



Spatial Distribution and Long-Term Changes in Surface Air and Wet-Bulb Temperature Thresholds for Classifying Cold-Season Precipitation Phase across Japan

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Abstract. The precipitation phase (rain or snow) strongly influences land-surface water and energy budgets, yet the thresholds used to distinguish rain from snow vary widely across regions and are not determined by air temperature alone. Because atmospheric humidity affects phase transitions through the cooling of falling particles, wet-bulb temperature has been proposed as an alternative to air temperature. However, spatial differences and long-term changes in wet-bulb thresholds across Japan remain insufficiently characterized. Using hourly surface meteorological observations from 158 stations across Japan (1989–2024), we analyzed the surface air temperature ($T_{s,50}$) and wet-bulb temperature ($T_{w,50}$) at which the probability of snowfall was 50 %, along with their difference, ΔT_{50} ($= T_{s,50} - T_{w,50}$). Rather than treating ΔT_{50} as a direct measure of cooling by evaporation and sublimation, we use it as a diagnostic index of humidity-related controls on the precipitation phase. This decomposition treats the conventional air-temperature threshold as the sum of a wet-bulb component and a humidity-related component ($T_{s,50} = T_{w,50} + \Delta T_{50}$). Across 115 stations, the mean $T_{s,50}$ was 2.63 °C and the mean $T_{w,50}$ was 1.31 °C. Inter-station variability in $T_{w,50}$ was less than half that in $T_{s,50}$, suggesting that a spatially uniform wet-bulb threshold is more broadly applicable. All three indices decreased with latitude and elevation, although these factors explained only a small fraction of the variability. ΔT_{50} was associated with relative humidity during precipitation, with larger values at drier sites. Stratifying snowfall frequency curves by relative humidity, station pressure, wind speed, and precipitation amount revealed systematic shifts in the rain–snow transition temperature. These shifts were generally larger for air temperature than for wet-bulb temperature, suggesting that the latter accounts for much of the variability associated with meteorological conditions. At 44 stations with continuous records, $T_{s,50}$, $T_{w,50}$, and ΔT_{50} decreased at more sites than they increased between 1990–2004 and 2005–2020. At more than half of the stations, wet-bulb and humidity-related components changed in opposite directions, indicating that at these sites the long-term changes in $T_{s,50}$ cannot be explained by a single factor. Because wet-bulb temperatures are widely available in reanalyses, climate simulations, and land-surface models, the proposed decomposition provides a practical basis for interpreting regional differences and future changes in the precipitation phase and associated hydrological responses.



30 1 Introduction

The precipitation phase (rain or snow) strongly affects water and energy budgets at the land surface (e.g., Oki and Kanae, 2006; Bonan, 2015). Rainfall runs off into rivers over relatively short timescales, whereas snowfall accumulates on the ground as snowpack and contributes to runoff through subsequent snowmelt after a delay. Snow cover increases the surface albedo and thereby affects the terrestrial energy budget and the climate system. Therefore, it is critically important to
35 characterize the phase of precipitation properly from both hydrological and climatological perspectives.

The precipitation phase observed at the Earth's surface is determined by whether precipitation particles melt before reaching the ground and is governed by the balance of sensible and latent heat exchanges during their fall (e.g., Matsuo and Sasyo, 1981; Stewart, 1992). The phase therefore strongly depends on the vertical profiles of air temperature and humidity through which particles pass. However, observational data for the upper atmosphere are limited in both time and space and are
40 difficult to use directly. For this reason, empirical methods based solely on surface observations are widely used to partition precipitation into rain and snow in hydrological and land-surface models.

Methods for estimating the precipitation phase from surface observations can be broadly classified into two groups. The first relies only on surface air temperature. Approaches include single-threshold classifications (e.g., Lynch-Stieglitz, 1994; Motoyama, 1990; Ohta, 1989), linear interpolation between temperatures corresponding to 100 % rain and 100 % snow (e.g.,
45 McCabe and Wolock, 2010; Takeuchi et al., 2016), and sigmoid functions representing snowfall probability as a continuous function of temperature (e.g., Dai, 2008; Jennings et al., 2018; Kienzle, 2008). Fixed-threshold methods generally have the largest errors, whereas sigmoid-curve methods have the smallest (Harpold et al., 2017). Because of their simplicity and broad data availability, air-temperature-based methods are widely used in hydrological and land-surface models. However, the rain-snow transition temperature varies considerably among stations (e.g., Jennings et al., 2018), limiting the
50 applicability of a single threshold across large regions.

The second group incorporates humidity information in addition to air temperature, including methods based on dew-point temperature (e.g., Ye et al., 2013) and wet-bulb temperature (e.g., Yamazaki, 2001). Dew-point temperature is the temperature at which air becomes saturated upon cooling, while wet-bulb temperature is the equilibrium reached through sensible and latent heat exchange between a moist body and surrounding air. Both equal the air temperature at 100 % relative
55 humidity and fall below it as humidity decreases. By accounting for humidity, these methods achieve higher discrimination accuracy than that of air-temperature-only approaches (e.g., Ding et al., 2014; Sugaya, 2005; Wang et al., 2019). Wet-bulb temperature, in particular, reflects both atmospheric water vapor content and cooling by evaporation and sublimation, making it closely related to the thermal conditions that govern melting and freezing of falling precipitation particles. Indeed, wet-bulb-based methods have been shown to outperform dew-point-based methods (e.g., Behrangi et al., 2018; Jennings et al., 2018). Moreover, recent studies indicate that long-term changes in snowfall are more closely related to wet-bulb
60 temperature trends than to air temperature alone (e.g., Tamang et al., 2020). On the other hand, because humidity data are available at fewer observation sites than are temperature data, these methods remain more limited in their applicability.



Several studies have examined regional differences in rain–snow threshold temperatures in Japan and the effectiveness of wet-bulb temperature for precipitation-phase classification. Hasemi (1991), using more than 16 years of observations at meteorological observatories, classified winter precipitation into winter-monsoon and cyclone types, reporting that the threshold temperature was lower for the latter and decreased with elevation for both. Ogawa and Nogami (1994), analyzing 23 years of data, determined monthly threshold temperatures for the six winter months across 15 climatic regions, and showed that thresholds were lower at higher latitudes and during midwinter. Sugaya (2005) targeted 35 stations with 10 years of observations in snowy regions and found that wet-bulb-based methods produced smaller estimation errors than did air-temperature methods, and that wet-bulb thresholds decreased with elevation. Collectively, these studies indicate that rain–snow discrimination thresholds in Japan vary with synoptic situation, latitude, season, and elevation, and that accuracy improves when the wet-bulb temperature is used.

However, most previous studies in Japan have focused on snowy regions or a limited number of observation sites. Few have comprehensively compared the spatial distribution and accuracy of rain–snow discrimination thresholds based on surface air temperatures and wet-bulb temperatures using data from sites across all of Japan, including regions with little snow. In addition, long-term changes in these thresholds remain underexplored, and no framework has been established for interpreting such changes by separating them into shifts in the wet-bulb-based boundary and changes in humidity conditions during precipitation, including cooling resulting from evaporation and sublimation. Furthermore, systematic comparison of how meteorological conditions such as relative humidity, pressure, wind speed, and precipitation amount influence rain–snow thresholds across Japan remains insufficient.

In this study, we not only quantify the spatial distribution of rain–snow transition thresholds across Japan, but also propose a diagnostic framework that decomposes the conventional air-temperature threshold into a wet-bulb component and a humidity-related component. To this end, using surface meteorological observations from 1989 to 2024, we analyze $T_{s,50}$ (the surface air temperature at which the snowfall probability is 50 %), the corresponding wet-bulb threshold $T_{w,50}$, and their difference ΔT_{50} ($= T_{s,50} - T_{w,50}$), investigating their spatial variability and long-term changes. We treat ΔT_{50} not as a direct physical measure of evaporation or sublimation cooling, but as a diagnostic index of humidity-related controls on the precipitation phase. We further examine how the rain–snow transition temperature varies with meteorological conditions during precipitation (relative humidity, station pressure, wind speed, and precipitation amount). In addition, by dividing the analysis period into 1990–2004 and 2005–2020 we compare inter-period differences in $T_{s,50}$, $T_{w,50}$, and ΔT_{50} to assess long-term changes.

2 Methods

2.1 Data

To determine the relationships between surface air temperature or wet-bulb temperature and snowfall frequency, we used observation data from 158 surface meteorological stations across Japan made publicly available by the Japan Meteorological



95 Agency (JMA). The dataset included hourly values of air temperature at a height of 1.5 m, water-vapor pressure, and station pressure, as well as visually observed present weather recorded every 3 or 5 h. The target period extended from 1 April 1989 to the date on which visual weather observations ended at each station. Visual observations of present weather ended at 108 stations between 1989 and 2019, at 39 stations in 2020, and at 9 stations in 2024. For Tokyo and Osaka, where observations continued as of 2025, the period through 31 December 2024 was used. We analyzed only the times at which the surface air temperature or wet-bulb temperature was within the range -5°C to 10°C , and the weather was recorded as “rain” or “snow.” Accordingly, the analysis period was not restricted to calendar-defined winter months. Instead, events were selected based on temperature conditions under which rain–snow transitions could occur, thereby representing cold-season precipitation events.

2.2 Calculation of wet-bulb temperatures

105 The wet-bulb temperature at each time was obtained by iterative calculation combining Sprung’s psychrometer formula with Tetens formula. Sprung’s psychrometer formula is expressed as:

$$e = e_{\text{sw}} - Ap(T_s - T_w) \quad (1)$$

where e is the water-vapor pressure (hPa), e_{sw} is the saturation water-vapor pressure (hPa) at the wet-bulb temperature T_w , A is the psychrometric coefficient (K^{-1}), p is the station pressure (hPa), T_s is the surface air temperature ($^{\circ}\text{C}$), and T_w is the wet-bulb temperature ($^{\circ}\text{C}$). For the psychrometric coefficient, $A = 0.000662$ was used when the wet bulb was not frozen and $A = 0.000583$ was used when the wet bulb was frozen.

The saturation water-vapor pressure e_{sw} is given by Tetens formula as:

$$e_{\text{sw}} = 6.1078 \times 10^{\frac{aT_w}{b+T_w}} \quad (2)$$

The coefficients a and b were set to 7.5 and 237.3, respectively, over a water surface and 9.5 and 265.3 over an ice surface.

115 The wet-bulb temperature T_w was obtained from the following nonlinear equation, derived by substituting Eq. (2) into Eq. (1):

$$f(T_w) = 6.1078 \times 10^{\frac{aT_w}{b+T_w}} - Ap(T_s - T_w) - e = 0 \quad (3)$$

Because Eq. (3) is difficult to solve analytically, we solved it numerically by taking $T_w = T_s$ as the initial value and iteratively updating T_w until $|f(T_w)| < 0.001$ hPa was satisfied. At each iteration step, the sign of T_w was evaluated (the wet bulb being taken as unfrozen for $T_w \geq 0$ and frozen for $T_w < 0$) and the psychrometric coefficient A and the Tetens coefficients a and b were switched to the corresponding values.

2.3 Fitting of snowfall frequency curves

At each observation site, we determined the relationships between surface air temperature or wet-bulb temperature and snowfall frequency (the snowfall frequency curve) using the procedure described below. We used only observations



125 recorded as “rain” or “snow” and excluded mixed precipitation such as “sleet.” Times containing a missing value for any variable were excluded from the analysis, and missing values were not interpolated.

First, the range of surface air temperatures from -5°C to 10°C was divided into bins 1°C wide, and the snowfall frequency was computed for each bin. For example, if a given bin contained 100 observations classified as “rain” or “snow,” of which 75 were “snow,” the snowfall frequency for that bin was taken as 0.75.

130 We fitted the snowfall frequency of each temperature bin to the following logistic function of Jennings et al. (2018) to obtain the snowfall frequency curve at each observation site:

$$p_{\text{snow}} = \frac{1}{1 + \exp(\alpha + \beta T_s)} \quad (4)$$

where p_{snow} is the snowfall probability, T_s is the surface air temperature ($^{\circ}\text{C}$), and α and β are parameters. Only temperature bins with 10 or more observations of “rain” or “snow” were treated as valid; others were excluded. Parameters were
135 estimated via nonlinear least squares, and no weighting by the number of observations in each temperature bin was applied. Sites with insufficient valid data to obtain an adequate fit were excluded from the analysis.

The surface air temperature $T_{s,50}$ at which the snowfall probability was 50 % was obtained by substituting $p_{\text{snow}} = 0.5$ into Eq. (4):

$$T_{s,50} = -\frac{\alpha}{\beta} \quad (5)$$

140 For the wet-bulb temperature as well, the snowfall frequency was computed for each 1°C temperature bin from -5°C to 10°C ; Eq. (4) was then applied to obtain the snowfall frequency curve, and $T_{w,50}$ was calculated.

2.4 Difference (ΔT_{50}) between $T_{s,50}$ and $T_{w,50}$, and inter-period changes

At each observation site, after determining $T_{s,50}$ and $T_{w,50}$, we defined their difference as:

$$\Delta T_{50} = T_{s,50} - T_{w,50} \quad (6)$$

145 Because the wet-bulb temperature falls increasingly below the surface air temperature as relative humidity decreases, at sites where ΔT_{50} was large, the atmosphere during precipitation was also considered relatively dry. Therefore, although ΔT_{50} is not a physical quantity that directly represents humidity conditions or cooling by evaporation and sublimation during precipitation, it can be interpreted as a diagnostic index that partly reflects these effects. By analyzing its spatial distribution and inter-period difference, we examined the contribution of humidity conditions to the regional differences and long-term
150 changes in the rain–snow boundary. To evaluate the relationship between ΔT_{50} and humidity conditions during precipitation, we also calculated, for each station, the mean relative humidity values for rain or snow events with surface air temperatures within $T_{s,50} \pm 2^{\circ}\text{C}$, and examined their correlation with ΔT_{50} .



Table 1. Classification of stations into four patterns based on the signs of $\delta T_{w,50}$, the change in the wet-bulb-temperature-based rain–snow boundary, and $\delta(\Delta T_{50})$, the change in $\Delta T_{50} (= T_{s,50} - T_{w,50})$.

	$\delta T_{w,50} > 0$ (more likely to be snow under the same wet-bulb temperature)	$\delta T_{w,50} < 0$ (more likely to be rain under the same wet-bulb temperature)
$\delta(\Delta T_{50}) > 0$ (suggesting drier conditions)	Pattern 1	Pattern 4
$\delta(\Delta T_{50}) < 0$ (suggesting moister conditions)	Pattern 3	Pattern 2

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Dividing the analysis period into the first (1990–2004) and second (2005–2020) halves, we defined the inter-period difference in each index (the second-half value minus the first-half value) as $\delta T_{s,50}$, $\delta T_{w,50}$, and $\delta(\Delta T_{50})$, respectively. From Eq. (6),

160
$$T_{s,50} = T_{w,50} + \Delta T_{50} \quad (7)$$

so the inter-period difference is

$$\delta T_{s,50} = \delta T_{w,50} + \delta(\Delta T_{50}) \quad (8)$$

Equation (8) decomposes the change in the air-temperature-based rain–snow boundary into the change in the wet-bulb-temperature-based boundary and that in the difference between them. This decomposition allows the change in $T_{s,50}$ to be understood by separating it into a change in how readily precipitation falls as snow at a given wet-bulb temperature and a change in humidity-related controls during precipitation, represented by ΔT_{50} . An increase in $T_{s,50}$ ($T_{w,50}$) indicates that the surface air temperature (wet-bulb temperature) corresponding to the rain–snow boundary has increased, suggesting that snow has become more likely to be maintained under the same surface air temperature (wet-bulb temperature). An increase in ΔT_{50} is consistent with drier atmospheric conditions during precipitation. Because ΔT_{50} is derived from statistically estimated rain–snow thresholds, it should be interpreted as a diagnostic index rather than as a direct physical measure of cooling by evaporation and sublimation. The change $\delta T_{s,50}$ at each site is classified into four patterns according to the signs of $\delta T_{w,50}$ and $\delta(\Delta T_{50})$ (Table 1). When both $T_{w,50}$ and ΔT_{50} increase (Pattern 1), snow becomes more likely under the same wet-bulb temperature and conditions during precipitation appear drier; both contribute to a shift toward the snow side under the same air temperature, so $\delta T_{s,50}$ increases. When both decrease (Pattern 2), rain becomes more likely under the same wet-bulb temperature and conditions during precipitation appear moister; both contribute to a shift toward the rain side under the same air temperature, so $\delta T_{s,50}$ falls. In Pattern 3, $T_{w,50}$ increases while ΔT_{50} decreases, so precipitation becomes more likely to be observed as snow under the same wet-bulb temperature, whereas conditions during precipitation appear moister. In Pattern 4, $T_{w,50}$ decreases while ΔT_{50} increases, so precipitation becomes more likely to be observed as rain under the same wet-bulb temperature, whereas conditions during precipitation appear drier. In Patterns 3 and 4, because $\delta T_{w,50}$ and $\delta(\Delta T_{50})$ act in opposite directions, the direction of change in $\delta T_{s,50}$ is determined by the relative magnitudes of $|\delta T_{w,50}|$ and $|\delta(\Delta T_{50})|$.

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3 Results and Discussion

3.1 Relationships between surface air or wet-bulb temperature and snowfall frequency

Figure 1a shows the snowfall frequency curves against surface air temperature at 115 stations nationwide over the 36 years from 1989 to 2024, together with histograms of the surface air temperatures at which the snowfall frequency was 10 %, 50 %, and 90 % ($T_{s,10}$, $T_{s,50}$, $T_{s,90}$) at each site. The 115 stations used were those for which sufficient rain or snow events were available to estimate the logistic curve using Eq. (4). At low temperatures (below about -1 °C), the snowfall frequency was 100 % at almost all sites, and at high temperatures (above about 7 °C), it was 0 % at almost all sites, indicating that the precipitation phase transitions from snow to rain roughly within the range of -1 °C to 7 °C. On the other hand, the temperature band over which that transition occurred varied widely from site to site. The overlap in the $T_{s,10}$ and $T_{s,90}$ histograms indicates that, at a given air temperature, the snowfall frequency was as high as 90 % at some sites but as low as 10 % at others. As shown in Table 2, the mean $T_{s,50}$ was 2.63 °C and the standard deviation was 0.73 °C. This nationwide mean exceeds the mean of 1.0 °C reported by Jennings et al. (2018) for the entire Northern Hemisphere, as well as the upper limit of their 95 % range of -0.4 °C to 2.4 °C. That study noted that Japan's $T_{s,50}$ is exceptionally high among regions with maritime climates, attributing this to the process in which cold air originating over Siberia acquires heat and water vapor over the Sea of Japan and is transformed; the resulting increase in the lapse rate promotes the formation of snow crystals aloft, so that snow is observed at the surface even at relatively high temperatures. $T_{s,10} - T_{s,90}$ represents the temperature

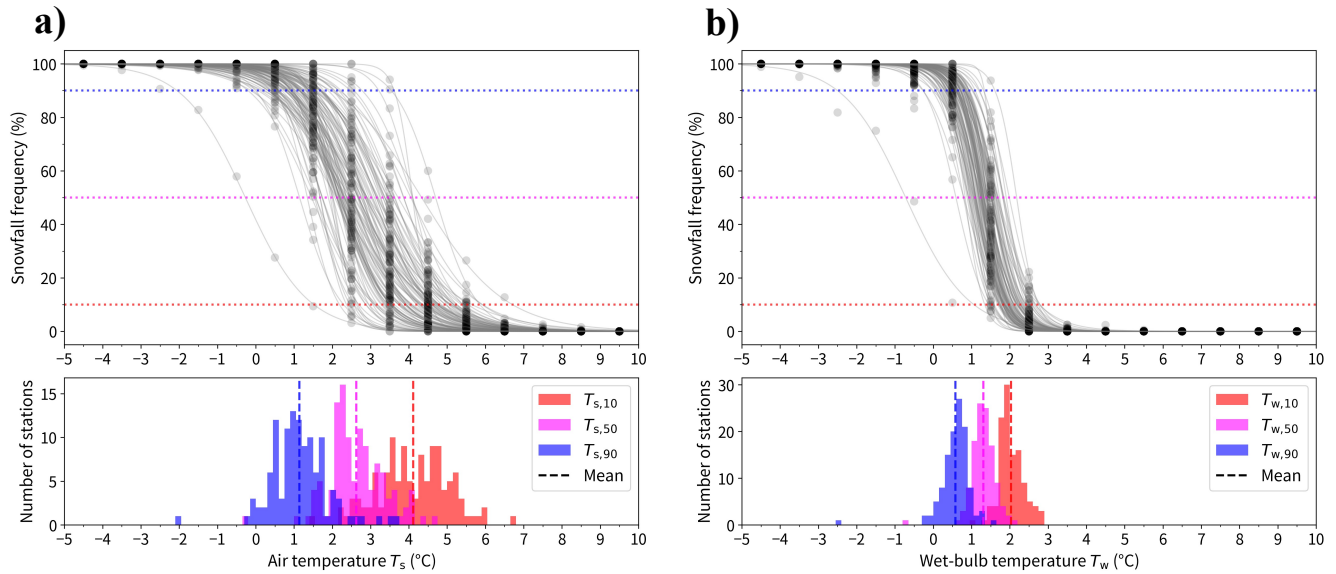


Figure 1. Data for 115 stations across Japan over 1989–2024. (a) Relationship between surface air temperature and snowfall frequency, and histograms of the surface air temperatures at which the snowfall frequency was 10 %, 50 %, and 90 % ($T_{s,10}$, $T_{s,50}$, $T_{s,90}$); (b) relationship between wet-bulb temperature and snowfall frequency, and histograms of the wet-bulb temperatures at which the snowfall frequency was 10 %, 50 %, and 90 % ($T_{w,10}$, $T_{w,50}$, $T_{w,90}$).



Table 2. Data for 115 stations across Japan over 1989–2024. The means and standard deviations of the air temperature $T_{s,50}$ and wet-bulb temperature $T_{w,50}$ at which the snowfall frequency was 50 %, the difference between the air temperatures at which the snowfall frequency was 10 % and 90 % ($T_{s,10} - T_{s,90}$), and the corresponding differences in wet-bulb-temperatures ($T_{w,10} - T_{w,90}$).

	$T_{s,50}$	$T_{w,50}$	$T_{s,10} - T_{s,90}$	$T_{w,10} - T_{w,90}$
Mean (°C)	2.625	1.305	2.977	1.450
Standard deviation (°C)	0.734	0.330	0.851	0.359

range over which the snowfall frequency decreased from 90 % to 10 % with increasing temperature, and can be considered an index of the width of the snow-to-rain transition zone. The larger the value, the more gradual the change in snowfall frequency with temperature, and the more readily rain and snow coexisted under the same air temperature, implying greater uncertainty in temperature-based rain–snow discrimination.

Figure 1b shows the snowfall frequency curves against wet-bulb temperature at the same 115 stations nationwide as in Fig. 1a, together with histograms of the wet-bulb temperatures at which the snowfall frequency was 10 %, 50 %, and 90 % ($T_{w,10}$, $T_{w,50}$, $T_{w,90}$). The precipitation phase transitioned from snow to rain at wet-bulb temperatures roughly between 0 °C and 3 °C; compared to the air-temperature case, the transition of the precipitation phase with increasing temperature was more abrupt, and the site-to-site variation in the transition temperature band was smaller. As shown in Table 2, the mean $T_{w,50}$ was 1.31 °C with a standard deviation of 0.33 °C, and the mean $T_{w,10} - T_{w,90}$, which represents the wet-bulb-temperature range over which the snowfall frequency decreased from 90 % to 10 %, was 1.45 °C, with a standard deviation of 0.36 °C.

The standard deviation of $T_{w,50}$ was less than half that of $T_{s,50}$, indicating smaller site-to-site variation in the wet-bulb threshold than in the air-temperature threshold. This suggests that a single, spatially uniform wet-bulb threshold can be applied across stations with less loss of accuracy than an air-temperature threshold, and is therefore more broadly applicable. In addition, the mean $T_{w,10} - T_{w,90}$ was about half that of $T_{s,10} - T_{s,90}$, indicating a narrower transition range for wet-bulb temperature. Because a narrower range means less overlap between rain and snow, wet-bulb-temperature-based discrimination is likely more accurate than air-temperature-based discrimination. These results suggest that, by integrating the effects of temperature, humidity, and pressure, wet-bulb temperature more consistently represents the thermal conditions controlling the precipitation phase than surface air temperature alone.



3.2 Spatial distributions of $T_{s,50}$, $T_{w,50}$, ΔT_{50}

Figures 2a–c show the spatial distribution of $T_{s,50}$ and its relationships with latitude and elevation. $T_{s,50}$ decreased significantly with increasing latitude and elevation; this tendency for lower values at higher latitudes and elevations is consistent with Ogawa and Nogami (1994) and Hasemi (1991), respectively. However, the correlations were weak to moderate – stronger for elevation than for latitude – and only part of the variation was explained by latitude and elevation. Indeed, the site-to-site variation was large even within the same latitude and elevation bands; in particular, some sites in the Kanto region and eastern Hokkaido showed lower $T_{s,50}$ than surrounding areas. Such regional differences may have been due not only to variation in humidity conditions during precipitation but also to differences in the synoptic situations that produced the precipitation. Hasemi (1991) classified winter precipitation in Japan into winter-monsoon and cyclone types and found that the cyclone-type had a lower $T_{s,50}$. Therefore, the relatively low $T_{s,50}$ values in the Kanto region and eastern Hokkaido may reflect a relatively large contribution of cyclone-type precipitation events in these regions.

Figures 2d–f show the spatial distribution of $T_{w,50}$ and its relationships with latitude and elevation. Values decreased significantly with increasing latitude and elevation, consistent with Sugaya (2005); the correlation was stronger with elevation than with latitude. In addition, $T_{w,50}$ showed less spatial variability than $T_{s,50}$ nationwide, consistent with the smaller inter-site variation shown in Fig. 1 and Table 2.

Figures 2g–i show the spatial distribution of ΔT_{50} and its relationships with latitude and elevation. Values significantly decreased with increasing latitude and elevation, but the correlations were the weakest among the three variables. This suggests that the elevation dependence of $T_{s,50}$ arises mainly through $T_{w,50}$, and that ΔT_{50} carries a component that is relatively independent of elevation. As noted in Sect. 2.4, the regional differences in ΔT_{50} may be related to differences in humidity conditions during precipitation, which we examine below.

Although $T_{s,50}$, $T_{w,50}$, and ΔT_{50} all tended to decrease with latitude and elevation, the coefficient of determination indicated that these factors explained only about 10–25 % of the variation (less than 10 % for ΔT_{50}). Therefore, much of the site-to-site variation was due to factors other than latitude and elevation. In particular, $T_{s,50}$ had larger inter-site variation than did $T_{w,50}$, and this excess variation is reflected in the regional differences in ΔT_{50} .

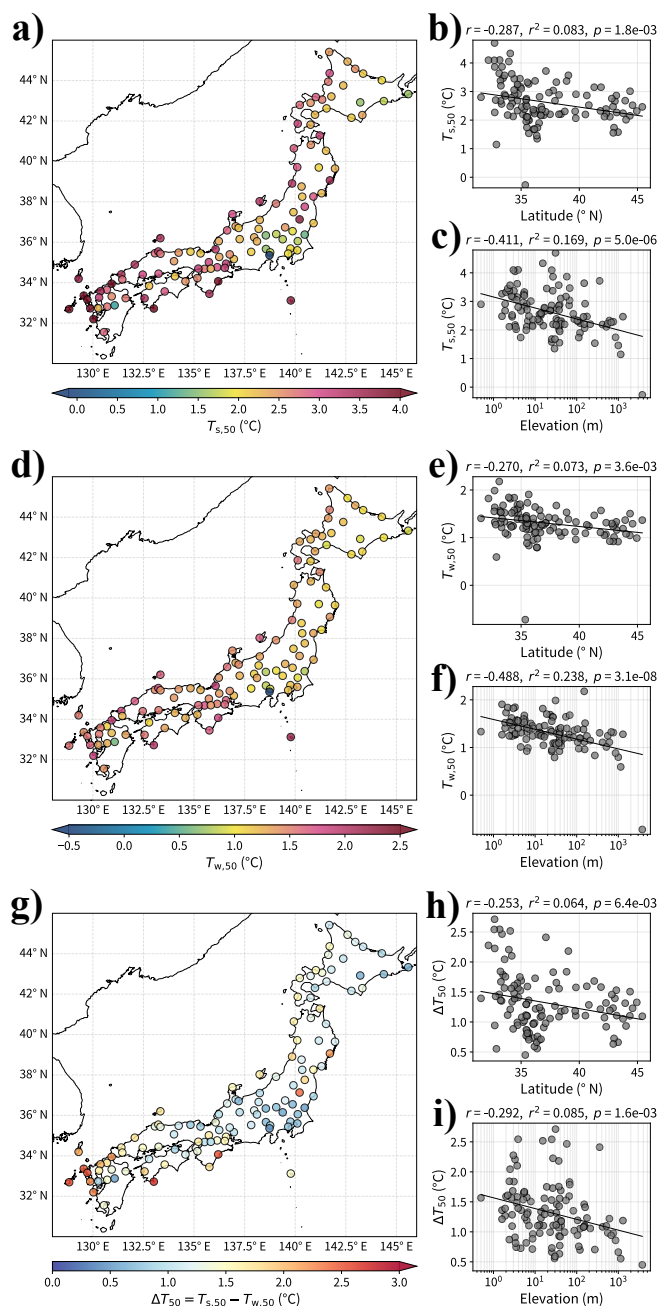


Figure 2. Spatial distributions of $T_{s,50}$ (a–c), $T_{w,50}$ (d–f), and ΔT_{50} (g–i) at 115 stations across Japan (1989–2024), and their relationships with latitude and elevation. For each variable, the left panel (a, d, g) shows the geographic distribution, the upper-right panel (b, e, h) the relationship with latitude, and the lower-right panel (c, f, i) the relationship with elevation (logarithmic axis). Solid lines in the scatter plots are linear regression lines; r is the Pearson correlation coefficient, r^2 is the coefficient of determination, and p is the significance probability of r .

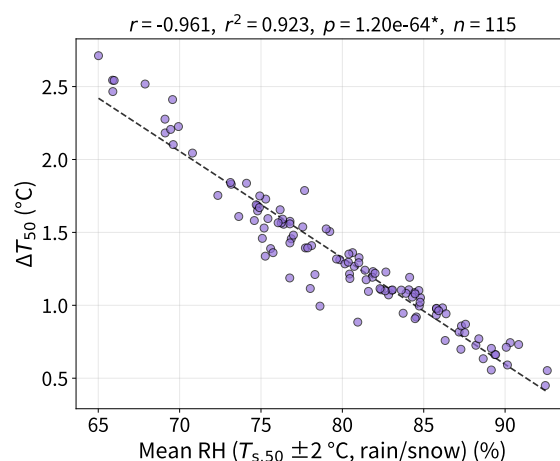


Figure 3. ΔT_{50} versus the mean relative humidity during rain or snow events at 115 stations across Japan (1989–2024). The relative humidity (RH) is averaged over the transition zone within ± 2 °C of $T_{s,50}$. Circles represent stations, and the dashed line is the linear regression. r is the Pearson correlation coefficient, r^2 is the coefficient of determination, and p is the significance probability of r .

To examine whether these regional differences in ΔT_{50} corresponded to humidity conditions during precipitation, we plotted ΔT_{50} against the mean relative humidity during the rain or snow events at each of the 115 stations, where the relative humidity is averaged over the transition zone within ± 2 °C of $T_{s,50}$ (Fig. 3). ΔT_{50} was strongly and significantly negatively correlated with relative humidity, with larger values at stations that were drier during precipitation. By definition, however, the wet-bulb temperature falls increasingly below the air temperature as relative humidity decreases, and ΔT_{50} corresponds to this reduction. The correlation between ΔT_{50} and relative humidity therefore reflects not only a physical link between the two but also a component that arises necessarily from this definition. Even so, this result shows that ΔT_{50} is statistically associated with humidity conditions during precipitation, and supports the use of ΔT_{50} as a diagnostic index of humidity-related controls on the precipitation phase.

That said, these regional differences may also reflect other meteorological conditions during precipitation, such as station pressure, wind speed, and precipitation amount. In the next section, therefore, we compare snowfall frequency curves stratified by relative humidity, station pressure, wind speed, and precipitation amount, and examine the influence of each factor on the rain–snow transition temperature.

3.3 Influence of meteorological conditions on precipitation phase

Figure 4 compares the relationships of snowfall frequency with surface air temperature and wet-bulb temperature, stratified by relative humidity, station pressure, wind speed, and precipitation amount. Under all conditions, the snowfall frequency monotonically decreases with increasing air temperature or wet-bulb temperature, but the position of the snowfall frequency curve differs systematically with the meteorological condition. Note that, in stratification by a single meteorological



condition, the stratification may simultaneously include differences in other conditions.

From Figs. 4a and 4b, the lower the relative-humidity category, the more the snowfall frequency curve is shifted toward the high-temperature side, and at the same surface air temperature or wet-bulb temperature, the proportion observed as snow tends to be higher. That is, under drier conditions, snow falls more readily even at higher temperatures. This tendency is physically consistent with enhanced evaporation and sublimation of precipitation particles in dry air, which would cool them through the consumption of latent heat. This humidity dependence is particularly pronounced when T_s is used as the reference, whereas the differences among the curves are small for T_w . This is consistent with T_w incorporating information on temperature, humidity, and pressure, and thereby already accounting for cooling by evaporation and sublimation; it also aligns with the interpretation in the previous section (Figs. 2 and 3) that ΔT_{50} may reflect humidity-related controls on the precipitation phase. Over Japan's high-density observation network, the dependence of the air-temperature-based snowfall frequency curves on relative humidity (Fig. 4a) is consistent with the trends reported by Jennings et al. (2018) for the entire Northern Hemisphere.

From Figs. 4c and 4d, the higher the station-pressure category, the more the snowfall frequency curve tends to be located toward the high-temperature side. However, because station pressure and elevation are strongly correlated, this stratification includes differences in elevation and site climate as well as differences in pressure. This is consistent with Figs. 2c and 2f, in which $T_{s,50}$ and $T_{w,50}$ decreased with increasing elevation. This tendency is clearer for T_s than for T_w , because the wet-bulb temperature includes pressure in its calculation, so part of the difference related to pressure (and the correlated elevation) may already be reflected in T_w . On the other hand, the fact that a slight difference still remains even for T_w suggests that these effects are not fully captured by wet-bulb temperature alone, and that differences in the descent of precipitation particles and in the vertical structure of the surrounding atmosphere may also play a role. Note that Jennings et al. (2018) showed, for the entire Northern Hemisphere, that the higher the pressure category, the more the air-temperature-based snowfall frequency curve is located toward the low-temperature side, the opposite of our findings for all of Japan. This suggests that pressure-based stratification reflects not the effect of pressure itself but the climate, particularly the humidity conditions, of the sites that are disproportionately included in each category. That is, when the entire Northern Hemisphere is stratified by pressure, the low-pressure (high-elevation) category includes many regions with dry continental climates, such as the Rocky Mountains and the Tibetan Plateau, where the associated dryness may raise the threshold temperature through humidity-related cooling. In contrast, in maritime-climate Japan, high-elevation sites are not necessarily dry, so the threshold temperature decreases with increasing elevation, producing a result opposite to the hemisphere-wide tendency.

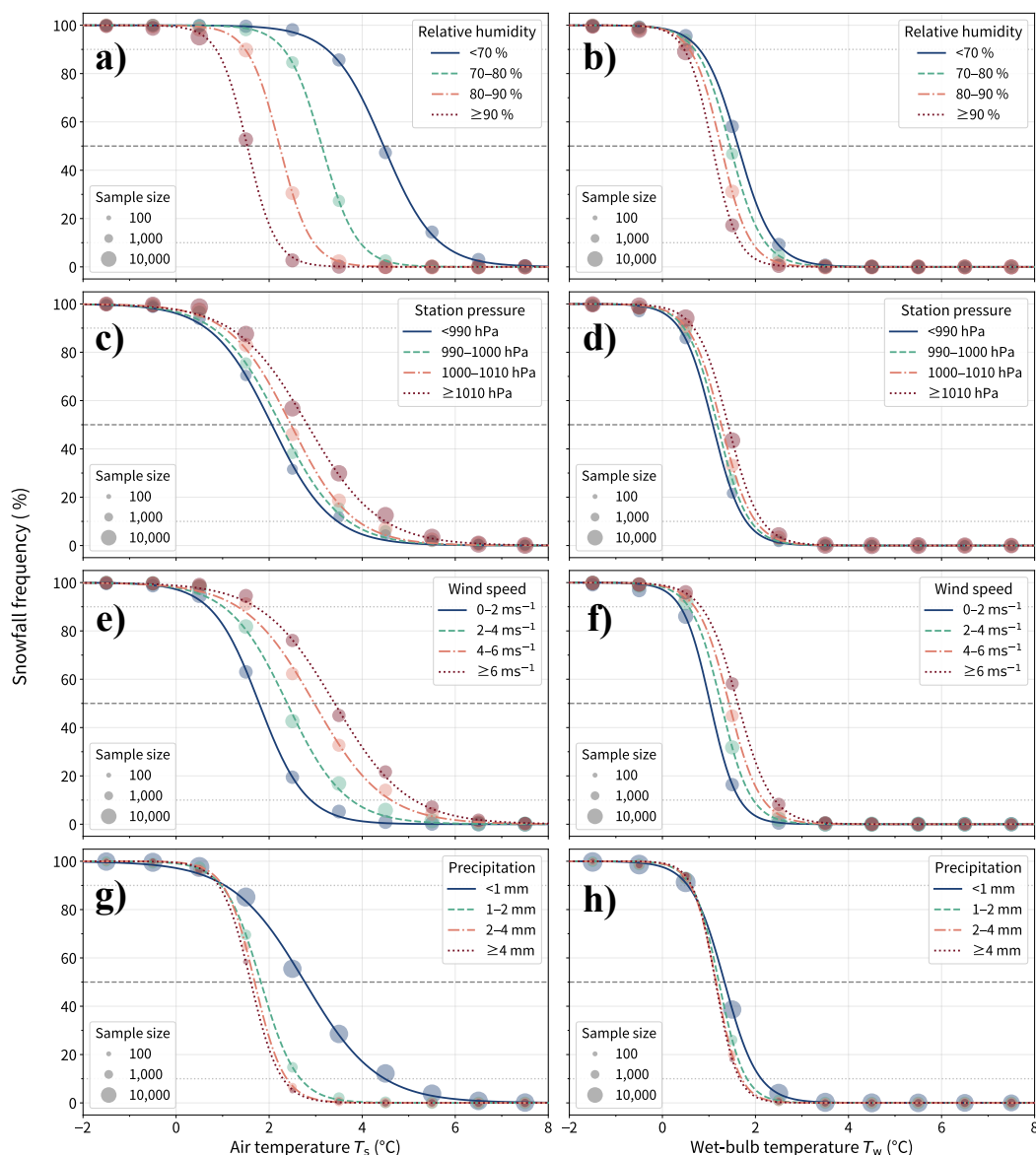


Figure 4. Relationships between snowfall frequency and surface air temperature (a, c, e, g) or wet-bulb temperature (b, d, f, h) at 115 stations across Japan, stratified by relative humidity (a, b), station pressure (c, d), wind speed (e, f), and precipitation amount (g, h).

315

As shown in Figs. 4e and 4f, the greater the wind speed, the more the snowfall frequency curve is located toward the high-temperature side, and the higher the rain–snow boundary temperature. That is, under strong winds, snow tends to be maintained even at higher temperatures. This tendency is clear for T_s , and a change in the same direction is also seen for T_w , although to a lesser degree. This relationship may partly reflect enhanced turbulent exchange of heat and water vapor around



320 falling hydrometeors, which can affect their melting (e.g., Szyrmer and Zawadzki, 1999); it may also reflect differences in the synoptic environments associated with strong winds.

From Figs. 4g and 4h, the larger the precipitation amount, the more the snowfall frequency curve shifts toward the low-temperature side, and the lower the rain–snow boundary temperature. That is, under stronger precipitation, the proportion observed as rain is higher even under the same temperature conditions. This shift is particularly large for T_s , and small for T_w .
325 Although precipitation intensity affects the thickness of the melting layer and the particle-size distribution, thereby contributing to the rain–snow transition temperature (e.g., Feiccabrino et al., 2015; Gjertsen and Ødegaard, 2005), in this study an increase in precipitation was associated not with the high-temperature shift reported previously but rather with a shift toward lower temperatures. The low-temperature shift under stronger precipitation may reflect the fact that intense precipitation events are often accompanied by more humid environments and the inflow of warm, moist air, rather than by
330 the increase in precipitation amount itself. In other words, the amount of precipitation likely reflects differences in other meteorological conditions, particularly humidity. The differences among the curves become small for T_w , consistent with much of the precipitation-amount effect being absorbed by the wet-bulb temperature, which integrates temperature, humidity, and pressure. This suggests that the difference arises mainly from humidity.

In sum, the influences of the various meteorological factors manifest differently for T_s and T_w . This difference can be
335 interpreted as reflecting the fact that T_w incorporates information on temperature, humidity, and pressure, and therefore represents the thermal conditions controlling the precipitation phase more effectively than does T_s . The same pattern holds for station pressure, though as noted above this difference is confounded by elevation and site climate, so the pure effect of pressure cannot be isolated. The influence of wind speed also becomes smaller when T_w is used instead of T_s , although a wind-speed-related shift in the curves still remains for T_w . This is consistent with the fact that wind speed is not included in
340 the calculation of T_w , so T_w does not capture its effect. In any case, using T_w rather than T_s alone reduces the variability due to meteorological conditions in rain–snow discrimination. On the other hand, the residual wind-speed dependence that T_w does not capture suggests that additionally accounting for wind speed could further improve discrimination accuracy, although verifying this is left for future work.

3.4 Changes in $T_{s,50}$, $T_{w,50}$, and ΔT_{50} between the first and second halves of the study period

345 To investigate long-term changes in $T_{s,50}$, $T_{w,50}$, and ΔT_{50} , we analyzed 44 stations at which visual observations continued after 2019 and where fitting by Eq. (4) was successfully performed for both the first half (1990–2004) and the second half (2005–2020). The second half spans one more year than the first because visual weather observations ended at many stations around 2020, and this boundary maximized the number of stations with sufficient data in both periods. These stations, distributed across Japan from Hokkaido to Kyushu, were used to compare the inter-period differences in each index (second-
350 half value minus first-half value). The results are shown in Fig. 5.

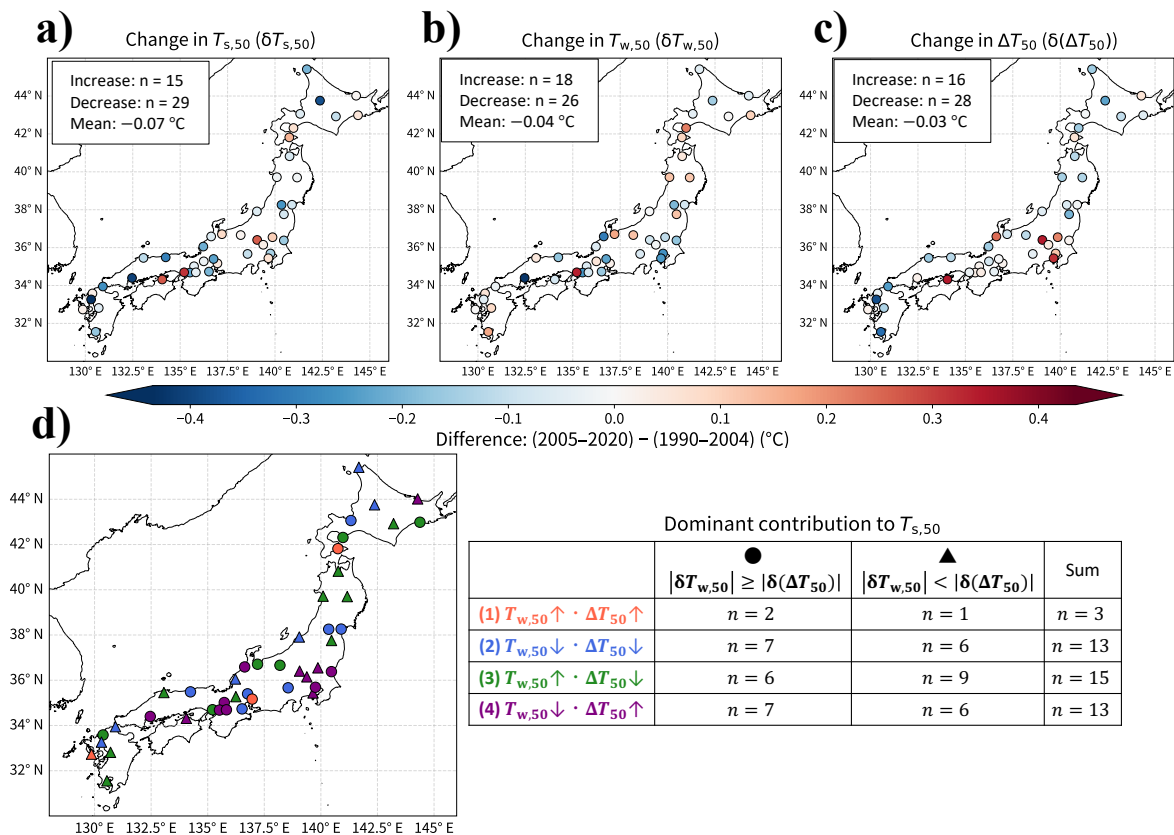


Figure 5. Data for 44 stations across Japan, for the first half (1990–2004) and the second half (2005–2020), showing changes in **(a)** $T_{s,50}$ ($\delta T_{s,50}$), **(b)** $T_{w,50}$ ($\delta T_{w,50}$), **(c)** and ΔT_{50} ($\delta(\Delta T_{50})$). Each value is the second-half value minus the first-half value; positive values indicate increases and negative values indicate decreases. **(d)** The contributions of the changes in $T_{w,50}$ and ΔT_{50} to the changes in $T_{s,50}$. Marker color indicates the combination of the signs of $\delta T_{w,50}$ and $\delta(\Delta T_{50})$: orange, both increased; blue, both decreased; green, $T_{w,50}$ increased and ΔT_{50} decreased; purple, $T_{w,50}$ decreased and ΔT_{50} increased. Marker shape indicates whether the contribution of $T_{w,50}$ (circle) or ΔT_{50} (triangle) was dominant.

As shown in Fig. 5a, the all-site mean of the inter-period difference in $T_{s,50}$ was -0.07°C , with decreases at 29 sites and increases at 15 sites. From Fig. 5b, that of $T_{w,50}$ was -0.04°C , with decreases at 26 sites and increases at 18 sites. For both, more sites showed decreases than increases, suggesting that at these sites precipitation was more likely to be observed as rain under the same surface air temperature or wet-bulb temperature conditions.

From Fig. 5c, the mean value for ΔT_{50} was -0.03°C , with decreases at 28 sites and increases at 16 sites. As described in Sect. 2.4, a decrease in ΔT_{50} is consistent with moister conditions during precipitation, and an increase with drier conditions. ΔT_{50} decreased at sites over a wide area nationwide, suggesting a moistening of the surface atmosphere during cold-season precipitation; on the other hand, many sites in the Kanto region showed an increase, suggesting a drying of the surface



atmosphere during cold-season precipitation in that region.

Figure 5d shows the results of decomposing $\delta T_{s,50}$ at each site into $\delta T_{w,50}$, which represents the change in the wet-bulb-
370 temperature-based rain–snow boundary, and $\delta(\Delta T_{50})$, which represents the change in humidity-related controls during precipitation, using the method presented in Sect. 2.4. The sites are then classified into the four patterns shown in Table 1 according to the combination of their signs. The number of sites classified as Pattern 1 (orange) is the smallest, 3 of the 44 sites, whereas Pattern 3 (green) has 15 sites, and Patterns 2 (blue) and 4 (purple) each have 13 sites; thus, the three classifications other than Pattern 1 have roughly comparable numbers of sites. In particular, the fact that more than half of
375 the sites are classified as Pattern 3 or Pattern 4 suggests that at many sites $T_{w,50}$ and ΔT_{50} changed in opposite directions; that is, the change in how readily precipitation falls as snow at the same wet-bulb temperature and the change in humidity-related controls during precipitation offset the change in $T_{s,50}$. This means that at many sites the change in $T_{s,50}$ appears as the net balance of the change in the wet-bulb-temperature-based rain–snow boundary ($\delta T_{w,50}$) and the change in humidity-related controls during precipitation ($\delta(\Delta T_{50})$). Thus, the change in $T_{s,50}$ is difficult to explain by a single factor such as drying or
380 moistening during precipitation. In addition, the sites classified as Pattern 4 are concentrated in the Kanto region. There, precipitation became more likely to be observed as rain under the same wet-bulb temperature, while $\delta(\Delta T_{50})$ increased, consistent with drier conditions during precipitation.

Previous studies have also emphasized the importance of wet-bulb temperature for snowfall under climate change (e.g., Tamang et al., 2020). Extending this line of work, we propose a framework that decomposes the long-term change in the air-
385 temperature-based rain–snow threshold $T_{s,50}$ into the change in the wet-bulb-temperature-based threshold $T_{w,50}$ and the change in their difference ΔT_{50} . This framework makes it possible to interpret the change in $T_{s,50}$ by distinguishing a shift in the wet-bulb-based boundary from a change in humidity-related controls during precipitation, represented by ΔT_{50} .

4 Conclusions

Using surface meteorological observation data from 158 stations across Japan over the 36 years from 1989 to 2024, we
390 analyzed the spatial distributions of, and long-term changes in, the surface air temperature $T_{s,50}$ and wet-bulb temperature $T_{w,50}$ at which the snowfall probability was 50 %, together with their difference ΔT_{50} ($= T_{s,50} - T_{w,50}$), a diagnostic index of humidity-related controls on the precipitation phase, and examined the influence of various meteorological conditions on the rain–snow transition temperature. The main results are presented below.

Across 115 stations nationwide, the mean $T_{s,50}$ was 2.63 °C and the mean $T_{w,50}$ was 1.31 °C. The standard deviation of $T_{w,50}$
395 was less than half that of $T_{s,50}$, indicating that wet-bulb-temperature-based discrimination is likely to be more broadly applicable than air-temperature-based discrimination when a spatially uniform threshold is used. In addition, the mean $T_{w,10} - T_{w,90}$, representing the wet-bulb-temperature width over which snow transitioned to rain, was about half that of the air-temperature width, $T_{s,10} - T_{s,90}$, suggesting that wet-bulb-temperature-based rain–snow discrimination is more accurate than air-temperature-based discrimination.



400 The spatial distributions of $T_{s,50}$ and $T_{w,50}$ both showed a tendency to decrease with increasing latitude and elevation, consistent with previous studies. ΔT_{50} likewise decreased with increasing latitude and elevation, but its dependence, particularly its dependence on elevation, was weaker than that of $T_{s,50}$ and $T_{w,50}$. For all indices, only part of the variation was explained by latitude and elevation, and the site-to-site variation was large even within the same latitude and elevation bands. In particular, the variation in $T_{s,50}$ was larger than that in $T_{w,50}$, and this excess variation is reflected in the regional differences in ΔT_{50} . These regional differences may reflect differences in humidity conditions during precipitation that are not explained by latitude and elevation. Regional differences in ΔT_{50} were statistically associated with humidity conditions during precipitation, with larger values at drier sites. Although this association partly follows from the definition of wet-bulb temperature, it is consistent with interpreting ΔT_{50} as a diagnostic index that represents humidity-related controls on the precipitation phase.

410 In analyses stratified by meteorological condition, systematic differences were found in the snowfall frequency curves stratified by relative humidity, station pressure, wind speed, and precipitation amount. The shifts in the curves due to relative humidity and precipitation amount were large for T_s but small for T_w , likely because the wet-bulb temperature integrates information on temperature, humidity, and pressure and better represents the thermal conditions controlling the precipitation phase than air temperature. For station pressure as well, the difference was large for T_s and small for T_w ; however, because

415 station pressure correlates with elevation, this difference may also include differences in elevation and site climate. The influence of wind speed also decreased when T_w was used, but a wind-speed-related shift in the curves still remained for T_w . In any case, using T_w rather than T_s alone can reduce the variability due to meteorological conditions in rain–snow discrimination. The residual wind-speed dependence that T_w does not capture, on the other hand, suggests that additionally accounting for wind speed could further improve discrimination accuracy, although verifying this is left for future work.

420 At the 44 stations for which the first half (1990–2004) and the second half (2005–2020) were compared, the all-site means of $T_{s,50}$ and $T_{w,50}$ were -0.07 °C and -0.04 °C, respectively, decreasing at many sites. This suggests that in recent years precipitation has become more likely to be observed as rain under the same surface air temperature or wet-bulb temperature conditions. ΔT_{50} decreased over a wide area nationwide, suggesting moister conditions during cold-season precipitation, whereas in the Kanto region many sites showed an increase in ΔT_{50} , suggesting drier conditions during cold-season

425 precipitation. Moreover, decomposing the change in $T_{s,50}$ into the changes in $T_{w,50}$ and ΔT_{50} revealed that at more than half of the sites the two changed in mutually opposite directions, with the change in how readily precipitation falls as snow at the same wet-bulb temperature and the change in humidity-related controls during precipitation offsetting each other. This indicates that, at many sites, the long-term change in $T_{s,50}$ is difficult to explain by a single factor.

In this study, we proposed a framework that decomposes the air-temperature-based rain–snow boundary temperature $T_{s,50}$

430 into the wet-bulb-temperature-based boundary temperature $T_{w,50}$ and their difference ΔT_{50} , a diagnostic index of humidity-related controls on the precipitation phase ($T_{s,50} = T_{w,50} + \Delta T_{50}$). This framework offers a unified way to understand both the regional differences and the long-term changes in rain–snow thresholds. Because wet-bulb temperature is widely available in reanalysis products, climate simulations, and land-surface models, the proposed framework may also provide a practical



435 basis for investigating future changes in the precipitation phase and the associated hydrological responses under climate change.

Data availability

The surface meteorological observations used in this study (hourly air temperature, water-vapor pressure, station pressure, and visually observed present weather) are publicly available from the Japan Meteorological Agency and can be downloaded from <https://www.data.jma.go.jp/stats/etrn/index.php>.

440 **Author contributions**

SH designed the study, performed the data analysis, and prepared the manuscript. TJY supervised the study and reviewed and edited the manuscript. All authors contributed to the interpretation of the results and approved the final manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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