Using a massive high-resolution ensemble climate data set to examine dynamic and thermodynamic aspects of heavy precipitation change

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Abstract
This study investigated the relationship between extreme precipitation and near-surface temperature (precipitation–temperature relation) from two different perspectives, the rate of change of precipitation with temperature and dynamic (i.e., effect of the change in atmospheric motion) and thermodynamic (i.e., effect of the change in atmospheric moisture content) aspects, using a 5-km dynamical downscaled hundreds-year data set for past climate condition (PAST; from 1951 to 2010) and future climate condition (FUTURE; 4°C warmer than the preindustrial condition). Initially, using the observation and the PAST and FUTURE data sets, it was found that the 99th and 99.9th percentile hourly precipitation for each temperature bin (P99 and P99.9, respectively) paralleled the slope of the Clausius–Clapeyron (C–C) relation for a certain temperature range over the Tokachi River basin in Hokkaido, the northern island of Japan; however, both P99 and P99.9 decreased in the high-temperature range. Next, we examined the cause of the P99 and P99.9 differences between PAST and FUTURE for each temperature bin by classifying dynamic and thermodynamic factors. The result showed that the thermodynamic effect dominates the differences in P99 and P99.9 between PAST and FUTURE, which means that the thermodynamic effect is the main component of the precipitation–temperature relation. Similar analyses were applied to the whole river basin, including the mountainous area. The results showed that the differences in P99 and P99.9 between PAST and FUTURE are mainly due to the thermodynamic contribution, regardless of plain or mountain area. Using such large model data sets, we could make a robust assessment of the precipitation–temperature relation and the dynamic and thermodynamic contributions to precipitation changes. Moreover, using the 5-km resolution hundreds-year data set enabled us to quantify the spatial distribution of such precipitation characteristics over a thousands of square kilometer catchment.
1 | INTRODUCTION

In 2016, Hokkaido, the northernmost island of Japan (Figure 1), was affected by four typhoons within 2 weeks, which caused severe flooding and landslides in many river basins, including the Tokachi River basin in east-central Hokkaido. The topographic effect enhanced the heavy precipitation over the Hidaka Mountains west of this river basin (Nguyen-Le and Yamada, 2017). Regarding the precipitation projected under climate change, Inatsu et al. (2015) investigated the seasonal mean precipitation change using dynamical downscaling with three global and three regional climate models. They found that the boreal summer precipitation in a future climate (the late 21st century of A1b scenario; Meehl et al., 2007) over Hokkaido was ~50% larger than in the past climate (1991–2000). After severe anomalous floods and landslides in 2016, the central government and Hokkaido Prefecture established a committee to discuss future flood risk assessments associated with climate change (Yamada, 2019).

Several studies have assessed the separate contributions of dynamics and thermodynamics to the change in extreme precipitation associated with climate change (Trenberth, 1999; Emori and Brown, 2005). Allen and Ingram (2002) showed that extreme precipitation as a function of temperature (precipitation–temperature relation) is close to the Clausius–Clapeyron (C–C) relation (the increase in atmospheric water-holding capacity associated with a temperature increase; i.e., 7% per 1°C). Some studies that focused on Japan have also discussed the precipitation–temperature relation based on in situ observations (Utsumi et al., 2011; Yamada et al., 2014;
Fujibe, 2016). Over Hokkaido, the focus of this study, Yamada et al. (2014), showed that greater than 99th percentile precipitation and precipitable water vapor in radiosonde observations follow the C–C relation. Trenberth (2011) stated that the most robust precipitation changes accompanying climate change are associated with the thermodynamic aspect related to the C–C relation. The effects of changes in the circulation (the dynamics effect) on precipitation changes depend on more uncertain model results and are therefore not as robust. Recently, a super C–C relation, close to or even exceeding the double C–C scaling, was demonstrated based on in situ observation (Lenderink et al., 2017). A scaling rate exceeding 5%–10% per 1°C is regarded as “controversial” in the Intergovernmental Panel for Climate Change (IPCC) fifth assessment report (AR5) (Boucher et al., 2013). Li et al. (2019) investigated the dynamic and thermodynamic effects on the slope of annual maximum 24-h precipitation as a function of annual global mean temperature over North America and concluded that the influence of the dynamic effect is larger on the first category (50-year return period) of extreme rainfall than the second category (2-year return period) of extreme rainfall. These studies improve our understanding of the effect of dynamics and thermodynamics on precipitation–temperature relations.

On the other hand, studies have also shown that precipitation scales negatively with temperature for temperatures exceeding a certain level (Utsumi et al., 2011; Yamada et al., 2014; Drobinski et al., 2016; Wang et al., 2017). Drobinski et al. (2016) investigated this negative gradient factor from the viewpoints of condensation process, vertical transport, and precipitation efficiency. They found that warm and dry conditions in summer result in the negative gradient of the precipitation–temperature relation in the high-temperature range. Wang et al. (2017) investigated the impact of climate change on precipitation–temperature relations over the globe using global climate model data from the Coupled Model Intercomparison Project 5 (CMIP5; Taylor et al., 2012). They concluded that daily precipitation extremes intensified with local temperature intensification over most of the globe under the future climate because the precipitation–temperature relation follows the C–C relation even in the future climate. The precipitation–temperature relation at high temperatures is a critical indicator for considering future heavy rainfall risk.

In this study, we investigated future changes of the relationship between extreme hourly precipitation and near-surface temperature from two different viewpoints, the rate of change of precipitation with temperature and the dynamic and thermodynamic aspects. Recently, the Database for Policy Decision Making for Future Climate Change (d4PDF), a meteorological data set with thousands of years of both past and future climate conditions, was developed (Mizuta et al., 2017). Because climate models with finer grid spacing better represent for hourly precipitation frequency and its frequency (Sasaki et al., 2011; Drobinski et al., 2016), we applied dynamical downscaling using a regional climate model from 20 to 5 km spatial resolution for d4PDF past (PAST) and future (FUTURE) climate conditions. The high-resolution large-ensemble data set enabled us to increase the statistical robustness for quantification of the dynamic and thermodynamic contributions to extreme precipitation change as a function of near-surface temperature. In addition, the spatial characteristics of precipitation change and contributing factors were investigated over a thousands of square kilometers catchment and the results for plain and mountainous areas were compared.

2 | METHODOLOGY

2.1 | Target area

This study focused on the central region of Hokkaido, the northern island of Japan. The target area was the Obihiro subcatchment (2677.8 km²) in the Tokachi River basin (Figure 1). The Obihiro subcatchment is surrounded by the Hidaka Mountains (highest altitude: 2053 m) and Daisetsu Mountains (highest altitude: 2291 m), which are located on the west side and north side of the target catchment, respectively, as shown in Figure 1 by colors representing elevation with a 5-km spatial resolution.

2.2 | Observation data

This study used hourly precipitation intensity, near-surface temperature, and near-surface dew point temperature data (OBS) observed by the Japan Meteorological Agency (JMA) (JMA, 2021). The locations of the observatories (Obs. 1–7) are shown in Figure 1b. Near-surface dew point temperature is observed at a single station (Obs. 1). The other two variables are available from all seven observatories (Obs. 1–7). The record lengths of the observatories used in this study are continuous from 29 to 42 years until the end of 2019 (the exact years for each observatory are listed in Figure 1b). The rainfall data are collected at intervals of 0.5 mm at Obs. 1 and 1.0 mm at the other observatories.


2.3 | d4PDF

d4PDF provides past and future climate data sets with a large number of ensemble members. It covers the entire globe at a spatial resolution of 60 km (d4PDF [60 km]) and East Asia at a spatial resolution of 20 km (d4PDF [20 km]) (Mizuta et al., 2017). d4PDF (60 km) is the output from the global atmospheric model (Meteorological Research Institute AGCM, version 3.2 [MRI-AGCM3.2]; Mizuta et al., 2012). d4PDF (20 km) is produced by dynamical downscaling from d4PDF (60 km) with the regional climate model (NHRCM; Sasaki et al., 2008) developed by MRI/JMA.

In d4PDF, the past climate condition (PAST) consists of 3000 years of data, that is, 60 years (from 1951 to 2010) from 50 ensemble members, with perturbed initial conditions. The Centennial Observation-Based Estimates of SST version 2 (COBE-SST2; Hirahara et al., 2014) were applied to all ensemble members. The future climate condition (FUTURE) assumes a 4°C increase in global mean temperature from the preindustrial condition. The FUTURE consists of 5400 years, a combination of six representative sea surface temperature patterns in CMIP5, 60 years, and 15 ensemble members. Details of the experimental framework are given in Mizuta et al. (2017).

2.4 | Dynamical downscaling

In this study, we applied dynamical downscaling using NHRCM to produce d4PDF (5 km) data sets for PAST and FUTURE from d4PDF (20 km). For the convective parameterization and atmospheric boundary layer process in NHRCM, the Kain–Fritsch convective parameterization (Kain and Fritsch, 1993) and Mellor–Yamada–Nakanishi–Niino atmospheric boundary layer scheme (closure level: 3; Nakanishi and Niino, 2004) were adopted, respectively. The improved MRI/JMA Simple Biosphere (iSiB; Hirai et al., 2007) model was used for the land surface process. The dynamical downscaling targeted Hokkaido and the surrounding area at a spatial resolution of 5 km (the area within the solid black line in Figure 1a). The number of grid cells for the dynamical downscaling was 161 × 161 in the horizontal and 50 in the vertical.

This study used 782 years of d4PDF (5 km) for PAST and FUTURE, respectively. We could not complete the dynamical downscaling for all of the ensemble members in d4PDF (20 km) due to limited computer resources, so the years including the top 782 annual maximum area-averaged 3-day cumulative rainfall events in the Obihiro subcatchment were selected from d4PDF (20 km) for PAST and FUTURE, respectively. Note that the 3-day total rainfall is used to determine the flood management in this river basin. Hoshino et al. (2020) showed that d4PDF (5 km) has high reproducibility for area-averaged annual maximum 3-day rainfall volume over the target catchment. The hourly precipitation intensity over the target catchment is underestimated in d4PDF (20 km), but it was improved by the 5-km dynamical downscaling (Figure S1).

2.5 | Precipitation–temperature relation

In this study, we estimated the 99th and 99.9th percentile hourly precipitation for each temperature bin (P99 and P99.9, respectively), those of each dew point temperature bin (Pdpt99 and Pdpt99.9, respectively), and scaling factors (SFs) indicating the rate of change of precipitation with temperature. Hourly precipitation was binned into near-surface temperature bins with 1°C intervals at the corresponding time, including no precipitation periods. Next, P99 and P99.9 were calculated for each temperature bin. Pdpt99 and Pdpt99.9 were calculated in the same way using the dew point temperature. SFs were estimated by two different methods, a binning approach and quantile regression. For the binning approach, the change rates of P99 and P99.9 with temperature [e.g., P99 (T) − P99 (T−1), where T is temperature in °C] were calculated for each temperature bin. We applied a 7°C moving window to the change rate to estimate SF for each temperature. For quantile regression, we selected temperature exceeding 5°C and hourly precipitation exceeding 0.5 mm h−1 to exclude snow events and the influence of no rainfall time on SF. It is because this method calculates a single SF from the targeted temperature range and percentile that is highly influenced (underestimated) by no rainfall time. The logarithmic hourly precipitation intensity as a function of temperature was expressed by

\[
\ln(P) = \beta_0^q + \beta_1^q T,
\]

which is equivalent to the expression of Wasko et al. (2015), where P is hourly precipitation intensity, q is the quantile of interest, and \( \beta_0^q \) is the regression coefficient of the q-percentile. We calculated \( \beta_{99}^1 \) and \( \beta_{99.9}^1 \) by fitting the quantile regression. The SF of the q-percentile was estimated as follows:

\[
\text{SF}(q) = \left( \frac{\Delta P}{\Delta T} \right) = 100\left( e^{\beta^q_1} - 1 \right).
\]
2.6 Dynamic and thermodynamic classification

Dynamic and thermodynamic effects on $P_{99}$ and $P_{99.9}$ were investigated for each temperature bin following Emori and Brown (2005) using the hourly precipitation ($P$) and the corresponding 500 hPa vertical velocity ($\omega$). Here, $\omega$ represents the strength of the dynamic disturbance. The average value of $P$, $\bar{P}$, for each temperature bin can be represented by

$$\bar{P}(T) = \int_{-\infty}^{\infty} P_{\omega}(T) Pr_{\omega}(T) d\omega,$$

where $P_{\omega}$, $Pr_{\omega}$, and $T$ denote hourly precipitation intensity as a function of $\omega$, relative frequency of occurrence of $\omega$, and temperature, respectively. The difference in hourly precipitation at each temperature bin between PAST and FUTURE is expressed by

![Image of precipitation intensity vs temperature for OBS, PAST, FUTURE, and P99 and P99.9](image)

**FIGURE 2** Relationship between precipitation intensity and near-surface air temperature for (a) OBS, (b) PAST d4PDF (5 km), and (c) FUTURE d4PDF (5 km). $P_{99}$ and $P_{99.9}$ of OBS, PAST d4PDF (5 km), FUTURE d4PDF (5 km), and PAST d4PDF (20 km) are shown in (d). The color bars, black solid line, black dashed line, purple solid line, purple dashed line, and dotted line indicate the number of occurrences corresponding to each hexagonal grid, $P_{99}$, $P_{99.9}$, $P_{99\text{dpt}}$, $P_{99.9\text{dpt}}$, and the $C$–$C$ relation (7% increase per 1 K), respectively. (e, f) SF calculated by the binning approach.
The results are similar to the relationships noted for 99.9th percentiles, respectively, and 99.8th percentiles are corresponding to the 99th and median of precipitation intensity exceeding the 98th.

The binning approach are shown in Figure 2e,f. The SFs of dynamic effects for each temperature range (Panthou et al., 2011; Yamada et al., 2016; Wang et al., 2017). The comparison between OBS and PAST indicates that 5-km grid resolution shows clear improvement for 1 h precipitation intensity in the target area (see also Figure S1). Therefore, d4PDF (5 km) is regarded as having sufficiently fine resolution and is used in this study.

Figure 2 shows the relationships between hourly precipitation and temperature using OBS and PAST d4PDF (20 km) as well as PAST and FUTURE from d4PDF (5 km) at the location of Obs. 1 (Figure 1b) for OBS and the corresponding closest grid cell for d4PDF (20 km) and d4PDF (5 km). The colors of Figure 2a–c indicate the number of occurrences corresponding to each hexagonal cell. The range of the color bars is adjusted according to the number of years (OBS: 29 years; d4PDF: 782 years). The measurement interval of the observed precipitation is 0.5 mm; therefore, there are no data between 0.5 and 1 mm in Figure 2a. Figure 2a,b,d shows that the frequencies of precipitation intensity for each temperature bin for OBS and PAST d4PDF (5 km) are similar, except in the high-temperature range (≥25°C). The SFs estimated by the binning approach are shown in Figure 2e,f. The SFs of OBS and PAST for \( P_{99} \) are close to the C–C relation (7% per °C) up to the temperature of 15°C but have a negative gradient at temperatures exceeding 15–20°C. The results are similar to the relationships noted for observations in Japan (Utsumi et al., 2011; Yamada et al., 2014; Fujibe, 2016). The \( P_{99.9} \) has the same characteristics; however, the upper limit for which the SF follows the C–C relation is higher (18°C) than in the case of \( P_{99} \). A confidence interval of SF was calculated through a random sampling process. We selected the number of years equal to the observation period (29 years) from PAST and calculated SF, with 1000 repetitions. The variability of SF (5–95th percentile range) was about 8% per °C and 12% per °C for \( P_{99} \) and \( P_{99.9} \), respectively. Those ranges overlapped the SF of OBS for almost all temperature bins. Note that the reason for the larger fluctuations of \( P_{99} \) and \( P_{99.9} \) of OBS is the limited sample size (29 years) (Figures S2 and S3).

The \( P_{99} \) and \( P_{99.9} \) of PAST d4PDF (20 km) are shown in Figure 2d. The target years of d4PDF (20 km) include 782 years, the same years used for d4PDF (5 km). The \( P_{99} \) and \( P_{99.9} \) of PAST d4PDF (5 km) and PAST d4PDF (20 km) are similar; however, PAST d4PDF (5 km) shows more intense precipitation and is closer to OBS around the peak precipitation intensity. According to previous studies, 5-km horizontal grid resolution of climate simulation is required to represent intense hourly precipitation (Sasaki et al., 2011). The comparison between OBS and PAST indicates that 5-km grid resolution shows clear improvement for 1 h precipitation intensity in the target area. The temperature range of the negative gradient is much smaller than in the case of the precipitation–temperature relations, which is similar to the results of other studies (Panthou et al., 2014; Drobinski et al., 2016; Wang et al., 2017). The \( P_{99dpt} \) and \( P_{99.9dpt} \) are shown in Figure 2 (frequencies of precipitation intensity for dew point temperature are shown in Figure S4). The \( P_{99dpt} \) and \( P_{99.9dpt} \) of OBS, PAST, and FUTURE follow slopes close to the C–C relation under almost all dew point temperatures. The temperature range of the negative gradient is much smaller than in the case of the precipitation–temperature relations, which is similar to the results of other studies (Panthou et al., 2014; Drobinski et al., 2016). This result indicates that the negative gradient of SF at the higher temperature range shown in Figure 2 is due to high temperatures with low humidity conditions. In other words, the precipitation intensity at the target point depends on the amount of near-surface water vapor.

Figure 2c–f shows that the SFs of \( P_{99} \) and \( P_{99.9} \) of FUTURE are also close to the C–C relation up to a certain temperature and are negative at higher temperatures. However, the temperatures corresponding to peak \( P_{99} \) and \( P_{99.9} \) are both 24°C, which is 3–4°C higher than those of PAST. The maximum SF of \( P_{99.9} \) is about 10% per °C, which is higher than that of PAST.

\[
\delta P(T) = \int_{-\infty}^{\infty} P_{\omega}(T) \delta P_{\omega}(T) d\omega + \int_{-\infty}^{\infty} \delta P_{\omega}(T) P_{\omega}(T) d\omega + \int_{-\infty}^{\infty} \delta P_{\omega}(T) \delta P_{\omega}(T) d\omega,
\]

where the terms with attached \( \delta \) denote differences of the term between PAST and FUTURE (i.e., FUTURE minus PAST). The first term on the right-hand side of Equation (4) represents the dynamic contribution to precipitation change because this term is influenced by the difference in the probability distribution function of \( \omega \). The second term is for the thermodynamic effect, which is mainly affected by the change in atmospheric moisture content. Finally, the third term, the covariance term, is the interaction of dynamic and thermodynamic effects. The data corresponding to precipitation intensity exceeding the 98th and 99.8th percentiles for each temperature bin was selected to calculate dynamic and thermodynamic effects for \( P_{99} \) and \( P_{99.9} \), respectively. It is because the median of precipitation intensity exceeding the 98th and 99.8th percentiles are corresponding to the 99th and 99.9th percentiles, respectively.

3 | RESULTS

3.1 | Precipitation–temperature relation
3.2 Dynamic and thermodynamic contributions

Figure 3 shows the differences between FUTURE and PAST at the same grid cell used in Figure 2 for each temperature bin. The precipitation difference as well as the dynamic, thermodynamic, and covariance contributions is defined as in Equation (4) (Emori and Brown, 2005). Note that we examined the sensitivity to sample size for quantifying the dynamic and thermodynamic contributions by the same method described in Section 3.1 (Figure S5). Figure 3 shows that for almost all temperature bins, except at the temperatures where precipitation change is close to 0, the 99% significance level is satisfied because the data used in this study had a large sample size for each temperature bin. The number of bins not satisfying the significance level for $P_{99.9}$ is larger than the number for $P_{99}$ because fewer samples (one-tenth of the samples) were used for $P_{99.9}$. At temperatures between 5°C and 17°C, the differences of $P_{99}$ and $P_{99.9}$ between PAST and FUTURE and all factors (dynamic, thermodynamic, and covariance terms) are less than 2 mm h$^{-1}$. At temperatures above 17°C, there was a significant difference in $P_{99}$ and $P_{99.9}$ for PAST and FUTURE due to the thermodynamic effect. In addition, the amount of near-surface water vapor at the temperature exceeding 25°C in FUTURE was larger than that of PAST (not shown). These results indicate that the thermodynamic effect was a dominant factor intensifying precipitation in FUTURE.

![Figure 3](image)

**FIGURE 3** Precipitation difference (black color) and dynamic (blue color), thermodynamic (red color), and covariance (green color) contributions to $P_{99}$ (solid line) and $P_{99.9}$ (dashed line) between PAST and FUTURE. Black dots and white dots with black outline indicate the temperature bins with precipitation intensity difference between PAST and FUTURE that does not satisfy the 99% significance level using Welch's $t$ test for $P_{99}$ and $P_{99.9}$, respectively.

3.3 Spatial distribution of dynamic and thermodynamic contributions

Figure 4 shows the spatial distribution of the SF calculated by the quantile regression. The SF of $P_{99}$(PAST) is about 1% per °C lower than the rate of 7% per °C (C–C relation) in many areas over the target catchment. On the other hand, the SF of $P_{99.9}$(PAST) is the same as the C–C relation in the plains and valleys of the Daisetsu Mountains and exceeds it in the ridges of the Hidaka and Daisetsu Mountains. The SF of $P_{99.9}$(FUTURE) shows a spatial distribution similar to the distribution of $P_{99.9}$(PAST). The SF of $P_{99.9}$(FUTURE) exceeds the C–C relation in almost all areas and reaches 10% per °C in high-altitude areas. The uncertainty in the calculated SFs was estimated at each of the seven stations using the corresponding closest grid cell and the resampling method described in Section 3.1. The variabilities (minimum to maximum) of SF $P_{99}$ obtained from the random sampling from 29 to 42 years are 5%–7% per °C, and those of $P_{99.9}$ are from 8% per °C to 12% per °C (Figure 4e,f). All SFs of OBS are within these ranges.

Next, we investigated the spatial distribution of dynamic and thermodynamic contributions to the differences in PAST and FUTURE precipitation for each grid cell in the area shown by the dashed line in Figure 1b. The results of each grid cell are summarized by elevation to clarify the topographic effect. Figure 5 shows the $P_{99}$, $P_{99.9}$, $P_{99\text{dpt}}$, and $P_{99.9\text{dpt}}$ for the 0–300 m and 1200–1500 m elevation areas (low-elevation area and high-elevation area, respectively). Those of other elevation areas are shown in Figures S6 and S7. The $P_{99}$, $P_{99.9}$, $P_{99\text{dpt}}$, and $P_{99.9\text{dpt}}$ in the low-elevation area follow the C–C relation for almost the entire temperature range, except for the high-temperature range. In the high-elevation area, the $P_{99}$ gradient does not follow the C–C relation; however, the $P_{99.9}$ gradient does follow the C–C relation. On the other hand, the gradients of $P_{99\text{dpt}}$ and $P_{99.9\text{dpt}}$ over the high-elevation area are greater than the gradients of the low-elevation area and close to twice the C–C relation (14% increase per 1°C) in a certain temperature range (PAST: 13–18°C; FUTURE: 16–23°C). According to previous studies, if the thermodynamic factor is dominant, the precipitation–dew point temperature relation following the C–C relation is generally within the expected responses (Lenderink *et al.*, 2011; Panthou *et al.*, 2014; Drobinski *et al.*, 2016). The larger gradients of precipitation–temperature relation in comparison to the C–C relation suggest that the dynamic factor partly contributes to $P_{99}$ and $P_{99.9}$ over the high-elevation area. This is the case in the high-elevation area because heavy
rainfall is generally caused by moist warm air from the east or southeast triggered by tropical cyclones in the summer season (Nguyen-Le and Yamada, 2017; Hoshino et al., 2020). Figure 5 (right column) shows the differences between FUTURE and PAST expressed by the factors for each temperature bin. The result shows that the differences in $P_{99}$ and $P_{99.9}$ for each temperature bin between PAST and FUTURE for both areas are mainly due to the thermodynamic contribution, although the precipitation–temperature relation over the high-elevation area is also influenced by the topographic effect (dynamic factor).

4 | SUMMARY

We performed dynamical downscaling from a spatial resolution of 20 km to a resolution of 5 km from past (PAST) and future (FUTURE) ensemble climate experiments. This high-resolution hundreds-year data set was used to investigate the precipitation–temperature relation under the past and future climate over the Tokachi River basin, Hokkaido, Japan. A comparison of extreme precipitation and the corresponding temperature for observation and PAST showed that the 5-km experiment better represents the precipitation–temperature relation than the 20-km experiment. Observation, PAST, and FUTURE showed that the rate of change in extreme precipitation with temperature follows slopes close to the C–C relation until a certain temperature and has a negative value at higher temperatures. The negative gradient factor is due to lower humidity, as was detected by the precipitation–dew point temperature relation. The thermodynamic factor dominates the differences of $P_{99}$ and $P_{99.9}$ between PAST and FUTURE. The result indicates that the thermodynamic effect (near-surface moisture availability) is a key factor for the gradient of the precipitation–temperature relation, which is the same interpretation drawn from the result using dew point temperature despite the different approach. In addition, the spatial characteristics of precipitation–temperature relations were investigated. The differences in $P_{99}$ and $P_{99.9}$ between PAST and FUTURE in
the whole catchment are mainly due to the thermodynamic contribution, regardless of the extent of the surface characteristics (e.g., flat vs. mountainous areas).

In summary, this study clarified the dynamic and thermodynamic contributions to the precipitation–temperature relation in the PAST and FUTURE. Using the 5-km resolution hundreds-year climate data set enabled us to quantify the spatial distribution of each contribution over the thousands of square kilometers river catchment. In the future, better computer resources and the demand for relevant adaptation measures will enable us to analyze precipitation and other hydrometeorological variables using the statistical methods of this paper, considering the increased climate information in large ensembles at high spatiotemporal resolution.

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AUTHOR CONTRIBUTIONS
Tomohito Yamada: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing - original draft; writing-review & editing.
Tsuyoshi Hoshino: Data curation; formal analysis; investigation; methodology; validation; visualization; writing - original draft; writing-review & editing.
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