A Comparison of Intra-Annual and Long-Term Trend Scaling of Extreme Precipitation with Temperature in a Large-Ensemble Regional Climate Simulation

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ABSTRACT: Long-term changes in extreme daily and subdaily precipitation simulated by climate models are often compared with corresponding temperature changes to estimate the sensitivity of extreme precipitation to warming. Such “trend scaling” rates are difficult to estimate from observations, however, because of limited data availability and high background variability. Intra-annual temperature scaling (here called binning scaling), which relates extreme precipitation to temperature at or near the time of occurrence, has been suggested as a possible substitute for trend scaling. We use a large ensemble simulation of the Canadian regional climate model (CanRCM4) to assess this possibility, considering both daily near-surface air temperature and daily dewpoint temperature as scaling variables. We find that binning curves that are based on precipitation data for the whole year generally look like the composite of binning curves for winter and summer, with the lower temperature portion similar to winter and the higher temperature portion similar to summer, indicating that binning curves reflect seasonal changes in the relationship between temperature and extreme precipitation. The magnitude and spatial pattern of binning and trend scaling rates are also quantitatively different, with little spatial correlation between them, regardless of precipitation duration or choice of temperature variable. The evidence therefore suggests that binning scaling with temperature is not a reliable predictor for future changes in precipitation extremes in the climate simulated by CanRCM4. Nevertheless, external forcing does have a discernable influence on binning curves, which are seen to shift upward and to the right in some regions, consistent with a general increase in extreme precipitation.

KEYWORDS: Precipitation; Temperature; Statistical techniques; Ensembles; Trends

1. Introduction

Warming increases the atmospheric water holding capacity at a rate about $7\% \text{ }^{\circ}\text{C}^{-1}$ according to the Clausius–Clapeyron (CC) relation, potentially resulting in enhanced precipitation rates (Boer 1993; Trenberth 1999; Trenberth et al. 2003). Many studies have estimated the sensitivity of mean and extreme precipitation to warming (e.g., including Kharin et al. 2013; Zhang et al. 2013). The sensitivity of global mean precipitation to warming is substantially less than the rate indicated by the CC relation because of atmospheric energy budget constraints on the overall intensity of the hydrologic cycle (Boer 1993; Allen and Ingram 2002). On the other hand, the globally

averaged sensitivity of annual maximum daily precipitation to warming is consistent with the CC relation in observations (Westra et al. 2013; Zhang et al. 2013; Sun et al. 2020) and global climate model simulations (Kharin et al. 2013).

A key concern when assessing the impacts of warming on extreme daily or subdaily precipitation events is to quantify how the intensities of the annual maxima of such events will change with warming. At-site trend scaling rates, expressed in percent per degree of warming, cannot be robustly estimated from observations at local and regional scales due to the limited length of the historical record (Sun et al. 2020) and the fact that expected anthropogenically induced change in extreme precipitation is small when compared with its variability (Li et al. 2019b).

Trend scaling rate estimates are typically based on samples of annual maxima, and thus they use only a small fraction of the observational precipitation data that is collected. Lenderink and van Meijgaard (2008) therefore introduced a method to estimate a precipitation scaling rate based on day-to-day variations in temperature and a binning technique that uses much more of the available observational data by estimating the extreme quantiles of precipitation conditional on local temperature at the time of the precipitation event and then

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FIG. 1. Schematic diagram for the statistical interpretation of binning and trend scaling approaches. Daily temperature and 3-h duration precipitation simulated by CanRCM4 at the location 35.2°N, 84.3°W are used. The dotted and solid red lines indicate the binning curves derived from data for the whole year for the 99th percentile of wet event precipitation amounts (3-hourly precipitation > 0.1 mm) conditional on daily air temperature for the 1950–2000 and 2051–2100 periods, respectively. (a),(b) The black dots indicate daily maxima of 3-hourly amounts above the 99.7th percentile level of all zero and nonzero values (corresponding approximately to the annual maximum of all zero and nonzero values). (c),(d) As in (a) and (b) except that black dots indicate the annual maxima of 3-hourly amounts with sample of size 50 (years) $\times$ 35 (simulations). The green and blue triangles and dots indicate the median and mean of black dots during the 1950–2000 and 2051–2100 periods, respectively. The units for precipitation are millimeters.

studying how those quantiles vary with temperature. A typical implementation of the method when applied to hourly rainfall amounts involves the following steps: 1) Hourly rainfall is stratified according to daily near-surface air temperature or dewpoint temperature in bins of equal width. 2) A high precipitation quantile, such as the 99th percentile, is determined from each bin to create a binning curve that relates these estimated conditional quantiles to the temperatures that correspond to the midpoint of each bin. 3) A scaling rate, which we term the *binning scaling rate*, is estimated by regressing precipitation onto bin temperature (or by simple visual inspection of precipitation and temperature bin plot). Note that Wasko and Sharma (2014) proposed a variant approach by using quantile regression to regress precipitation onto daily temperatures to obtain a description of how the conditional quantiles of precipitation vary with temperature. These two approaches have been used to study binning scaling rates for different regions, different seasons, and different precipitation types (e.g., Hardwick Jones et al. 2010; Lenderink et al. 2011; Utsumi et al. 2011; Mishra et al. 2012; Panthou et al. 2014; Ali

and Mishra 2017; Lochbihler et al. 2017; Gao et al. 2018; Wang et al. 2018; Wasko et al. 2018; Van de Vyver et al. 2019; Zhang et al. 2019). Note that binning rates may vary seasonally owing to seasonal changes in weather patterns and large-scale circulation (Berg et al. 2009; Shaw et al. 2011; Mishra et al. 2012).

The fundamental methodological distinction between the two methods is that trend scaling describes the relationship between the annual extremes of precipitation and temperature based on the joint, *inter-annual* variation of these two variables, whereas binning scaling describes the relationship between precipitation extremes and temperature based on their *intra-annual* variation. A key question is whether the binning scaling rate, which is based on relatively abundant daily and subdaily data, provides a useful estimate of the trend scaling rate, which is based on much sparser samples of annual values but provides information about the expected change in extremes that is most often sought for engineering and other applications.

Figure 1 illustrates the calculation of the binning and trend scaling rates for two cases: when trend scaling is based on

exceedances above a high threshold (Figs. 1a,b), and when it is based on annual maxima (Figs. 1c,d). A simple idea often used in trend scaling is to compute the mean or median of exceedances above a high threshold in the current period (green dot and triangle, Fig. 1a), reset the threshold for the future period so that the frequency of exceedance remains unchanged, calculate another mean or median (blue dot and triangle, Fig. 1b), and connect the two to obtain a sensitivity to warming. In contrast, the binning scaling method provides estimates of quantiles that are conditional on two things, the occurrence of precipitation above some thresholds (e.g., >0.1 mm) and daily temperature. These conditional percentiles calculated in each bin are plotted (red dashed curve, Fig. 1a). In this example, which is based on daily maxima of 3-hourly precipitation amounts simulated by a regional climate model at a location in eastern North America, it is difficult to see how the shape of the red dashed curve in Fig. 1a could be used to predict the trend that connects the green and blue dots (Fig. 1b). The slopes connecting the dots and triangles used to calculate trend scaling rates for extreme precipitation are different from the slopes of the rising parts of the binning scaling curves, and in fact, at this location, suggest that the trend scaling rate is higher. This also holds when trend scaling is based on annual maxima rather than threshold exceedance (Figs. 1c,d) and when binning scaling curves specific to summer [June–August (JJA)] and winter [December–February (DJF)] are considered (see Figs. S1 and S2 in the online supplemental material).

As we will show in this paper, binning scaling rates are generally not predictive of trend scaling rates in the climate simulated by the regional climate model that we use, consistent with Zhang et al. (2017). From a statistical perspective, the binning scaling procedure estimates conditional quantiles of precipitation, where conditioning is on air or dewpoint daily temperature (Zhang et al. 2017; Wasko et al. 2018). In contrast, trend scaling estimates changes in unconditional quantiles between epochs, where one epoch happens to be warmer than the other. The binning scaling curve does provide a very useful description of variation of the intensity of extreme precipitation with the annual cycle, as it progresses from cooler to warmer temperatures and back again. Zhang et al. (2017) suggested that as the climate warms, it might be reasonable for the entire curve to respond to warming, where the shift in the location of the curve in the temperature/intensity plane occurs at roughly the trend scaling rate. Indeed, this is exactly what is seen in Figs. 1b and 1d, where the red dashed curves depict a binning scaling relationship based on simulated climate data for the period 1951–2000 and the solid red curves depict the binning scaling curve derived from data for the period 2051–2100. Prein et al. (2017) also showed that the binning curves are shifted under climate change over different regions of United States in a convection-permitting simulation.

There is previous observed and modeling evidence that binning scaling for the recent climate cannot predict the response of extreme precipitation response to warming. For instance, Zhang et al. (2017) compared the binning scaling and long-term trend scaling of precipitation extremes over the Netherlands based on the observations and six simulations conducted by four regional climate models driven by two

global climate model simulations. The historical trend scaling rates were found to be consistent with the CC rate, while the estimated binning scaling curve suggested a super-CC scaling rate for the same locations. Bao et al. (2017) found a uniform increase in projected precipitation extremes across Australia, including the northern half of the country where binning scaling shows a decrease in high precipitation quantiles with daily temperature in historical observations (Hardwick Jones et al. 2010; Herath et al. 2018; Barbero et al. 2018). Ban et al. (2015) and Prein et al. (2017) showed that, based on convection-permitting model (CPM) simulations, changes in the intensity of hourly precipitation in response to warming over the greater Alpine region and the continental United States, respectively, are not consistent with the binning scaling rate reported (Ban et al. 2014).

The binning scaling approach can produce negative scaling rates as well as positive rates, depending on the characteristics of the local climate. For example, negative binning scaling rates are often obtained in tropical and dry regions when daily mean temperature is used as a predictor. This behavior has been attributed to the occurrence of lower relative humidity in higher temperature bins (e.g., Barbero et al. 2018; Lenderink et al. 2018). As extreme precipitation is closely linked to moisture availability, some recent studies have suggested the use of dewpoint temperature as the binning variable rather than dry surface air temperature (e.g., Ali and Mishra 2017; Barbero et al. 2018; Lenderink et al. 2018; Zhang et al. 2019) since it accounts for changes in both relative humidity and surface air temperature. Indeed, the percentage of tropical and dry region stations with negative binning scaling rates is drastically reduced from 96% when surface air temperature is used as the binning variable to about 40% when dewpoint temperature is used (Ali et al. 2018). Wasko et al. (2018) and Bao et al. (2018) showed that many regions presented negative binning scaling rate when dry-bulb temperature is used, particularly in the northern parts of Australia, while the use of dewpoint temperature resulted primarily in positive binning scaling rates. Evidently, the form of the binning scaling curve can be affected by the choice of conditioning temperature variable. How this choice is made would depend on the purpose of the binning scaling analysis, with the latter likely providing a closer link with the moist physics that govern the production of extreme precipitation under different thermal conditions (Barbero et al. 2018; Lenderink et al. 2018).

While previous studies have discussed the difference between binning scaling and trend scaling from a statistical perspective and based on different model simulations, they did not have sufficient data to produce statistically robust trend scaling estimates. The availability of a 50-member large ensemble simulation conducted with the Canadian Regional Climate Model (CanRCM4; Scinocca et al. 2016) covering North America for which precipitation was archived hourly for 35 members provides an opportunity to revisit this question, albeit in the context of the climate simulated by that model. The ability of CanRCM4 to simulate extreme precipitation has previously been assessed by Whan and Zwiers (2016). Scaling rates can be affected both by the choice of temperature variable that is used as an indicator of climate change (e.g., Wasko

and Nathan 2019), and by sampling uncertainty, which can be large when samples are small. Li et al. (2019b) showed that an ensemble the size of the CanRCM4 ensemble is large enough to produce estimates of short-duration extreme precipitation sensitivity at the local scale that are essentially free from uncertainties due to internal climate variability. Here, we will make use of these simulations to produce statistically robust estimates of both binning and trend scaling rates across North America for the full year, winter, and summer by using dewpoint temperature or surface air temperature as the scaling variable. We will show that, in both cases, temperature scaling rates estimated with the binning approach are different from trend scaling estimates. To save space, figures based on dewpoint temperature are shown in the main paper while those based on surface air temperature are displayed in the supplemental material. The remainder of this paper is structured as follows: We describe the climate model data and scaling rate estimation methods in section 2. The main results are presented in section 3. Conclusions are given in section 4.

2. Data and methods

a. Regional climate model simulations

The Canadian Centre for Climate Modeling and Analysis recently produced a 50-member large ensemble simulation over the North American domain (Scinocca et al. 2016) using the Canadian Regional Climate Model (CanRCM4), which has a horizontal resolution of ~ 50 km. The simulations were conducted for 1950–2100, with driving data provided by a 50-member ensemble simulation conducted with the Canadian Earth System Model (CanESM2). Individual ensemble members use the historical external forcings for 1950–2005 that were prescribed for phase 5 of the Coupled Model Intercomparison Project (CMIP5) and RCP8.5 forcings for 2006–2100 (Fyfe et al. 2017). Hourly output for surface variables is available from 35 members of the large ensemble RCM simulation. We extracted hourly precipitation, daily mean near surface air temperature, and daily mean dewpoint temperature from those simulations. Hourly precipitation for each grid cell is aggregated into 3- and 24-h accumulations.

While the CanRCM4 dynamical core can operate in either nonhydrostatic or hydrostatic mode, the model was implemented using the hydrostatic approximation for cost reasons and for compatibility with the driving model (Scinocca et al. 2016). The use of the hydrostatic approximation and parameterized convection is clearly a limitation and could have some impact on the simulation of precipitation and the form of the binning scaling curve (Yang et al. 2017). Nevertheless, we believe that the CanRCM4 large ensemble can be helpful in understanding the difference between binning scaling and trend scaling analyses of extreme precipitation, and in understanding whether the conditional quantile function that is estimated via binning scaling can be used to project unconditional change in extreme precipitation. CanRCM4 may not be able to provide the definitive answer to this question, but inconsistency between the two approaches should nevertheless raise important cautionary flags. Empirical evidence does suggest enough similarity between CanRCM4 results and available observational

and convection permitting model results to suggest that concerns arising from the analysis of its output should be taken seriously. For example, binning scaling curves for the daily maxima of 1-h precipitation and their future shifts over different Bukovsky regions (see Fig. S3 in the online supplemental material; Bukovsky 2011) that are inferred from the CanRCM4 simulations (Fig. S4 in the online supplemental material) are similar to those obtained from a very high-resolution convection-permitting model (Prein et al. 2017).

b. Scaling rates estimation

1) BINNING CURVES AND BINNING SCALING

For the estimation of binning scaling, we follow the methods of Lenderink and van Meijgaard (2008). First, for each simulation and each grid box, we calculate the daily maxima of 1- and 3-h precipitation accumulations and the total accumulation for each day, which we refer to as P_{d01} , P_{d03} , and P_{d24} respectively. These values are then binned according to daily mean air temperature or dewpoint temperature for each duration (1 h, 3 h, and 1 day) separately, using a bin width of 2.0°C and allowing a 1°C overlap between bins. For each bin, we then find the 99th percentile of wet (>0.1 mm) $P_{d_{hh}}$ values ($P_{99_{hh}}$, where $hh = 01, 03$, and 24 , respectively), thereby obtaining estimates of the 99th percentiles of $P_{d_{hh}}$ conditional on the air temperature or dewpoint temperature at the center of each bin.

The $P_{99_{hh}}$ values are estimated only for bins with sample sizes larger than 100 and are smoothed across bins using a 3-bin moving-window average, producing a binning curve. An exponential scaling rate can be calculated from two points (T_d , P_1) and ($T_d + 1$, P_2) on the binning curve if it varies monotonically between temperatures T_d and $T_d + 1^\circ\text{C}$. The binning curves do not always rise monotonically however, and can display a hooklike shape that peaks and then declines (Drobinski et al. 2016, 2018). For this reason, we define a peak temperature (T_{peak}) below which the scaling is positive, and above which the scaling is generally negative. The highest peak corresponds to the most extreme precipitation values that are likely to occur in a year and is chosen if there is more than one peak on the curve since our main interest is in high-impact events. Scaling rates for 1°C temperature increments T_d to $T_d + 1^\circ\text{C}$ are calculated for temperatures T_d beginning with first bin with positive scaling and continuing until $T_d = T_{\text{peak}} - 1^\circ\text{C}$; the average of these scaling rates is taken as the binning rate. We calculate binning scaling rates for the periods 1951–2000 and 2051–2100 separately.

We have used a 5-yr block bootstrap procedure to estimate scaling analysis uncertainties so as to account for interannual serial dependence at time scales up to a few years, such as that associated with El Niño–Southern Oscillation (Zhang et al. 2010). The bootstrap method is used to estimate scaling analysis uncertainties as follows: For each grid cell, we draw a sample from the collection of $P_{d_{hh}}$ values in 5-yr blocks with replacement to produce another data sample of size 365 (days) $\times 50$ (years) $\times 35$ (simulations) in each period. The daily temperatures corresponding to the sampled $P_{d_{hh}}$ values are extracted to maintain the relationship between precipitation and daily temperature. A binning scaling rate is then

estimated using this resampled data. This resampling procedure is repeated 200 times, thereby producing a sampling distribution for the binning scaling rate. The median, 5th, and 95th percentiles are obtained from this empirical distribution and are used as estimates of the scaling rate and its uncertainty.

We estimate binning scaling for the full year, winter (DJF), and summer (JJA) precipitation separately. The minimum sample size required for the estimation of $P99_{hh}$ in each bin is reduced to 50 when analyzing the seasonal scaling rates. We plot binning curves for the full year, summer, and winter, respectively. Regional binning curves are also displayed for Bukovsky regions (Fig. S3 in the online supplemental material); these curves are produced by computing, for each bin, the arithmetic average of the $P99_{hh}$ values for all grid boxes within each region.

2) TREND SCALING

Trend scaling rates are estimated for each accumulation period using annual or seasonal maxima. For a given accumulation period, we first extract annual, summer, and winter maximum precipitation amounts, and then compute medians of these maxima for the period 1951–2000 (P_a) and the period 2051–2100 (P_b). We also average annual, summer, and winter mean temperatures or dewpoint temperatures for the two periods, referred to as T_a and T_b , separately. A trend scaling rate γ is then computed as

$$\gamma = \{\exp[(\ln P_b - \ln P_a)/(T_b - T_a)] - 1\} \times 100\%.$$

This operation is conducted for individual grid boxes and for each of the 35 ensemble members separately. Finally, ensemble averages are taken to obtain best estimates of the trend scaling rate. These rates represent the sensitivity of extreme precipitation with a 2-yr return period because they are based on the medians of annual and seasonal maxima.

3. Results

a. Comparison of binning and trend scaling rates

1) SPATIAL PATTERNS

The spatial patterns of binning scaling rates and trend scaling rates with dewpoint temperature and surface air temperature as binning variable are shown in Fig. 2 and online supplemental Fig. S5, respectively. The binning scaling rates have broadly similar spatial patterns irrespective of which temperature variable is used for scaling, although there are nevertheless some differences that can be noted, especially in summer. Dewpoint temperature-based binning scaling rates are larger than those for air temperature over most regions, especially in the northwestern United States and parts of the northeastern North America. Also, the area with negative binning scaling rates over the southernmost regions is smaller. On the other hand, the historical binning scaling rates simulated by the RCM have a spatial pattern that is qualitatively similar to that of the observed extreme hourly precipitation regardless of the temperature variables. For instance, there are larger binning scaling rates for 1-hourly precipitation extremes

in the northern part of the coterminous United States and smaller rates over the southeast and western part of the United States (Fig. S6a in the online supplemental material), which is consistent with results reported in previous observational studies (Mishra et al. 2012; Ivancic and Shaw 2016; Lepore et al. 2015). This indicates that the model performs reasonably well in simulating the observed conditioning of precipitation on temperature.

The trend scaling rate for the annual maximum precipitation, however, exhibits a spatial pattern that is different from both the simulated and observed binning scaling rates (Mishra et al. 2012; Ivancic and Shaw 2016; Lepore et al. 2015), with larger trend scaling rates over the eastern part and western coastal regions of the United States and smaller values in the interior of the continent (Fig. 2 and online supplemental Fig. S5). The use of dewpoint temperature as the scaling variable does not resolve the discrepancy with trend scaling as proposed by some authors (Zhang et al. 2019). When dewpoint temperature is used as the binning variable, the spatial patterns of binning scaling rates are quite similar in the historical and future periods, but they are noticeably different from the spatial pattern of the trend scaling rates (Fig. 2). The spatial correlation coefficient between full year binning scaling rates for the two periods is 0.71 while the spatial correlation coefficient between the binning and trend scaling rates is -0.02 and 0.21 for the historical and future periods respectively. Similar results are obtained for full year binning scaling rates when surface air temperature is used as the scaling variable (Fig. S5; respective spatial correlations are 0.68 , -0.09 , and 0.16). Therefore, while historical period binning scaling rate may be a useful predictor for binning scaling rate in a future warming world, it is not a useful predictor of the trend scaling rate.

The spatial pattern of the binning scaling rate for summer precipitation is different from that for the whole year, with negative scaling rates in summer precipitation in the southern tier of North America (Fig. 2; see also Fig. S5). This pattern also distinctly different from that of the trend scaling rates for summer maximum precipitation, with a spatial correlation coefficient of 0.06 between the historical period binning scaling rates and trend scaling rates. The trend scaling rate is positive in the southern tier of North America but negative in the central and northern Great Plains. The winter binning scaling rate pattern is similar to that of the full year binning scaling rate but somewhat different from the trend scaling of winter maximum precipitation. The spatial correlation coefficient between the historical period binning scaling rate and the trend scaling rate for winter is -0.09 . These spatial correlations between historical binning scaling rates and trend scaling rates are similar (0.24 and 0.16 for summer and winter respectively) when using surface air temperature as the scaling variable. In comparison with the trend scaling rate for annual maximum precipitation, winter maximum precipitation intensifies more strongly over western and southeastern North America, with intensification occurring at higher than the CC rate in the West Coast, Southeast, and Atlantic regions.

Results for the 1-h and 1-day accumulation periods are very similar to those for 3-h precipitation (Figs. S6 and S7 in the online supplemental material). To summarize, it appears that

FIG. 2. Binning and trend scaling rates ($\% \text{ }^{\circ}\text{C}^{-1}$) for extreme 3-h precipitation accumulations based on hourly precipitation from a 35-member ensemble of CanRCM4 simulations for (a)–(c) the whole year, (d)–(f) summer, and (g)–(i) winter. Binning scaling rates are based on the variation of $P99_{03}$ with daily dewpoint temperature during the (top) 1951–2000 and (middle) 2051–2100 periods. (bottom) Trend scaling rates are based on changes in the median of annual/seasonal maximum 3-hourly precipitation during the two periods.

the historical period binning scaling rate for extreme subdaily and daily precipitation is able to predict the binning scaling rate in a future warmer world reasonably well but that it is not a reliable predictor for trend scaling.

2) SCALING RATE MAGNITUDES

Figure 3 shows zonal averages of binning and trend scaling rates with dewpoint temperature as the scaling variable for the whole year, summer, and winter extreme precipitation of 1-h, 3-h, and 1-day durations. The trend scaling of the annual maximum precipitation projects larger increases with warming for shorter-duration than for longer-duration extreme precipitation events (Fig. 3), while binning scaling rates are opposite, with larger binning scaling rates for 1-day precipitation and smaller scaling rates for 1- and 3-h precipitation, especially in high-latitude regions (Fig. 3). The binning scaling rate increases slightly for the 2051–2100 period, but its magnitude is not consistent with trend scaling regardless of the accumulation duration.

The zonal averages of summer trend scaling rates have a shallow U-shape with lower magnitudes in the middle latitudes

and larger values in the low and high latitudes (Figs. 3d–f). On the other hand, the binning scaling rates are largest around 40°N and drop to negative values in the low latitudes. The magnitudes of the trend scaling rates for winter maximum precipitation appear to have a generally similar shape to those of the binning scaling rates for 1- and 3-h duration, although there are some differences. In particular, trend scaling rates can be much larger than the historical binning rates between 32° and 45°N . In contrast, the trend scaling rates for 1-day precipitation can be much smaller than corresponding binning rates, especially at high latitudes. Similar to annual results, the intensity of shorter-duration extreme winter precipitation events increases more than that of longer-duration events (Figs. 3g–i). Moreover, consistent with results from observations (Barbero et al. 2017), the trend scaling rates are higher at midlatitudes in DJF than in other seasons. Binning scaling rates do not capture this tendency (Figs. 3g–i). Barbero et al. (2017) showed that changes in the mean intensity of annual maximum precipitation across the United States are smaller than the CC rate when the local surface air temperature is used

FIG. 3. Zonal averages of the binning scaling rate during the 1951–2000 period (blue lines) and the 2051–2100 period (red lines) together with those of the trend scaling rate (black lines) for the (a)–(c) annual and (d)–(f) JJA and (g)–(i) DJF seasonal maximum (top) 1-h, (middle) 3-h, and (bottom) 1-day precipitation. Dewpoint temperature is used as the scaling variable for both the binning scaling and trend scaling. Grid boxes over oceans were removed to calculate the zonal averages. Thick lines for binning scaling show the median scaling rates, and shaded areas show the 5th–95th-percentile spread from 200 block bootstrap samples (see section 2). Units are percent per degree Celsius.

as the covariate. The estimated trend scaling rates in our study also are lower than the CC rate and the binning estimates regardless of the choice of temperature variable that is used as an indicator of climate change (Fig. 3; see also Fig. S8 in the online supplemental material).

Figure 4 displays meridional averages of binning and trend scaling rates for the whole year, summer, and winter extreme precipitation of 1-h, 3-h, and 1-day durations. As expected, the meridional variations of binning scaling rates are noticeably different from that of trend scaling for all durations.

We notice considerable differences in the binning and trend scaling rates among full year and seasonal series. These arise for different reasons. The differences in dominant storm types and sources and characteristics of moisture supply may explain the differences in the summer and winter binning scaling rates (Berg et al. 2009). Negative values for the summer binning scaling rate were found in the south of the United States, where summertime drying of the soil may also lead to negative summer binning rates (Trenberth and Shea 2005; Berg et al. 2009).

Trend scaling rates for annual and seasonal maxima are also different, possibly due to different storm type systems associated with these extreme events. In particular, the seasonality of

occurrence of annual maxima differs in different regions, with dominant winter occurrence on the west coast but a wider timing of occurrence in other regions. Precipitation extremes for shorter durations occur more unevenly throughout the year than for longer durations with a larger fraction of annual maxima for 1-h duration occurring in a specific season, which is consistent with Barbero et al. (2019). Additionally, the timing may also shift in response to warming (Pfahl et al. 2017; Brönnimann et al. 2018; Marelle et al. 2018). Figure S9 in the online supplemental material shows the seasonal timing of the annual maximum 3-h precipitation event in the CanRCM4 ensemble simulation in the 1951–2000 and 2051–2100 periods. It appears that the timing of the occurrence of the annual maximum may shift away from the warm season in the twenty-first century over much of North America. For example, annual maximum precipitation is projected to occur earlier in the year over large parts of North America, with more annual maximum precipitation events occurring during March–May (MAM) but fewer events occurring in JJA (Figs. S9b,d). Over the West Coast regions and the Southeast region, the annual maximum precipitation event is projected to occur more frequently in winter (Fig. S9h). The summer drying over the

FIG. 4. As in Fig. 3, but showing meridional averages over land grid boxes.

northern and central Great Plains regions and the higher trend scaling rates for the winter maximum, especially in the West Coast regions, may be a reflection of the shift in the seasonality of extreme precipitation toward the colder seasons. Results for 1-h and 1-day precipitation are similar to those for 3-h precipitation (Figs. S10 and S11 in the online supplemental material). CMIP5 simulations (Brönnimann et al. 2018; Marelle et al. 2018) also show the indicated changes in seasonality, and suggest that thermodynamic factors are dominant in the high latitudes, while dynamical factors may be more important in the lower latitudes for such changes. Polade et al. (2017) showed that the dynamically strengthened onshore vapor transport delivered in more intense atmospheric rivers (Hagos et al. 2016) and the thermodynamic enhancement of vapor transport owing to climate warming jointly lead to an increased intensity of winter precipitation extremes, particularly over the western of the United States. Nevertheless, a comprehensive understanding of the processes responsible for the shift in the seasonality of extreme precipitation is yet to be developed and thus awaits further study.

b. Shifts in binning curves with warming

Figure 5 and online supplemental Fig. S12 display binning curves for 3-h precipitation extremes (P9903) for selected regions in North America, including the so-called CPlains, PacificSW, and MidAtlantic Bukovsky regions (Bukovsky 2011), for the whole year, summer, and winter precipitation

extremes over 1951–2000 and 2051–2100 with dewpoint temperature and surface air temperature as the binning variable respectively. Results show that the shape of the binning curve can be sensitive to the choice of binning temperature in some regions. For example, the CPlains and PacificSW regions do not have obvious hook-shaped curves in winter when dewpoint temperature is used as the binning variable (Figs. 5d,e) whereas this feature is evident when surface air temperature is used as the binning variable (Figs. S12d,e). Hook-shaped binning curves are, nevertheless, generally prevalent across all regions regardless of the choice of binning temperature, especially when based on full year data (Fig. 5; see also Fig. S12). Previous observational studies also showed that the slopes of binning curves against dewpoint temperature for the Central and East regions are similar to those against daily mean surface air temperature (see Figs. 2 and 3 in Lepore et al. 2015), with, for example, similar parabolic shapes for the full year and summer binning curves for the Central region. Extreme precipitation increases with temperature at colder temperatures, and then decreases with temperature after reaching a maximum value. That is, the slope of binning curves is generally positive below a certain temperature and then becomes negative for higher temperatures. When the binning curves for 1951–2000 and 2051–2100 are plotted on the same figure, it is very clear that the peak temperature (i.e., for which P99₀₃ is greatest) is higher for 2051–2100 than for 1951–2000. This is important, as this means that the peak temperature for

FIG. 5. Binning curves with daily dewpoint temperature and trend scaling rates for the (left) CPlains, (center) PacificSW, and (right) MidAtlantic Bukovsky regions. Binning curves for (a)–(c) the whole year, (d)–(f) DJF, and (g)–(i) JJA 3-h precipitation extremes (P_{9903}) during 1951–2000 (blue) and 2051–2100 (red) together with a version of the curve for 1951–2000 that has been shifted by 7% per 1°C of projected warming between the two periods (gray). Thick lines, circles, and crosses indicate binning curves based on data for the full year, DJF, and JJA, respectively. Shaded areas show the 5th–95th-percentile spread determined via bootstrapping. (j)–(l) Trend scaling rates for annual and seasonal maximum 3-h precipitation for the three regions.

1951–2000 is not the peak temperature for extreme precipitation in a warmer world. This is a clear indication that the binning scaling rate cannot be used to project the impact relevant highest amount of extreme precipitation. This is consistent with findings of earlier studies (Prein et al. 2017; Wang et al. 2017; Zhang et al. 2017). In general, binning curves shift upward and to the right with warming. Similar to Prein et al. (2017), we also find that shifting the binning curves for 1951–2000 along the

CC scaling rate, about 7% $^{\circ}\text{C}^{-1}$, by the projected temperature increase, generally matches the binning curves from 2051–2100 very well (gray lines in Figs. 5a–c). This means that the conditioning of precipitation on temperature driven by the annual cycle and seasonal changes in weather patterns is similar in both the current and warmer future worlds, except that the peak temperature is higher along with more intense extreme precipitation. Using the projected temperature under the CC scaling

assumption provides a reasonable prediction for future binning curves, with best results in the CPlains. Future binning curves in the PacificSW and MidAtlantic deviate from the “adjusted historical” scaling of precipitation extremes in details, implying that other factors, such as changes in large-scale circulation patterns (Chan et al. 2016), may also be important.

Binning curves based on precipitation and temperature data for the whole year often appear to be the composite of summer and winter binning curves (e.g., in the CPlains and MidAtlantic regions), with the lower temperature portion similar to that of winter and higher temperature portion similar to that of summer. Some previous studies have attempted to evaluate the processes that affect the shape of the binning curve (Berg et al. 2009, 2013; Drobinski et al. 2016). Large-scale precipitation has been found to dominate in winter, generally scaling exponentially with temperature in winter (Berg et al. 2009; Drobinski et al. 2016). For instance, many western U.S. extreme precipitation events are associated with atmospheric rivers that transport moisture over long distances (Leung and Qian 2009). Binning curves show a greater diversity of shapes between regions in summer. For instance, in the CPlains region, a positive relationship between $P_{99_{03}}$ and temperature occurs in a narrow temperature range, with a reversal for warmer temperatures (Fig. 5g). On the other hand, the summer binning curve of the PacificSW is below the full year curve as it does not rain much in summer (Fig. 5h). That is, at the same temperature, it rains less in summer than in other seasons. The processes involved in producing extreme precipitation evidently vary with region and season, resulting in variations in the binning curve form.

Considerable research has focused on the causes of the diversity of shapes of summer binning curves and on specifically where and when to observe the binning temperature. Berg et al. (2009) suggested that variations in the relative contributions of convective and large-scale precipitation could play a role, arguing that a generally decreasing slope for large-scale precipitation may due to a lack of saturation, while there may be a hook shape for convective precipitation in summer with decreasing extreme values and dry conditions at high temperatures. Drobinski et al. (2016) suggested that since clouds and precipitation form at high levels owing to the arid environment, surface temperature would largely overestimate the actual temperature at condensation. Bao et al. (2017) suggested that apparent decreases in extreme precipitation with temperature in summer may reflect temporary local cooling due to both the local evaporative cooling of falling precipitation and larger-scale impacts. Similarly, Barbero et al. (2017) suggested that the dewpoint temperature a few hours before the rainfall event may provide a better proxy of potential precipitation intensity. This is consistent with Lenderink et al. (2011), who used dewpoint temperature a few hours before the rainfall event for binning. It should be noted, however, that while the timing of the temperature observation used for binning could shift the peak of the binning scaling curve to the right compared to when daily dewpoint temperature is used (Lenderink and van Meijgaard 2010), the average binning scaling rate over the positive portion of the temperature range should not change greatly. Our conclusions about the inconsistency of the

binning scaling rate and trend scaling rate should still hold, particularly for JJA, even though we only use the daily dewpoint temperature as the scaling variable.

It has been argued that the use of dewpoint temperature as the binning variable makes binning scaling more suitable for projection of precipitation extremes for the future (Barbero et al. 2018; Zhang et al. 2019), especially for subdaily precipitation (Barbero et al. 2018). This is not, however, the case in the climate simulated by CanRCM4. The conditional quantiles obtained from the binning scaling calculation concisely and usefully describe the variation of extreme precipitation with variations in daily air or dewpoint temperature in a given climate, providing insights into the controlling processes, but that variation does not appear to be able to skillfully predict the change in intensity of the most extreme events in the future climate under anthropogenic warming.

4. Conclusions and discussion

From a statistical perspective, binning scaling describes an aspect of joint distribution of temperature and precipitation within the epoch that is used to calculate the binning scaling relation. This contrasts with trend scaling, which describes an aspect of the joint distribution of temperature and precipitation across two different epochs, one warmer than the other. It is not evident from a statistical perspective that a within-epoch relation should be informative of a between-epoch relation, although this could be evaluated empirically if a suitable statistical model could be developed for the joint distribution of temperature and precipitation considering the two epochs simultaneously. Developing such a statistical model is beyond the scope of this paper given the complexity of the task. A more tractable task is to assess whether an estimated within-epoch scaling relationship is consistent with an estimated between-epoch scaling relationship. The assessment is, unavoidably, somewhat ad hoc since some of the information used to identify the within-epoch scaling relationship is also used to identify the between-epoch relationship.

From a physical perspective, there is generally an expectation that a warmer atmosphere should, in most locations, correspond to more intense extreme precipitation. The primary physics that govern cloud condensation processes and are responsible for the production of precipitation function similarly at all temperatures at which precipitation occurs, leading to an expectation that binning scaling might, in fact, be predictive of trend scaling. Local and large-scale circulation, however, complicate the relation between temperature and precipitation. Indeed, the identification of super-Clausius-Clapeyron scaling rates in areas with ample atmospheric moisture, whether via binning or trend scaling calculations, would necessarily indicate a change in precipitation efficiency (precipitation expressed as the fraction of precipitable water in the atmospheric column at the time of the event), and thus moisture convergence—a strong indication that circulation is at play, either at local scales via vertical motion induced by latent heat released during cloud condensation (Lenderink et al. 2017) or at larger scales (Pfahl et al. 2017; Tandon et al. 2018; Norris et al. 2019; Li et al. 2019a). Studies of binning curves in specific regions that have attempted to understand the

processes that underlie the hook shape that is often seen also tend to implicate circulation and temperature related moisture deficits (e.g., Chan et al. 2016; Drobinski et al. 2016; Gao et al. 2018; Wang et al. 2017). Whether the kind of circulation change that occurs within an epoch, and particularly, within individual annual cycles, is indicative of the circulation change that might occur between epochs at the time of year with the most intense precipitation events occur is not evident.

We assessed binning and trend scaling relations in a large ensemble simulation with a regional climate model that has previously been assessed to simulate extreme precipitation reasonably well (Whan and Zwiers 2016). The large volume of hourly and daily data available from this experiment (hourly precipitation is available for 35 ensemble members) allowed us to obtain statistically robust estimates of both binning and trend scaling rates for the climate simulated by CanRCM4. We found that binning scaling and trend scaling are quantitatively different in their values and that they have different spatial patterns, particular for summer extreme precipitation. Binning curves based on data for the whole year generally look like the composite of curves obtained individually for winter (DJF) and summer (JJA), with the lower temperature portion similar to winter and higher temperature portion similar to summer. Binning curves shift to upward and to the right toward higher intensity extremes with warming in some regions, indicating a general increase in extreme precipitation and a similar conditioning of precipitation on temperature in the future warmer climate as determined for the historical period by the binning technique. Using dewpoint temperature as the scaling variable seemed to improve correspondence over the southern United States, but still produced a binning scale rate similar to that obtained when near-surface air temperature is used as the scaling variable in most regions, and therefore does not resolve the discrepancy between the binning and trend scaling rates. While this finding may be specific to CanRCM4, it contrasts with suggestions that binning scaling with dewpoint temperature as the binning variable may provide a useful indication of how climate change will influence extreme precipitation (Barbero et al. 2018; Lenderink et al. 2018; Zhang et al. 2019).

Initial-condition large ensembles, like the CanRCM4 ensemble used in this study, provide plentiful data about extremes in the climates that they represent thereby allowing statistically well-constrained estimates of short-duration extreme precipitation sensitivity (Li et al. 2019b). It should be recognized, however, that conventional RCMs have limitations in their ability to simulate short duration precipitation well because of limited spatial and temporal resolution and because convection is not explicitly resolved. Our analysis based on a large ensemble simulation with a conventional RCM raises a concern about whether binning scaling is suitable for projecting long-term change in subdaily or daily precipitation extremes. The evidence from this model, obtained in a context where uncertainty due to sampling variability is largely eliminated, suggests that it may not be suitable. High-resolution convection-permitting models that provide a more realistic representation of the local storm dynamics and skillfully simulate short duration precipitation extremes at scales similar to those represented by station data may be required to ultimately resolve this question.

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