

# High-resolution statistical downscaling in southwestern British Columbia

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# High-Resolution Statistical Downscaling in Southwestern British Columbia

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## ABSTRACT

Knowledge from high-resolution daily climatological parameters is frequently sought after for increasingly local climate change assessments. This research investigates whether applying a simple postprocessing methodology to existing statistically downscaled temperature and precipitation fields can result in improved downscaled simulations useful at the local scale. Initial downscaled daily simulations of temperature and precipitation at 10-km resolution are produced using bias correction constructed analogs with quantile mapping (BCCAQ). Higher-resolution (800 m) values are then generated using the simpler climate imprint technique in conjunction with temperature and precipitation climatologies from the Parameter-Elevation Regression on Independent Slopes Model (PRISM). The potential benefit of additional downscaling to 800 m is evaluated using the “Climdex” set of 27 indices of extremes established by the Expert Team on Climate Change Detection and Indices (ETCCDI). These indices are also calculated from weather station observations recorded at 22 locations within southwestern British Columbia, Canada, to evaluate the performance of both the 10-km and 800-m datasets in replicating the observed quantities. In a 30-yr historical evaluation period, Climdex indices computed from 800-m simulated values display reduced error relative to local station observations than those from the 10-km dataset, with the greatest reduction in error occurring at high-elevation sites for precipitation-based indices.

## 1. Introduction

As regions of interest for climate impacts assessments narrow in size to municipal or smaller domains, high-resolution climate information is required to understand local climate conditions effectively, particularly in regions of complex topography (Murdock et al. 2016; Koppala et al. 2013; Salathe et al. 2007). Present climate modeling methods can explore scales from continental to subcontinental (using global climate models; Taylor et al. 2012) to provincial and state (using regional climate models; Mearns et al. 2012) for a range of climatic parameters (Mote and Salathe 2010). However, when examining municipal or metropolitan areas, even moderately resolved climate fields can be insufficient to replicate the spatial variability observed in these regions. Further, research focused on phenomena in remote or varied topography such as glaciology, ecology, or hydrology often requires spatially detailed information regarding climate effects not always available from typical climate model datasets. In these instances, kilometer scale or finer horizontal

resolution is necessary to provide useful information about local climate patterns.

High-resolution data and maps of basic climate variables (precipitation and temperature) currently exist for western North America (Daly et al. 2008; Wang et al. 2011) but typically are limited to historical monthly climatologies. Many derived variables and extreme events requested for assessments require daily temporal resolution (Zhang et al. 2011). Increasing daily climate simulation spatial resolution to serve this purpose can be accomplished via postprocessing methods incorporating weather station observations such as interpolation (e.g., kriging, bilinear), constructed statistical models (e.g., Daymet; Thornton et al. 1997), or multisite weather generators (Wilks 2009). Alternatively, regional climate models (RCMs) offer the ability to dynamically downscale meteorological variables at varying resolutions (Salathe et al. 2008). Emerging high-resolution (kilometer scale) regional models could feasibly simulate climate at local scales, even allowing for improved representation of processes like convection (Prein et al. 2015), but come with considerable computational cost (Kendon et al. 2012).

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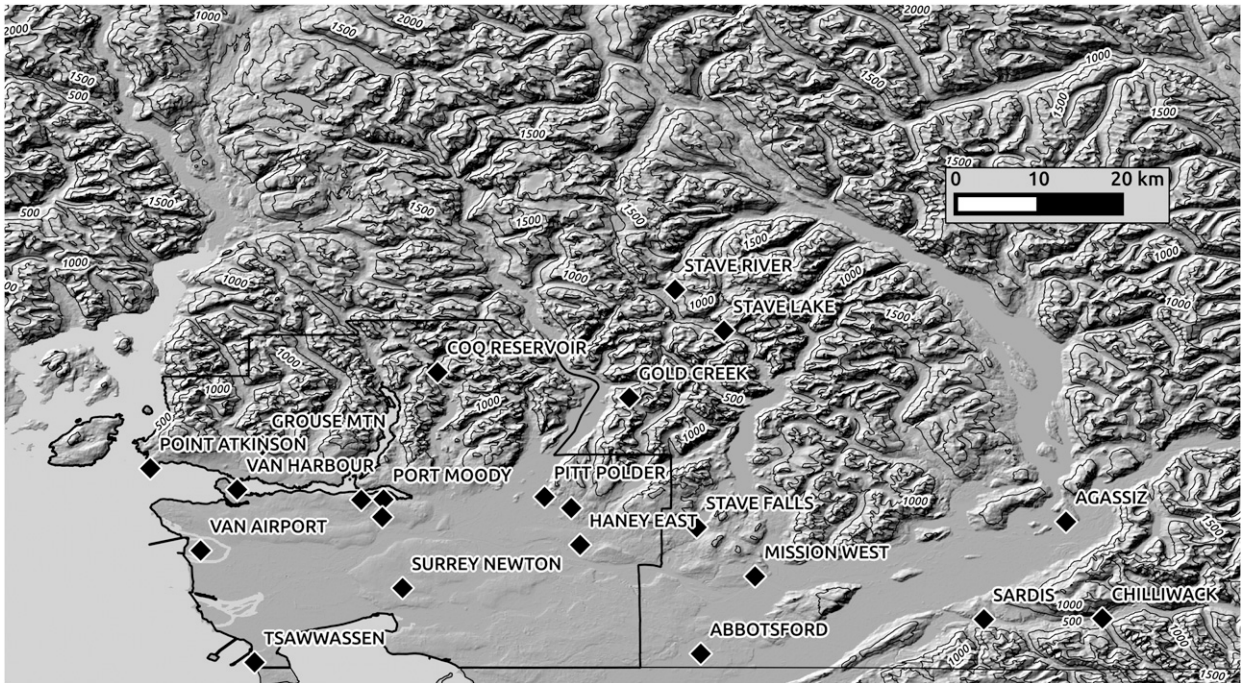


FIG. 1. Weather station locations in southwestern British Columbia used for evaluation in this study. The boundary of metropolitan Vancouver, British Columbia, is outlined in black. Elevation contour lines are drawn at every 500 m.

One potential method (with lower computational costs) for producing higher-resolution temperature and precipitation data is to combine existing statistically downscaled simulations (Murdock et al. 2014) with

high-resolution climatologies of precipitation and temperature (Daly et al. 2008). This can be performed using a simple downscaling method known as climate imprint (Hunter and Meentemeyer 2005). Climate

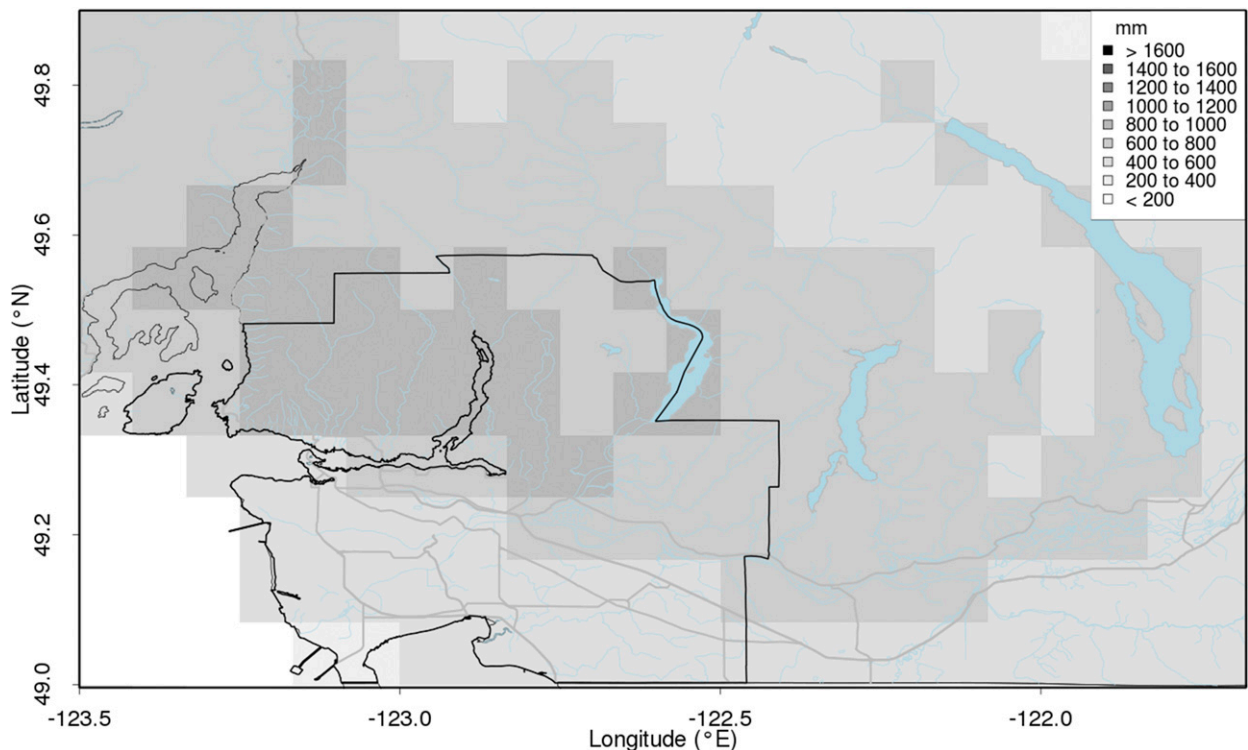


FIG. 2. DJF total precipitation (mm) climatology generated from ANUSPLIN 10-km-resolution historical gridded observations (1971–2000).

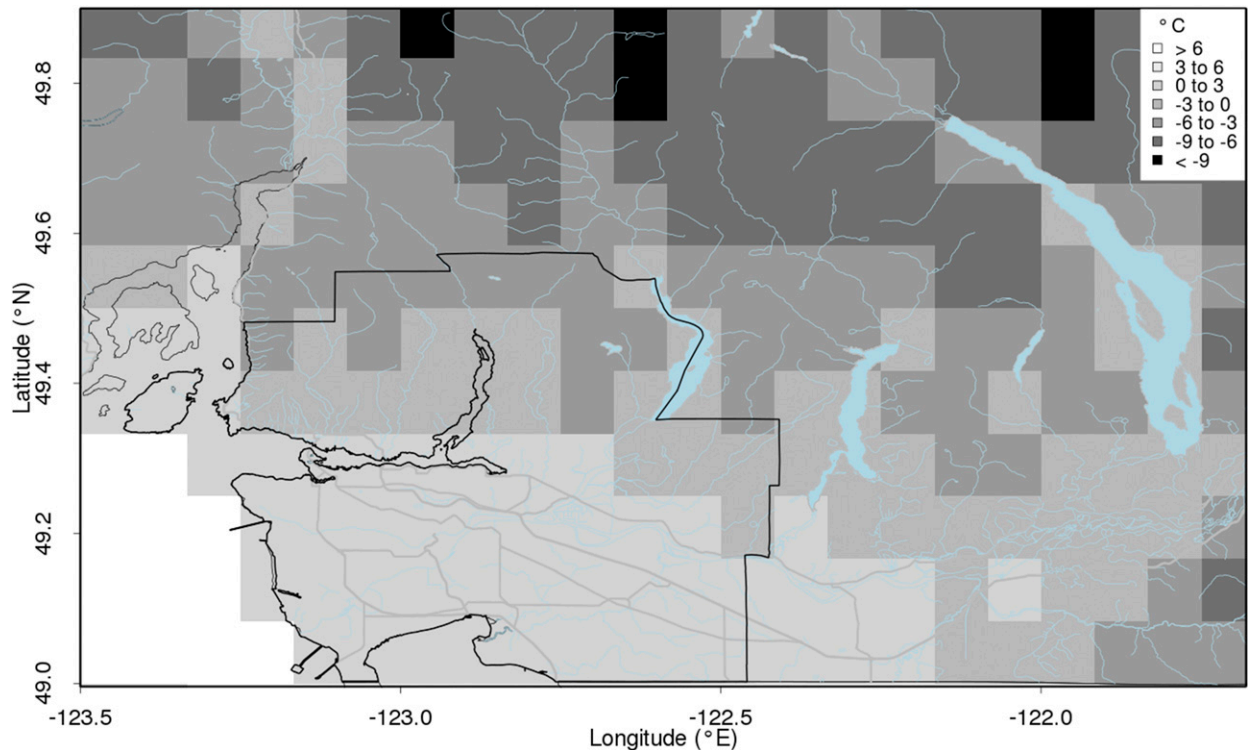


FIG. 3. As in Fig. 2, but for DJF minimum temperature ( $^{\circ}\text{C}$ ).

imprint, also known as the delta method, is a statistical bias correction technique using annual or monthly climatologies (Hay et al. 2000) to increase the spatial resolution of a dataset. The method is often used as a benchmark against which the performance of other more complex downscaling methods is measured (Hamlet et al. 2010; Chen et al. 2011).

Climate imprint is less frequently used as a post-processing step (Teutschbein and Seibert 2013), as the primary statistical or dynamical method is normally designed to achieve a target resolution without need for further downscaling. Postprocessing can add information when a new target dataset is unsuitable for downscaling with the original method. For example, Parameter-Elevation Regression on Independent Slopes Model (PRISM; Daly et al. 2008) offers a high-resolution (800 m) observational dataset but in the form of monthly climatologies rather than a daily series. As many downscaling methods require datasets with daily temporal resolution for calibration, this precludes PRISM from being used as a downscaling target in spite of its high spatial resolution. Starting from previously downscaled climate data also reduces the influence of known limitations (e.g., the magnitude and spatial extent of extreme events) when using climate imprint to downscale large-scale simulations directly (Ekström et al. 2015). It also reduces the

disparity in spatial resolutions that must be bridged between the coarse-scale data and the final finescale target data, lessening the possibility of spatial artifacts in the final result (Cornejo et al. 2013).

Of interest is whether or not this form of further downscaling to higher resolution can improve simulated average and extreme events relative to existing downscaled data. Users requiring high-resolution data for a variety of assessment applications could benefit from knowing whether existing datasets are sufficient and understanding specifically where the existing dataset may be biased compared to observations. This paper tests the effectiveness of postprocessing daily climate simulations at 10-km to 800-m resolution using PRISM climatologies for southwestern British Columbia, Canada. The method is evaluated by comparing the simulation of historical moderate and extreme events at both spatial scales against those same parameters derived from weather station observations over a 30-yr period.

## 2. Data and methodology

### a. Data

Downscaled climatological data are evaluated using weather station observations within the study area.

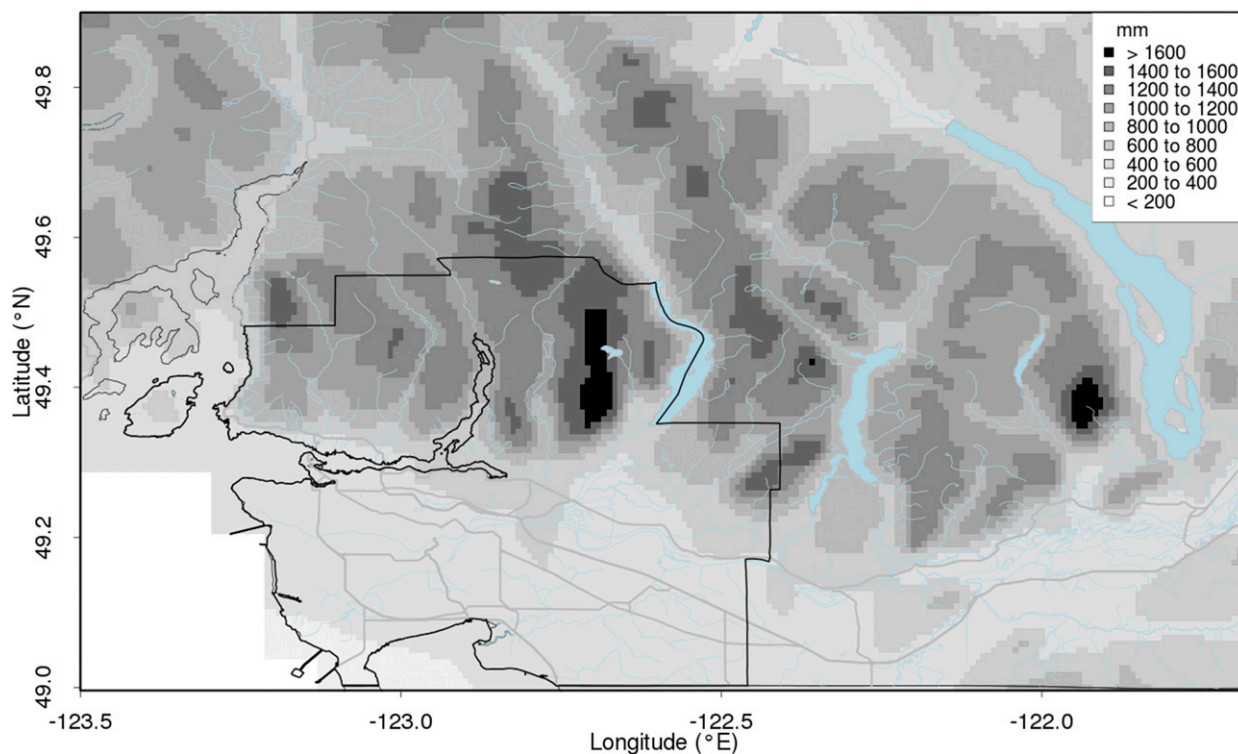


FIG. 4. DJF total precipitation (mm) climatology generated from PRISM 800-m resolution historical gridded observations (1971–2000). At 800-m resolution, the effects on winter precipitation climatologies of more detailed topographic and meteorological information derived from PRISM can be seen relative to those from 10-km ANUSPLIN (Fig. 2).

Suitable stations are identified from those available in the Pacific Climate Impacts Consortium (PCIC) British Columbia provincial climate dataset (PCDS; Pacific Climate Impacts Consortium 2015), and 22 stations from Environment Canada and British Columbia Hydro were selected from the dataset that possessed records spanning at least 30 years with fewer than 5% of observations missing. The stations are primarily located close to population centers in southwestern British Columbia and range in elevation from 2 to 1200 m MSL (Fig. 1).

Regional-scale downscaling is produced using  $1/12^\circ$  (10 km for British Columbia)-resolution historical gridded daily observations of precipitation and temperature spanning 1950 to 2010 produced by Hopkinson et al. (2012) and McKenney et al. (2011). The gridded dataset interpolates quality-controlled weather stations from Environment Canada using the Australian National University Spline (ANUSPLIN; Hutchinson 2004) method, which uses thin-plate smoothing splines incorporating elevation and geographic corrections to produce homogeneous daily precipitation and temperature fields, illustrated in Figs. 2 and 3.

Final, high-resolution downscaling is produced using monthly climate normals spanning 1971 to 2000 for

southwestern British Columbia obtained from weather station data assimilated using PRISM (Daly et al. 2008). Long-term climatologies used in this study were obtained through the Pacific Climate Impacts Consortium data portal (Pacific Climate Impacts Consortium and PRISM Climate Group 2014). The PRISM method both interpolates and adjusts temperature and precipitation observations using information from digital elevation models, geographic properties, and upper-air conditions from the North American Regional Reanalysis (Mesinger et al. 2006) to generate detailed maps of historical climate at 30-arc-s (800 m for British Columbia) resolution, illustrated in Figs. 4 and 5.

#### b. Downscaling

High-resolution downscaled simulations are produced using a two-stage process. Large-scale ( $2.5^\circ$  resolution) daily precipitation and temperature values from the NCEP reanalysis (Kalnay et al. 1996) are first statistically downscaled to 10-km resolution using a hybrid downscaling method, bias correction constructed analogs with quantile mapping (BCCAQ; Werner and Cannon 2016; Murdock et al. 2014). This method combines previously established downscaling tools of bias correction climate imprint (BCCI; Hunter

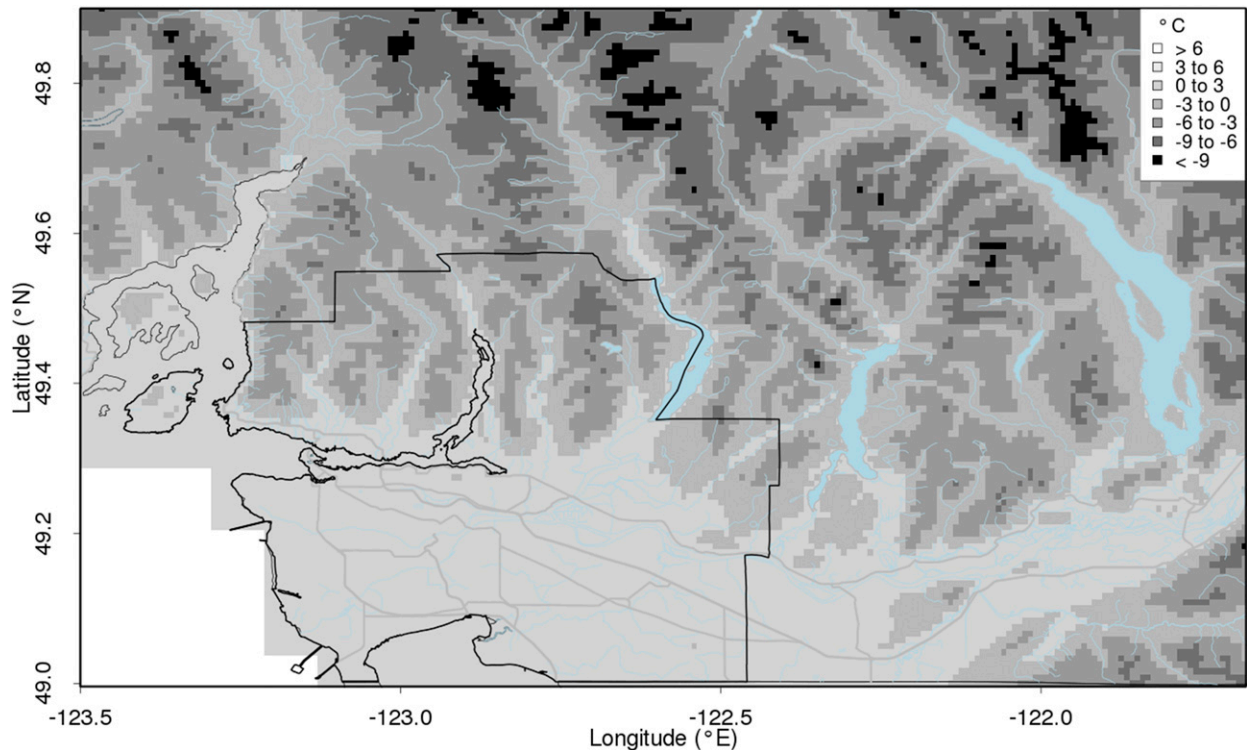


FIG. 5. As in Fig. 4, but for minimum temperature ( $^{\circ}\text{C}$ ) (cf. Fig. 3).

and Meentemeyer 2005) and bias correction constructed analogs (BCCA; Maurer et al. 2010) via a postprocessing step to produce simulated daily precipitation and temperature values that replicate extreme events, daily sequencing, and spatial covariance more effectively than when either of the techniques is used independently (Werner and Cannon 2016). The postprocessing step of BCCAQ is performed to address the shortcomings of the component methods. BCCI consists of interpolating coarse-resolution simulation data to finescale resolution then performing quantile mapping bias correction. This results in poor spatial covariability (i.e., results are simply smooth interpolation from coarse to fine resolution) but preserves changes in day-to-day sequencing from the original dataset and improves the representation of extreme events (Maraun 2013). BCCA, on the other hand, performs quantile mapping between coarse-scale simulation data and historical observations aggregated to the coarse resolution and uses that relationship to bias correct the coarse-scale data. To attain high spatial resolution (and maintain realistic spatial covariability), linear combinations of historical days replace each of the bias corrected coarse-resolution days. However, this step of BCCA eliminates any correspondence between changes in day-to-day sequencing simulated and reintroduces some bias (especially for large domains);

in particular, it causes a preponderance of low-level precipitation (or drizzle) and an underestimation of extreme events (Gutmann et al. 2014). Applying BCCAQ's postprocessing step of performing quantile mapping on BCCA using BCCI retains the best features of each method while addressing the shortcomings discussed above (Werner and Cannon 2016).

Final high-resolution (800m) downscaled simulations are completed using the method of climate imprint (Hunter and Meentemeyer 2005). Climate imprint is also used within the BCCI methodology; however, here, the coarse-scale data are the output of the first stage of downscaling described above and the calibration data are taken from PRISM climatologies. As the calibration dataset for this stage of the process is only available as monthly climatologies, this limits the number of downscaling methodologies that are feasible. In addition, given the first stage of downscaling involves a more complicated method, limiting any further complexity to the secondary process helps constrain added uncertainty from another technique (Bürger et al. 2012; Chen et al. 2011).

Climate imprint takes advantage of high-resolution PRISM fields of temperature and precipitation to bias correct, by month, the daily anomalies calculated from the initial BCCAQ downscaled output. Time series in the high-resolution fields are generated by combining

time-varying interpolated BCCAQ anomalies with PRISM climatologies. Maximum and minimum temperature are adjusted through absolute differences [Eqs. (1) and (2)], while precipitation is corrected by relative changes [Eqs. (3) and (4)]. Adjusting daily anomalies with monthly climatologies maintains spatial coherence over the study domain from PRISM while deriving daily sequencing, extreme event frequency, and secular trends from the statistically downscaled large-scale output.

Daily temperature anomalies of BCCAQ output  $T_{\text{anomaly}}^{10\text{km}}$  are calculated by subtracting 30-yr climatologies  $\bar{T}_{\text{monthly}}^{10\text{km}}$  from the daily 10-km data  $T_{\text{daily}}^{10\text{km}}$ . BCCAQ anomalies are bilinearly interpolated to 800 m ( $T_{\text{daily}}^{\text{interpolated}}$ ) before being added to PRISM climatologies ( $\bar{T}_{\text{monthly}}^{\text{PRISM}}$ ) to produce 800-m daily temperatures  $T_{\text{daily}}^{800\text{m}}$ :

$$T_{\text{anomaly}}^{10\text{km}} = T_{\text{daily}}^{10\text{km}} - \bar{T}_{\text{monthly}}^{10\text{km}} \quad \text{and} \quad (1)$$

$$T_{\text{daily}}^{800\text{m}} = T_{\text{daily}}^{\text{interpolated}} + \bar{T}_{\text{monthly}}^{\text{PRISM}}. \quad (2)$$

Daily precipitation ratios of BCCAQ output  $P_{\text{ratio}}^{10\text{km}}$  are derived from 10-km data  $P_{\text{daily}}^{10\text{km}}$  divided by 30-yr climatologies  $\bar{P}_{\text{monthly}}^{10\text{km}}$  of that same data. High-resolution (800 m) daily precipitation  $P_{\text{daily}}^{800\text{m}}$  are generated by multiplying PRISM climatologies ( $\bar{P}_{\text{monthly}}^{\text{PRISM}}$ ) with BCCAQ ratios bilinearly interpolated to 800 m ( $P_{\text{daily}}^{\text{interpolated}}$ ):

$$P_{\text{ratio}}^{10\text{km}} = P_{\text{daily}}^{10\text{km}} / \bar{P}_{\text{monthly}}^{10\text{km}} \quad \text{and} \quad (3)$$

$$P_{\text{daily}}^{800\text{m}} = P_{\text{daily}}^{\text{interpolated}} \times \bar{P}_{\text{monthly}}^{\text{PRISM}}. \quad (4)$$

### c. Evaluation

Comparison of the differences between 800-m and 10-km downscaled NCEP simulations against the station values is performed for the periods from 1950 to 1970 and 2000 to 2010. The historical period is split to exclude the years from 1971 to 2000, which acts as both the calibration period for 10-km downscaling and the averaging period for the PRISM climatologies. These station values are assimilated in both the ANUSPLIN and PRISM gridded datasets; thus, there is not complete independence between the 800-m downscaled values and their reference stations. Bias and root-mean-square error (RMSE) values may therefore be underestimated relative to an independent set of stations.

Differences between the two downscaled datasets are evaluated using quantile–quantile maps as well as bias and RMSE between the modeled data and station values. Error and RMSE are evaluated using the ‘‘Climdex’’ set of indices of moderate and rare climate extreme events as defined by the Expert Team on Climate Change Detection and Indices (ETCCDI; Zhang et al. 2011) that is commonly used to analyze derived

TABLE 1. The ETCCDI set of extreme indices (Climdex) used to evaluate the effect of downscaling to 800 m. The variables span a range of magnitudes and frequencies of occurrence for temperature and precipitation.

Index	Definition	Interval	Units
PRCPTOT	Annual precipitation	Annual	mm
R99p	Extremely wet days	Annual	mm
R95p	Very wet days	Annual	mm
CWD	Consecutive wet days	Annual	days
CDD	Consecutive dry days	Annual	days
R20mm	No. of very heavy precipitation days	Annual	days
R10mm	No. of heavy precipitation days	Annual	days
SDII	Simple day intensity index	Annual	mm
RX5day	Max 5-day precipitation amount	Monthly	mm
RX1day	Max 1-day precipitation amount	Monthly	mm
DTR	Diurnal temperature range	Monthly	°C
CSDI	Cold-spell duration	Annual	days
WSDI	Warm-spell duration	Annual	days
TX90p	Warm days	Monthly	days
TN90p	Warm nights	Monthly	days
TX10p	Cold days	Monthly	days
TN10p	Cold nights	Monthly	days
TNN	Monthly min of daily min temperature	Monthly	°C
TXN	Monthly max of daily min temperature	Monthly	°C
TNX	Monthly min of daily max temperature	Monthly	°C
TXX	Monthly max of daily max temperature	Monthly	°C
GSL	Growing-season length	Annual	days
TR	Tropical nights	Annual	days
ID	Ice days	Annual	days
SU	Summer days	Annual	days
FD	Frost days	Annual	days

daily climate parameters (Sillmann et al. 2013; Murdock and Sobie 2013). Climdex indices (Table 1) include parameters ranging from annual total precipitation and monthly temperature extremes to multiday precipitation extremes and event sequential dependencies such as heat waves.

Error [Eq. (5)] is evaluated as the difference between the predicted value  $P_i$  (whether at 10 km or 800 m) and the observed station value  $O_i$  averaged over  $n$  years or months, depending on which of the Climdex indices is considered. RMSE [Eq. (6)] is similarly defined, evaluating a sum of squared difference rather than an absolute one:

$$\text{Error} = \frac{1}{n} \sum_{i=1}^n (P_i - O_i) \quad \text{and} \quad (5)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2}. \quad (6)$$

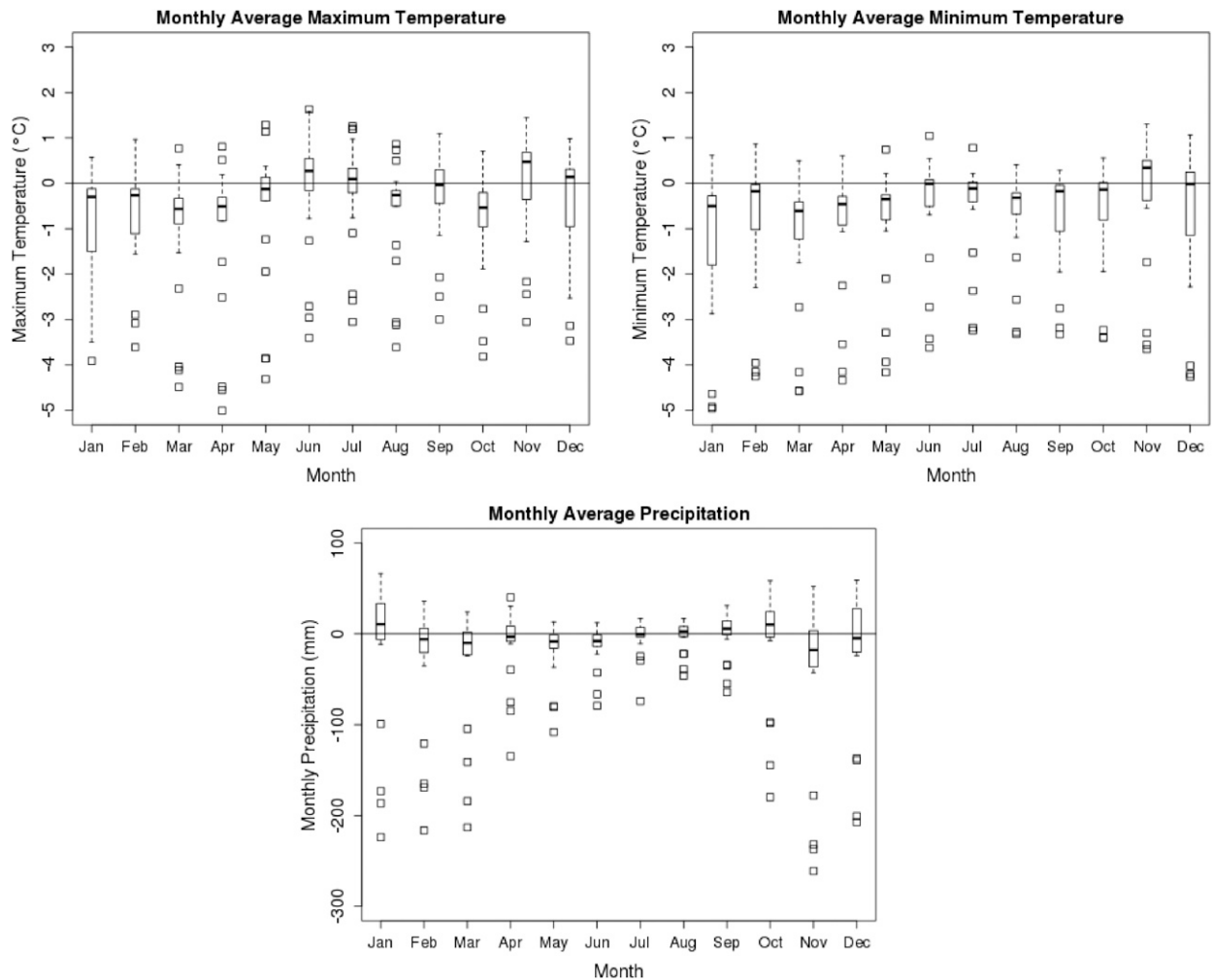


FIG. 6. Climatological monthly average differences (10 km – 800 m) of temperature and precipitation between the 10-km dataset and the 800-m PRISM value for each of the 22 station locations.

Climdex indices (Table 1) are used to evaluate the two modeled datasets for two reasons. First, Climdex indices are frequently used in impacts assessments, so it is useful to measure the performance of the downscaled dataset in the context of these parameters. Second, Climdex indices represent a range of moderate to extreme events that may be altered more subtly by monthly bias correction with PRISM. For example, percentile and threshold-based indices such as R95p and TX90p would show no difference between the two datasets if an annual correction was applied. Thus, they provide a useful metric to investigate exactly how much benefit is gained by the additional downscaling step.

### 3. Results

Differences between the climatological monthly averaged values of temperature and precipitation from

the 10-km dataset and the corresponding 800-m PRISM value (displayed as 10 km – 800 m) for each of the station locations are displayed in Fig. 6. These values denote the magnitude of bias correction applied by climate imprint downscaling at the station sites and illustrate the seasonal variability to the bias values. Different patterns of bias are observed among the three variables downscaled. Maximum temperature differences are similar across most months, though winter [December–February (DJF)] and early spring months possess a greater cool bias. Minimum temperature differences show an overall cool bias with a greater effect in winter among a minority of stations. Monthly precipitation displays a relatively constant annual bias at the majority of stations. However, there is also a strong seasonal cycle in a subset of stations, with the largest dry biases occurring during the winter months and relatively lower biases in summer. In all variables,

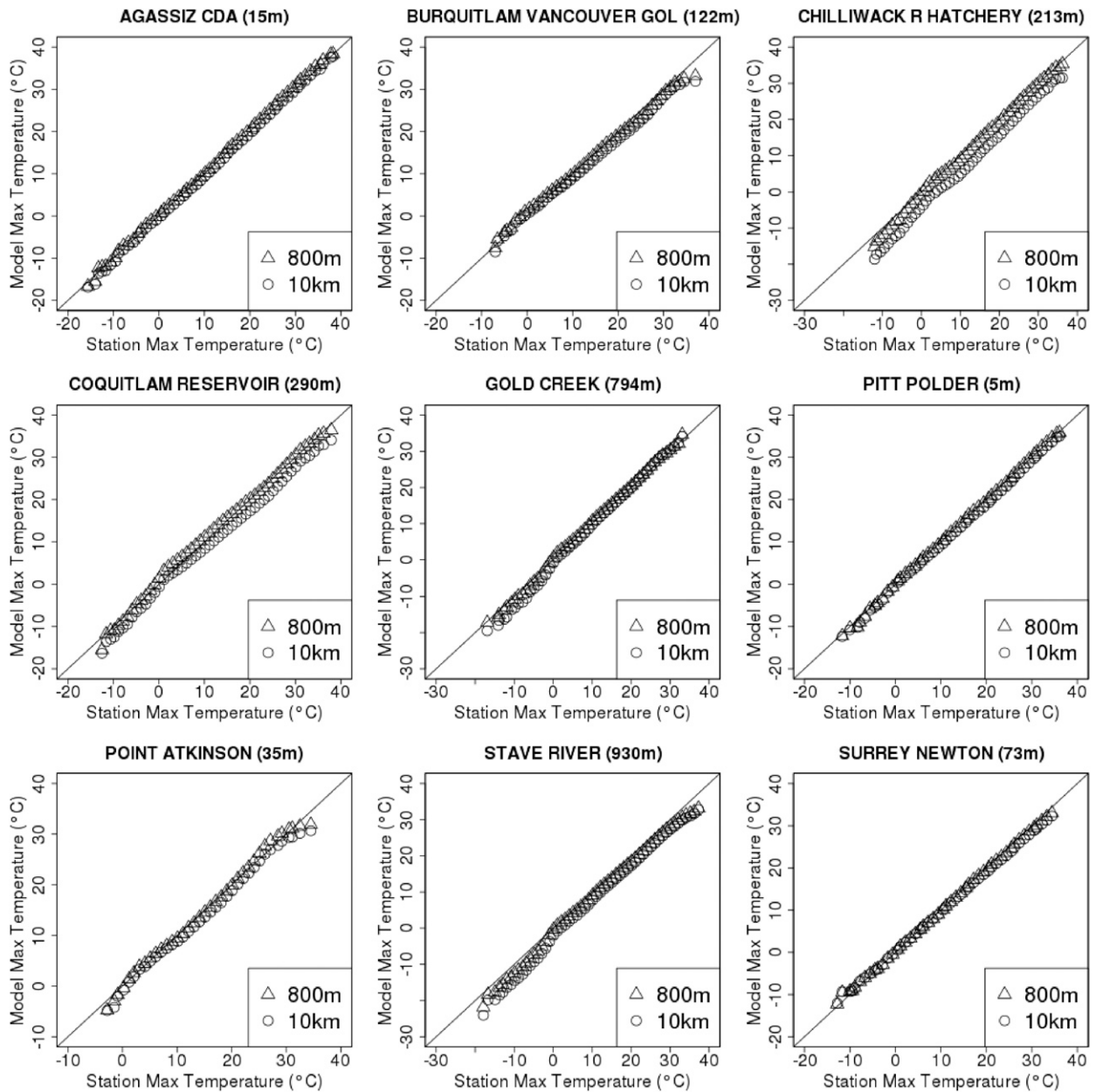


FIG. 7. Quantile–quantile plots of daily maximum temperature from climate imprint downscaled 800-m resolution data and BCCAO downscaled 10-km-resolution data for nine selected stations in southwestern British Columbia. Station elevations are noted next to the station name above each plot.

the largest and most seasonally dependent bias magnitudes originate from a minority of the set of stations.

Quantile–quantile plots of daily values from both 10-km and 800-m resolutions relative to station values illustrate a simple comparison of both downscaling methods (Figs. 7, 8, and 9). Here, 9 of the 22 stations are displayed as a representative sample. Given the downscaling method from 10 km to 800 m involves only a monthly bias correction with spatial interpolation,

one would not expect substantial differences in the distribution of daily values. In the majority of sites, simulated temperature distributions are nearly identical to those of the stations, and there is little difference between modeled datasets. Where differences are seen (such as Chilliwack River Hatchery), there is a systematic cold bias across the distribution of simulated 10-km temperature. In terms of precipitation, certain stations' (e.g., Gold Creek, Stave River) daily precipitation

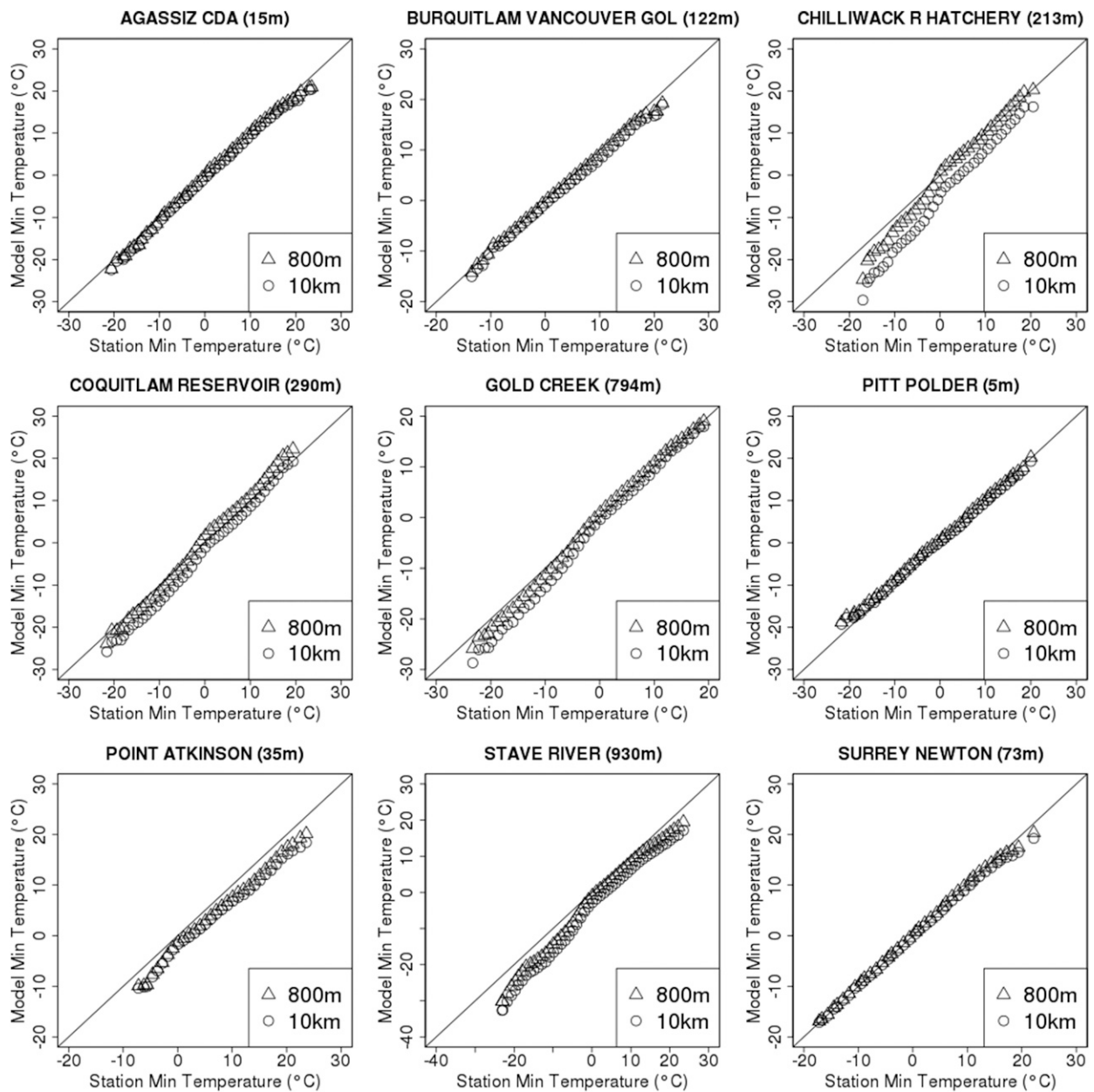


FIG. 8. As in Fig. 7, but for daily minimum temperature.

values are underestimated by the 10-km dataset compared to the higher-resolution values (Fig. 9). At these (predominantly higher elevation) sites, the effect worsens as precipitation intensities grow larger.

Figures 10 and 11 display the normalized error and normalized RMSE between the Climdex indices for downscaled and observed data. Among the Climdex indices, the largest errors occur in the threshold-based temperature parameters (e.g., TX90p) and in consecutive day indices (e.g., CDD, CDSI). Both the 10-km and 800-m data possess similar biases, namely,

underestimating precipitation intensities at most stations and a cold bias at many sites. The differences between the errors of the two datasets are displayed in the third panel of Fig. 11. Where the difference is negative, the 800-m indices agree more closely with the station values, while where the difference is positive, the 10-km indices have smaller errors. At many of the stations, there is little difference in agreement with station data regardless of whether 10-km or 800-m downscaled data are compared. However, at several sites, there is improvement in the 800-m data

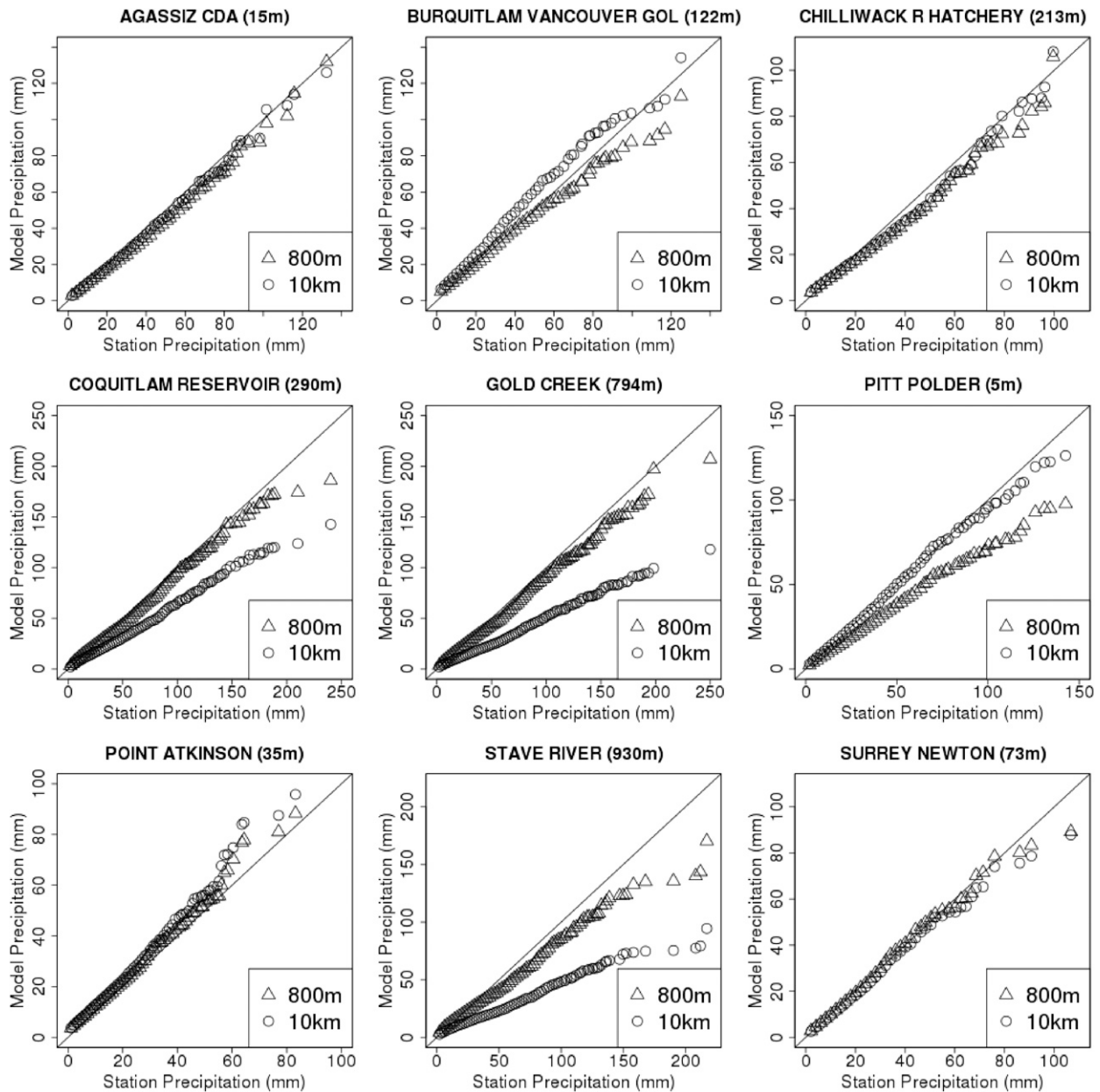


FIG. 9. As in Fig. 7, but for daily precipitation.

over the 10-km data for temperature and precipitation extreme values.

These results can be examined more closely by focusing on a few individual indices that illustrate the overall results. In Figs. 12 and 13, the errors of Climdex indices from 10-km and 800-m data compared to station values are plotted against station elevations. Common to most of the indices is that the largest improvements from 10 km to 800 m occur at higher elevations. Precipitation total (PRCPTOT) and precipitation exceeding the 95th percentile (R95p) both show large decreases

in error at four of the highest elevation sites and negligible or small changes at the other locations. Similar improvements can be seen for extreme daily maximum (TXX) and minimum (TNN) temperatures and growing-season length (GSL). For cold nights (TN10p), as minimum temperatures were generally too cold at most stations, monthly bias correction adjusts those cold night temperatures (generally occurring in winter) upward, and the error values at all stations become more positive, equating to a reduction in days with very cold temperatures at 800 m. Errors of indices related to

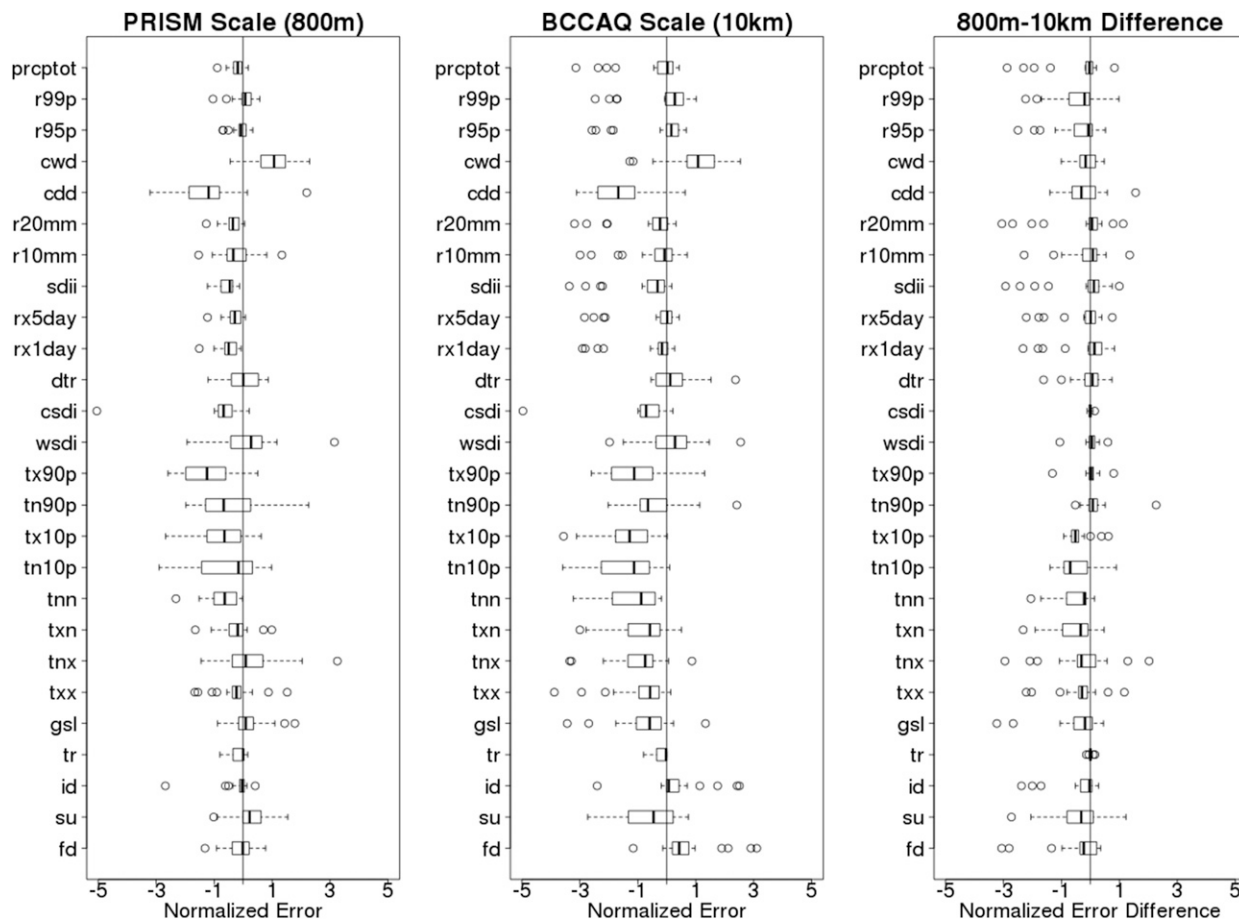


FIG. 10. Absolute differences (bias) between 800-m PRISM and 10-km-resolution BCCAQ data for 27 Climdex variables. Bias values are calculated by month for monthly Climdex variables and annually for annual indices (see Table 1 for full variable names and definitions). Each box plot displays the range of error values from all 22 station locations. (left) Error between 800-m resolution data and station values, (center) error between 10-km-resolution data and station values, and (right) the difference between the 800-m and 10-km bias values.

sequential events like consecutive dry days (CDD) or warm spells (WSDI) are largely unchanged. From one to two individual sites do see change in the error magnitudes where bias corrected temperature or precipitation values are close to the index definition threshold, and small changes push the values above or below the Climdex threshold.

Examining RMSE of temperature and precipitation extreme events at a monthly scale reveals a seasonal dependence to the accuracy of the two downscaled datasets (Fig. 14). Maximum temperature extremes (TXX) display the largest RMSE values during the spring and early summer months (March through June), while minimum temperature (TNN) RMSE peaks between November and March. The 800-m dataset produces slightly lower RMSE values in all months at most sites, but the greatest reductions occur during the same peak RMSE periods in the decreased size of RMSE outliers. The largest improvements in extreme

precipitation RMSE values occur during the fall and winter months. These intervals coincide with those months possessing the largest precipitation amounts climatologically (Murdock et al. 2016). As seen previously, the greatest improvement in error when comparing 10-km and 800-m RMSE values occurs in a minority of high-elevation stations.

#### 4. Discussion and conclusions

Employing climate imprint postprocessing with PRISM climatologies for British Columbia to bias correct existing downscaled daily precipitation and temperature offers a simple way to add high-resolution information to existing downscaled data. Though results may only show small improvements at low-elevation sites, the correction of larger biases at high elevation is noteworthy given the predominance of high-elevation terrain in British Columbia. This result is also consistent

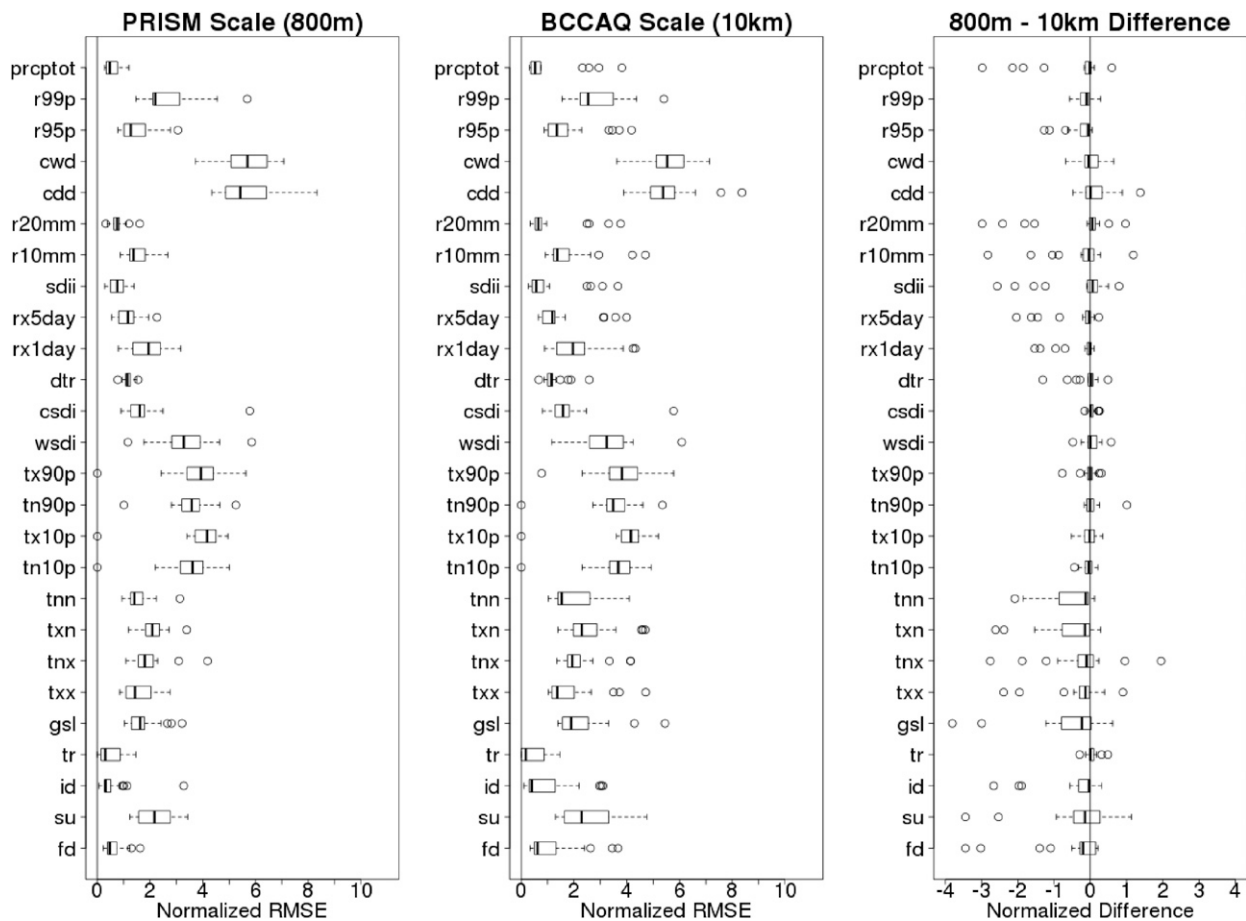


FIG. 11. As in Fig. 10, but for RMSE.

with the fact that differences between 800-m PRISM climatologies and 10-km ANUSPLIN climatologies are much smaller at low elevation than at high elevation. At low elevation, much of the value of performing the correction results from filling in spatial maps with realistic values at 800 m compared to 10 km rather than increased accuracy at individual sites. Improved representation of precipitation averages and extreme events at higher elevation is especially promising given the known biases in precipitation by the calibration data (McKenney et al. 2011) and in reanalysis products (Kalnay et al. 1996).

The weather stations used to evaluate downscaled performance are predominantly in low-elevation locations and are relatively small in number. Evaluating improved representation of Climdex indices from increasing spatial resolution could conceivably be done with alternative (though more complex) methods. Supplying the 800-m data to a hydrologic model and comparing simulated streamflow against observed gauges could provide a means to test the high-resolution precipitation in regions without stations at high elevation.

Precipitation events could also be compared against radar observations or satellite-radar products such as Global Precipitation Measurement (GPM; Hou et al. 2014). Finally, expanding the scope of analysis to regions in the United States where PRISM climatologies have also been produced would also be informative, though it would require a new 10-km dataset as the extent of ANUSPLIN is limited to terrestrial Canada. The present analysis could be expanded to other parts of British Columbia as PRISM climatologies have been generated for the entire province. However, other regions of the province have much sparser coverage from long-term weather stations compared to the southwestern region examined in this study, which would mean relatively fewer opportunities for additional evaluation of the climate imprint method.

In southwestern British Columbia, precipitation and temperature experience strong seasonal variations, leading to biases between the 10-km and 800-m datasets that follow an annual cycle (Fig. 6). Applying a monthly rather than annual correction with climate imprint addresses seasonal variability, leading to potential improvements in

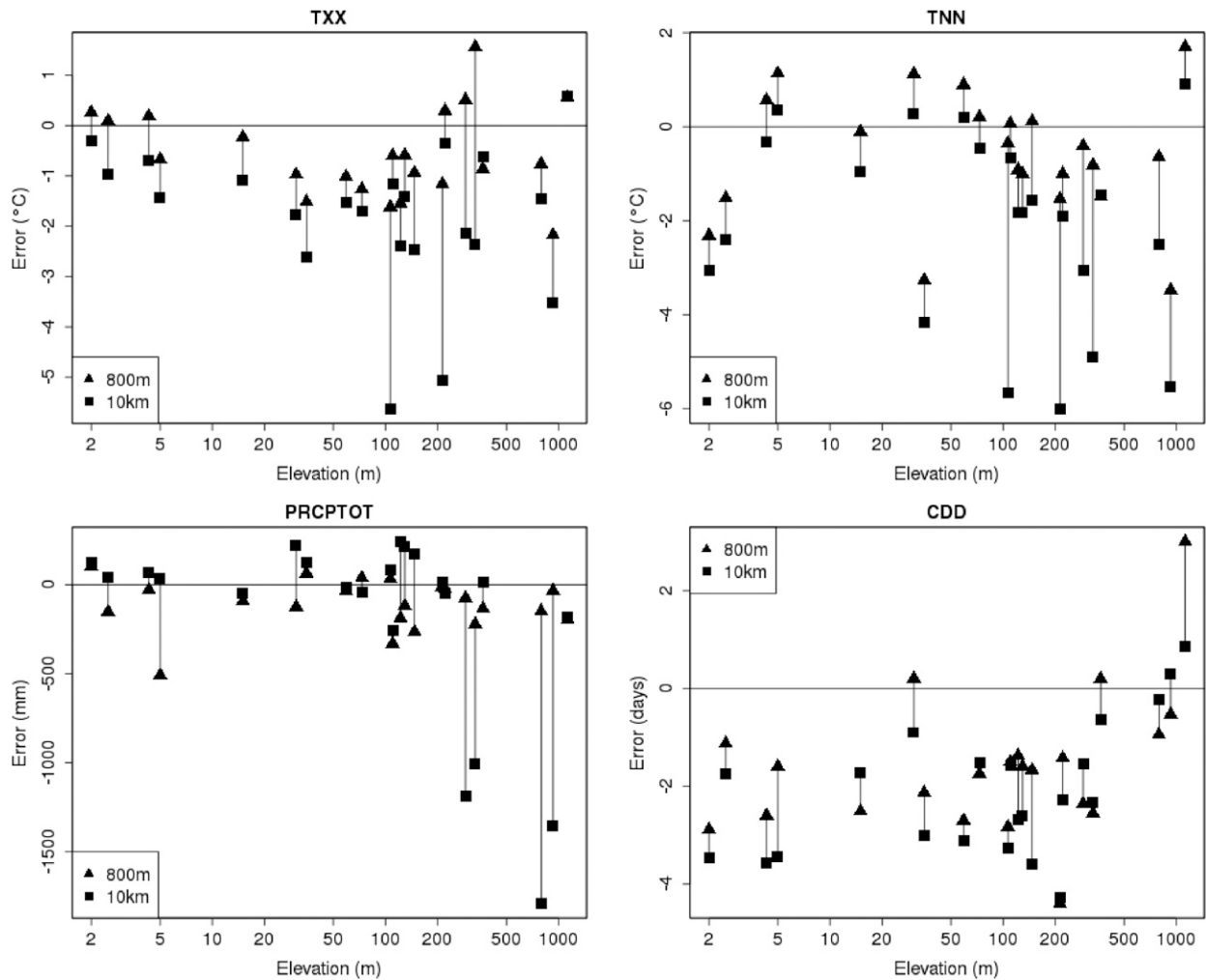


FIG. 12. Bias values for four selected Climdex variables (TXX, TNN, PRCPTOT, and CDD) from 800-m and 10-km-resolution data when evaluated against station values. Values are plotted as a function of the station elevations.

the representation of all Climdex variables. If only an annual correction was applied, quantile-based parameters such as TX90p and CSDI would be unchanged as the entire annual distribution of temperature or precipitation values would be increased or decreased uniformly. Events such as extreme precipitation or cold temperatures that occur primarily in winter or consecutive dry days that occur primarily in summer would see diminished improvement as an annual adjustment would smooth out the seasonal corrections. Taking advantage of monthly PRISM climatologies provides greater information over an annual correction to the high-resolution dataset and is likely necessary in any locations with strong seasonal precipitation or temperature variability.

Some issues remain outstanding following downscaling with climate imprint. Bias correction by monthly climatologies does not address differences in spatial variability within a 10-km cell. By design, the high-resolution

climatological pattern from PRISM is magnified or diminished based on the anomaly derived from the 10-km downscaled data. Thus, patterns that differ from the climatological pattern such as temperature inversions (which occur with low to moderate frequency during winter months because of radiative cooling and in summer months because of high-pressure airmass subsidence) or atypical daily precipitation patterns cannot be replicated at 800-m scale within the area spanned by one 10-km cell. Related to this, temperature and precipitation spatial patterns in the PRISM data are derived from monthly averaged quantities. Differences between spatial patterns of low- and high-magnitude extreme events can indeed be substantial at high resolution. While developing separate PRISM climatologies for events of different magnitudes is beyond the scope of this study, doing so could improve the representation of Climdex indices at low-elevation stations where there is greater

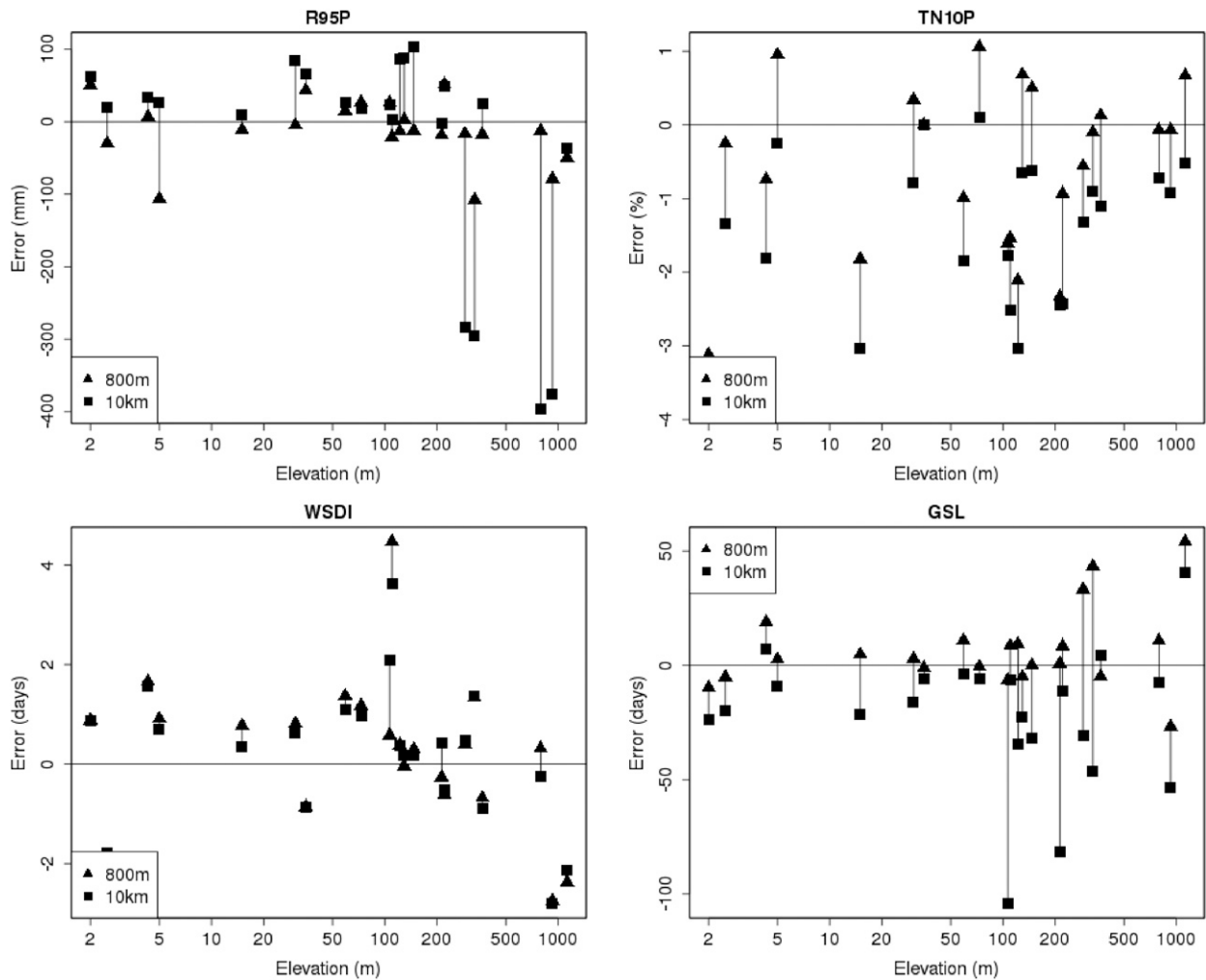


FIG. 13. As in Fig. 12, but for R95p, TN10p, WSDI, and GSL.

variation in spatial structure from event magnitude than from topography. For similar reasons, the interpretation of differences between adjacent 800-m cells must be approached carefully as bias correction does not contribute additional information about local processes (such as small-scale feedbacks in complex terrain).

Bias correction using PRISM can also exacerbate error between an 800-m cell and its coincident station in individual cases. For example, at Pitt Polder station (the site at 5-m elevation in Fig. 12), adjusting daily precipitation with monthly climatologies causes a greater dry bias at the 800-m scale than the 10-km scale for annual precipitation. In this instance, the 10-km cell in question includes both low-lying terrain (including Pitt Polder) with reduced precipitation intensities and more mountainous terrain with greater precipitation intensities. The resulting average in the 10-km ANUSPLIN cell happens to match that of Pitt Polder station but

exceeds the value in the 800-m PRISM cell. Bias correction attempts to resolve the difference but instead causes an underestimation of precipitation at the 800-m cell. Though this issue occurs infrequently, it emphasizes that the advantages of this form of bias correction occur primarily at higher elevations, using additional information from the PRISM dataset.

Sequentially based indices, in particular, sequences of consecutive wet or dry or warm or cold days, are largely unaffected by this postprocessing step as monthly mean bias correction to high resolution leaves day-to-day sequencing mostly unaltered. The downscaled results do show a small but systematic overestimation of the number of wet days (associated with an underestimation of dry days) at the majority of stations. This is likely a combination of an increased frequency of nonzero precipitation at spatial scales larger than point scales and a persistence of “model drizzle” from the large-scale

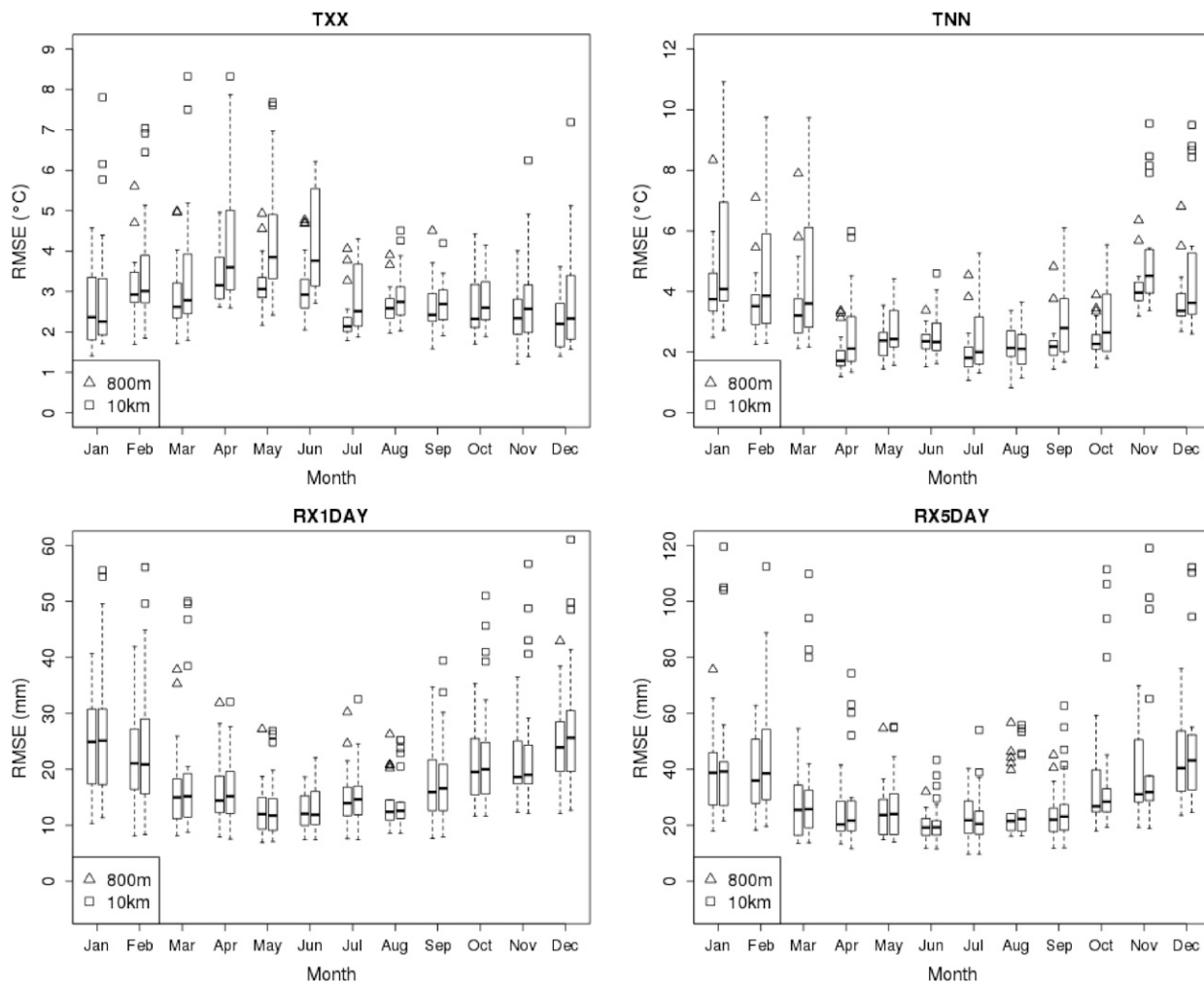


FIG. 14. RMSE values by month for four selected Climdex variables from 800-m and 10-km-resolution data. Each box plot displays the range of RMSE values from all 22 station locations.

simulated data that remains despite the downscaling steps (Dai 2006). Warm and cold spells display more minor systematic discrepancies and negligible differences between the two spatial scales. A general cold bias in modeled temperature values is likely caused both by stations located in valley bottoms and by the known small but significant cooling caused by the climate imprint methodology (Hunter and Meentemeyer 2005).

The additional benefits to increased resolution must be balanced against the cost of achieving that resolution. At 10-km resolution, the area of study in this project (southwestern British Columbia) is represented by 630 model grid cells. By contrast, at 800-m resolution, the same area encompasses 61 020 cells, a difference of two orders of magnitude. Increased resolution results in greater computational storage and increased processing requirements both to generate the higher-resolution dataset and for any postprocessing such as the calculation

of Climdex indices. The requirements would grow further still for future projections or if an ensemble of models is used. For small regions or users with sufficient resources, the issue may not be a concern; however, it is a possible constraint as study areas grow in size.

Common to the majority of the climate indices examined are larger decreases in error for stations at high elevation and small improvements or marginal increases in error for a minority of low-elevation sites after post-processing to 800 m. The main advantage in using PRISM climatologies is extra information supplied for locations at higher elevation with more complex topography. At low-elevation sites, both ANUSPLIN 10-km and PRISM 800-m data assimilate a similar group of stations into their gridding processes. In these regions, PRISM precipitation and temperature values do not differ substantially from those of ANUSPLIN, and there are only small improvements in the resulting high-resolution indices compared

to station values. At higher elevations, the inclusion of additional station networks, upper-air values, and high-resolution slope and aspect data provides PRISM with greater information with which to derive climatologies. That additional information produces better agreement when compared to station values, particularly for precipitation. When considering Climdex indices of extreme events in southwestern British Columbia, for low-elevation locations, 10-km-scale climate data would suffice in most cases, while higher elevation and topographically complex sites are better represented by high-resolution data.

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