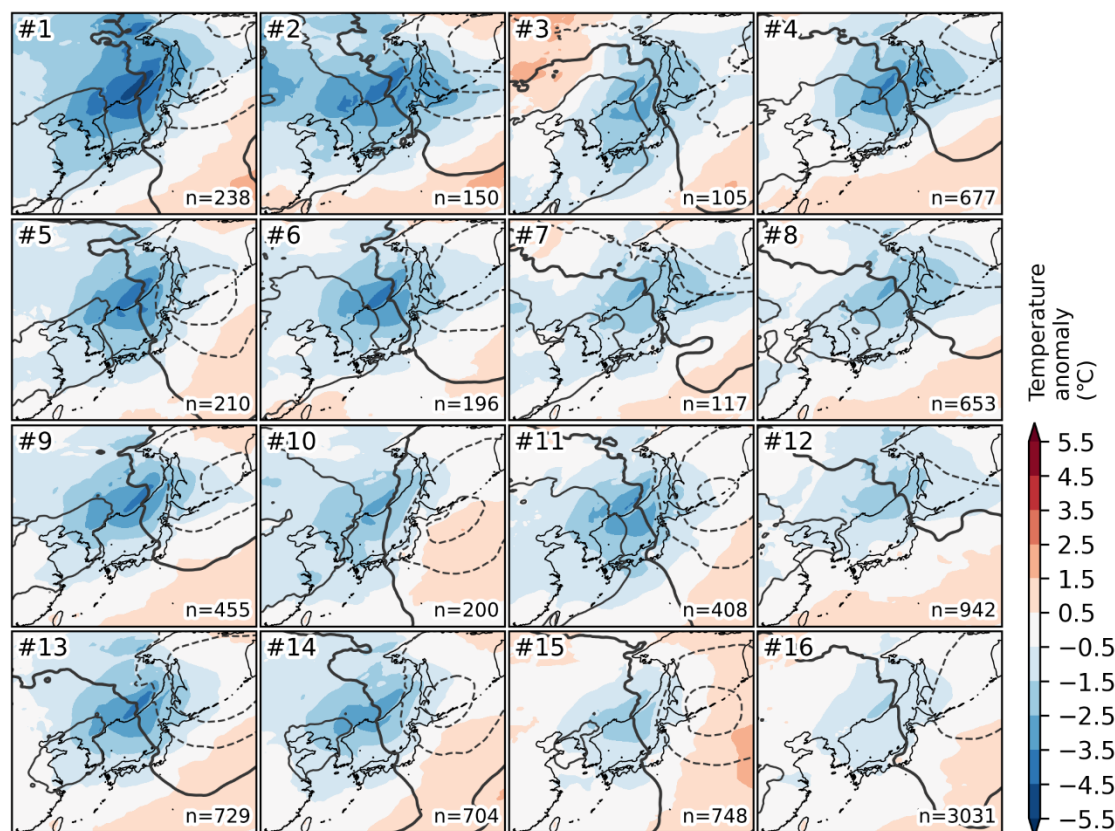


Figure 10: Composite maps of mean sea level pressure (mSLP) anomaly and air temperature anomaly at the 850 hPa level for each SOM node corresponding to the superposition patterns shown in Fig. 4 for Sapporo and Asahikawa.

Furthermore, composite maps were generated for cases in Kitami and Obihiro, where snowfall primarily occurs in association with the passage of extratropical cyclones (Fig. 11). For nodes #1, #5, #9, #10, #13, and #14—corresponding to PSVD patterns composed of the S, A2, and/or G groups (Fig. 4)—the composite maps revealed significantly more pronounced cyclone signals around Hokkaido than those for Sapporo and Asahikawa (Figs. 10, 11). Moreover, these cyclone signals were approximately identical among the nodes even though the particle number concentrations increased toward the upper nodes of the map (Fig. 4). Similarly, pronounced cyclone signatures were evident for nodes #2–4 (Fig. 11), which consist of either the S group alone or a mixture of the S and A1 groups with high particle concentrations (Fig. 4).

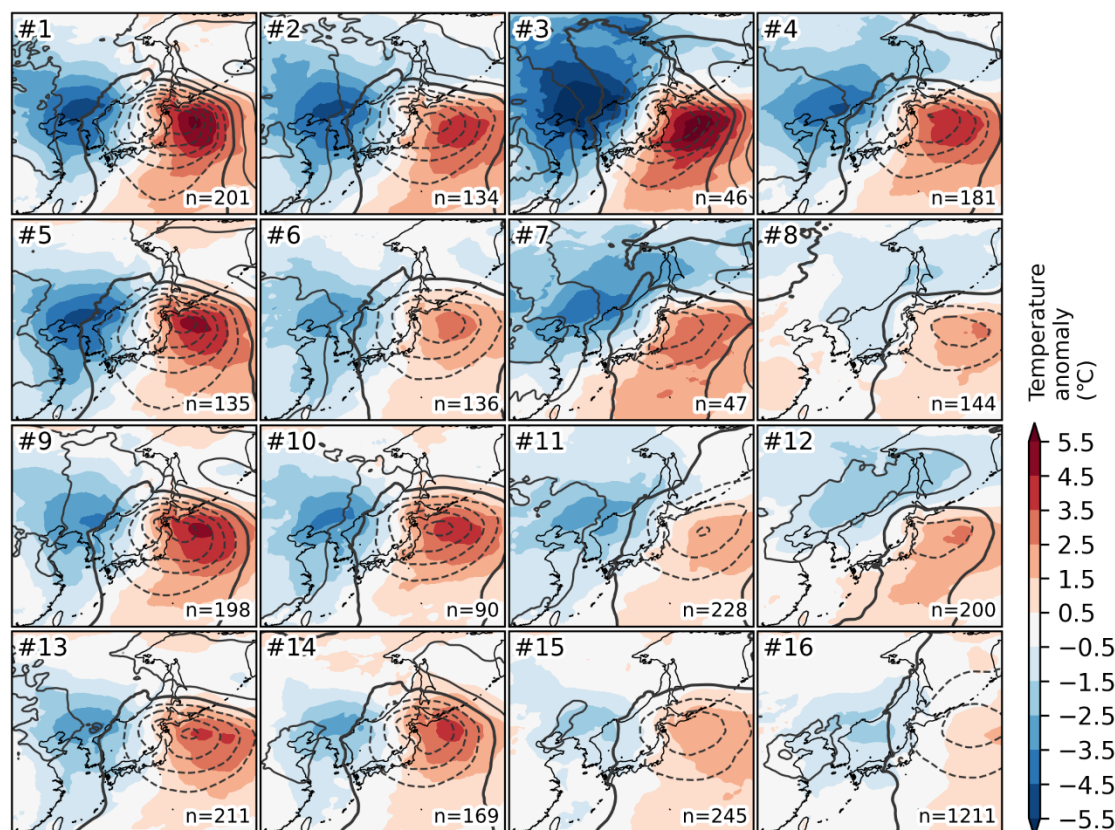


Figure 11: Same as Fig. 10, but for Kitami and Obihiro.

4 Discussion

To investigate long-term PSVD patterns—which often consist of multiple PDFs due to the potential mixture of various precipitation particle types—this study adopted a novel approach combining the EM algorithm with SOM analysis. This method approximates observed PSVD data as a superposition of several representative "child" patterns, each defined by a single PDF. These representative patterns were derived from 6×6 SOM map and subsequently categorized into four groups: S, A1, A2, and G (Fig. 2). The results were robust to both the SOM map size and the parameter configurations employed during the learning step (Supplement S2). Additionally, long-term observations spanning up to nine years across five sites—covering a broad range of winter climates in Japan—were utilized as training data for the SOM. Consequently, the child PSVD patterns derived from the SOM map (Fig. 2) and their resulting mixture patterns (Fig. 4) are considered to be well-generalized for snowy regions across Japan. Furthermore, while the EM algorithm typically requires the user to predetermine the number of components (K in Eq. (1)) at each time step (Katsuyama and Inatsu, 2020), the proposed approach offers a significant advantage by eliminating the need to estimate the number of potential PSVD elements prior to analysis. Moreover,



the overfitting problem inherent in the EM algorithm was mitigated, as similar elements extracted via the EM algorithm were clustered into identical patterns on the SOM map.

Some of the mean parameter combinations (a and b in Eq. (1)) of the obtained PSVD child patterns were comparable to conventional values. For instance, the parameters for node #13, belonging to the A1 group (Fig. 2), were similar to those of aggregates of unrimed radiating assemblages of dendrites or dendrites (Locatelli and Hobbs, 1974). This is consistent with our Spearman's correlation analysis, which demonstrated that the A1 group was positively correlated with P0 and P1 (Fig. 5). Regarding the A2 group, although the correlation analysis revealed a positive correlation between the A2 group and CP particles (Fig. 5), no clearly comparable parameter combination for a and b were identified in the SOM map, likely due to the absence of data for CP aggregates in Locatelli and Hobbs (1974). For the G group, while node #6 (Fig. 2) exhibited parameters similar to those of lump graupel (Locatelli and Hobbs, 1974), the correlation analysis did not exhibit a clear relationship between the G group and R3/R4. This is likely because graupel rarely occurs continuously over an hour; thus, the PSVD observed hourly for R3/R4 events probably represents a mixture of graupel and other precipitation types (Fig. 6). This is supported by the fact that the 1-minute VSVD data during R3/R4 events mainly included distributions similar to those of the G group (Fig. 12). Nevertheless, the fraction of the G group was higher during R3/R4 events than for other groups (Fig. 6). Hence, although the obtained PSVD child patterns do not exhibit a strict one-to-one correspondence with specific particle types, it is considered that P, CP, and R particles are the predominant components of the A1, A2, and G groups, respectively.

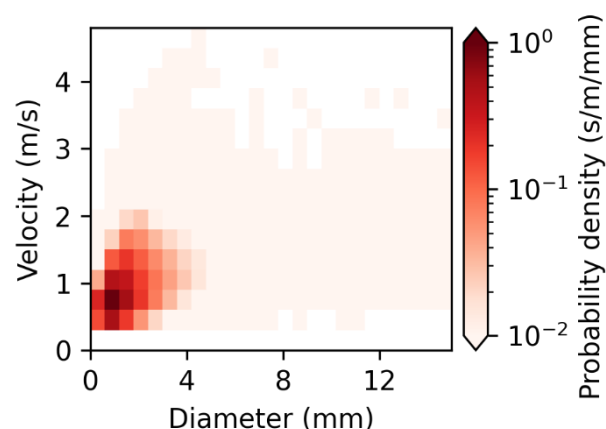


Figure 12: PSVD calculated by accumulating all 1-minute VSVD data corresponding to the times when R3 or R4 snowfall particles were visually observed.

The frequency of PSVD child element mixture patterns (Fig. 4) was site-specific, with the exception of node #16 (Fig. 9), and was characterized by different synoptic-scale atmospheric patterns (Figs. 10, 11). Specifically, PSVD mixture patterns containing the A2 group—such as nodes #1, #5, #9, #13, and #14 (Fig. 4)—occurred during the passage of extratropical cyclones in Sapporo and Asahikawa (Fig. 10). Similarly, in Kitami and Obihiro, where cyclone passages primarily produce snowfall, approximately 25% of all cases were associated with A2 mixture patterns (Fig. 11). Thus, the



A2 pattern occurred more frequently in association with cyclone passages. Given that CP0 is a predominant component of the A2 group, this is consistent with visual observations in New York reporting cold-type crystals such as side-planes and
430 bullets with low riming degrees on the northern side of cyclones (Colle et al., 2014), as well as observations reporting an abundance of non-rimed P and C/CP crystals during a cyclone's approach to Hokkaido (Matsushita, 2021). However, since various other PSVD patterns, including mixtures of S+A1 and S+G, are also associated with cyclone passages (Fig. 11), a cyclone does not exclusively determine a specific PSVD pattern. In contrast, PSVD patterns consisting of an S and A1 mixture—such as nodes #4, #8, and #12—were associated with winter monsoon patterns (Fig. 10). However, these winter
435 monsoon patterns were not particularly distinct, indicating the partial influence of other synoptic patterns, such as cyclone passages. Therefore, while the A1 pattern predominantly occurs during the winter monsoon in Sapporo and Asahikawa, it can also be produced under other synoptic conditions. In fact, a case in Tokamachi from 11–13 January 2022, a typical case for winter monsoonal snowfall, exhibited several varying PSVD patterns over time (Fig. 7), as well as various crystal types from nonrimed to heavily rimed crystals produced by convective clouds following winter monsoon (Murakami et al., 1994).
440 As demonstrated above, while certain PSVD patterns are preferentially associated with specific synoptic conditions, they are not exclusively linked to them; rather, a diverse range of patterns can emerge under various atmospheric conditions at any given site. This inherent variability explains why the total fractions of PSVD child elements over the entire observation period exhibited only minor variations among the sites (Fig. 8), despite the presence of distinct regional preferences in short-term event scales (Fig. 9). However, because VSVD observations at Asahikawa and Obihiro were occasionally interrupted
445 due to power failure, especially during the latter period of long-duration snowfall events, strictly speaking, the frequency of PSVD child element mixture patterns may be biased (as exemplified by the peculiar frequency of node #1 in Fig. 9).

These contrasting PSVD patterns associated with cyclone passages and winter monsoon snowfall are likely related to stratiform and convective precipitations in terms of fundamental processes. Large-scale stratiform precipitation systems are often located on the eastern side of extratropical cyclones, associated with the warm conveyor belt (WCB) (Browning, 1986).
450 In such regions, a predominance of cold-type crystals with low riming is expected due to the limited amount of supercooled liquid water within weak stratiform convection and a colder environment resulting from higher altitudes of major deposition growth (Colle et al., 2014), which leads to the A2 pattern during cyclone passages (Figs. 10, 11). However, because isolated convection embedded within the WCB can generate significant amounts of supercooled liquid water and graupel (Gehring et al., 2020; Oertel et al., 2021) while simultaneously enhancing aggregation (Gehring et al., 2020), the PSVD patterns in
455 Kitami and Obihiro—where cyclones are a primary source of precipitation—sometimes include the A1 group (Fig. 9). Regarding convective precipitation, which is the dominant system during winter monsoon snowfall in Sapporo, Asahikawa, and Tokamachi, both A1 and A2 patterns were identified (Fig. 9), as riming degrees and aggregation vary depending on the development stage of convective clouds and updraft intensity (Murakami et al., 1994). Consequently, PSVD patterns exhibited temporal variability under winter monsoon conditions (Fig. 7d). It should be noted, however, that this study does
460 not provide definitive evidence to distinguish between stratiform and convective precipitation; therefore, integrating remote sensing data in future studies is desirable. Moreover, the Process-Tracking Scheme (Hashimoto et al., 2020) may provide



more detailed insights into the links between microphysical processes and PSVD patterns by accounting for the complex processes of particle growth within clouds, such as water vapor deposition and riming.

Applying our combined EM-SOM approach to observation data from a broader range of sites, including those outside Japan, would likely require its application to conventional disdrometers such as LPM and PARSIVEL, as VSVD is less widely used. However, two points must be carefully considered in advance. The first is the limited measurable range of conventional disdrometers and the resulting truncation problem when estimating PSVD child elements. For instance, the maximum detectable diameter for LPM is 8 mm, which is significantly smaller than that of snowfall particles, thereby causing a truncation issue (Handwerker and Straub, 2011). Since VSVD possesses a sufficiently wide detection range, no specific treatment was required in the present study. However, truncation at the lower limit is a common issue among most of disdrometers, including our VSVD, because the observed data are often masked using thresholds of approximately 0.5 mm and 0.5 m s^{-1} in practice due to the limited detection capability for small and slow particles. This masking process, for instance, potentially bias the shape and slope parameters (μ and λ in Eq. (1)) towards positive values when μ is small (Handwerker and Straub, 2011). While it is technically possible to account for this truncation issue using Markov Chain Monte Carlo simulations, our preliminary experiments indicated that the computational cost would be prohibitively high for long-term observation dataset. Nevertheless, these experiments also suggested that biases between truncated and non-truncated PSVD estimations were minor in many cases, implying that the truncation problem may not pose a significant hurdle for long-term analyses (Katsuyama et al., 2024). The second issue—which may be more critical—is instrument-specific precision. For example, in both the LPM and PARSIVEL, the detection efficiency depends on particle size, thereby biasing the resulting size distribution (Fehlmann et al., 2020; Raupach and Berne, 2015). Moreover, since conventional disdrometers are generally flux-scan types requiring velocity-based unit conversion, inaccuracies in this process can bias PSVD estimations (Katsuyama and Inatsu, 2021). Therefore, additional quality control and bias correction may be necessary for data from conventional disdrometers. By addressing these issues, our proposed method could be applied to LPM and PARSIVEL data, enabling the derivation of more generalized PSVD patterns covering a broader range of climates both within Japan and internationally.

As another potential application, the findings of this study could be utilized to refine bulk microphysical schemes within numerical atmospheric models. A typical microphysical scheme categorizes precipitation into types such as rain, snow, and graupel, with each category assigned a prescribed size distribution and terminal velocity (e.g. Tomita, 2008). How best to define these categories has long been a topic of discussion within the cloud microphysics community (e.g. Milbrandt and Morrison, 2016). Incorporating the S, A1, A2, and G groups identified in this study—rather than relying on conventional, simplified snow and graupel categories—may reduce uncertainties in numerical predictions, as these groups represent generalized PSVD patterns derived from long-term observations. This approach is supported by Kondo et al. (2021), who demonstrated that adjusting the relationship between particle size and fall velocity to match observational data improved model performance; thus, refining microphysical schemes using our generalized PSVD patterns could similarly enhance numerical prediction accuracy.



5 Conclusions

This study presented a novel EM-SOM framework to identify generalized PSVD patterns from long-term observations using VSVDs—disdrometers specialized for snowfall—at five sites covering various climates of Japanese snow-covered areas. This framework successfully identified four general PSVD child element groups (S, A1, A2, and G) from complex PSVDs potentially consisting of multiple particle types, while avoiding the overfitting problem and the need to subjectively preconfigure the number of child elements within the EM algorithm. Integration with visual observations suggests that the S pattern serves as a fundamental background component, while the A1, A2, and G patterns primarily comprise aggregated P-type, aggregated C/CP-type, and rimed particles, respectively. While a strict one-to-one correspondence was not exhibited, these groups effectively represent the primary physical constituents of the observed distributions. Consequently, the original PSVD data were approximated by a superposition of the identified PSVD child elements, which were furthermore clustered into 16 patterns mainly composed of S group, S+A1 group, solely A2 or S+A2 group, and partially G group. In analyzing these patterns at each location, although the S group with small particle number concentrations was commonly the most frequent, the PSVDs were secondarily characterized by either A1 or A2 mixture patterns. Since A2 mixture patterns are associated with the passage of extratropical cyclones, the frequency of the A2 pattern was relatively high in Kitami and Obihiro, where cyclones are the primary source of precipitation. In contrast, in Sapporo, Asahikawa, and Tokamachi, where precipitation is predominantly produced by winter monsoon, A1 mixture patterns occurred more frequently than A2 due to their association with monsoonal conditions. As a generalizable framework, the findings of this study could refine bulk microphysical schemes, potentially reducing uncertainties in snowfall predictions. However, future studies, for instance integrating remote sensing data and numerical simulation, will be essential to further validate the link between these PSVD patterns and cloud-precipitation systems.

Code and data availability

Processed data used in the figures of this study are available from the corresponding authors upon reasonable request during the review process. These data will be archived in Zenodo and made publicly available upon acceptance of the manuscript. The software code for the EM algorithm is available at <https://github.com/ykatsu111/EM-PSVD>. The ERA5 reanalysis data are publicly available via the Copernicus Climate Data Store (CDS) at <https://cds.climate.copernicus.eu/>.

Author contributions

YK and MI designed the study. YK, MI, MK (Kawashima), MK (Kondo), TS, TK, and YT contributed to the observations, including field site setup, maintenance, and decommissioning. YK carried out the data analysis, and prepared the manuscript with contributions from all co-authors. MI, MK (Kondo), and KN contributed to the scientific discussion and interpretation of the results.



Competing interests

The authors declare that they have no competing interests.

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