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# Monthly High-Resolution Historical Climate Data for North America Since 1901

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## ABSTRACT

Interpolated grids of historical climate variables are widely used in climate change impact and adaptation research. Here, we contribute monthly historical time series grids since 1901 for our data product *ClimateNA*, which integrates historical data and future projections to generate high-resolution gridded data and point estimates for North America. The historical climate grids in this study are based on interpolations of monthly anomalies (change factors) with thin-plate splines, but a novel aspect is that we rely on high-quality 1961–1990 normal estimates from *ClimateNA* to serve as reference for the change factor calculations instead of the reference being derived from station data itself. This allowed us to utilise records from 66,282 climate stations for interpolations, regardless of their temporal coverage. Another aspect that deviates from standard practice is that we reduce overfitting by optimising thin-plate splines at a 0.5° grid level instead of fitting weather station observations directly. The high-resolution grids generated with this approach compared favourably with other time series products, such as Daymet and advanced multi-source products, such as MSWEP, in statistical and mapped visual comparisons, and provide additional historical coverage since the beginning of the 20th century.

## 1 | Introduction

Interpolated climate grids are widely used in climate change research to investigate ecological responses to climate variability or directional climate trends. Gridded climate data can be developed through various approaches. A common method is the interpolation of weather station data, such as CRU-TS (Harris et al. 2020), UDEL-TS (Matsuura and Willmott 2018), PRISM (Daly et al. 2008) or Daymet (Thornton et al. 2021). Alternatively, re-analysis products take a more complex approach by building on general circulation models that are informed by weather station data but also many other ocean, land and atmospheric parameters, such as ERA5 (Hersbach et al. 2020) and CHELSA, which downscales ERA5 (Karger et al. 2017). Furthermore, multi-source products are available that draw on weather station data, re-analysis and satellite data, such as MSWEP (Beck et al. 2019).

Most interpolated historical climate data products are available at a relatively coarse spatial and temporal resolution of 0.25°–0.5° and monthly time steps (e.g., CRU-TS, UDEL-TS), but have historical coverage since 1901 or earlier. In contrast, re-analysis products are typically generated at hourly time steps and then aggregated into daily and monthly products (e.g., ERA5). They typically provide data coverage at around 0.25° resolution and date back to the 1980s, although ERA5 now has temperature grids since the 1940s and precipitation grids since the 1960s. The CHELSA data set, a downscaled version of ERA5, provides

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monthly climate variables since 1979 at approximately 1 km resolution (Karger et al. 2017). Gridded historical products at both high spatial and temporal resolution (daily and approximately 1 km resolution) are also available since 1980 for the North American continent through Daymet (Thornton et al. 2021).

Our data product for North America, *ClimateNA* (Wang et al. 2016, 2012) provides high-resolution data coverage for climate normal periods, decadal averages, annual, seasonal and monthly historical data since 1901, as well as future projections from the CMIP6 collection (Mahony et al. 2022). A large number of standard and bioclimatic variables can be estimated for point locations (scale-free), or users can generate custom-gridded climate data at high spatial resolution. The data are widely used, for example, by ecologists tracking and predicting climate change impacts in topographically complex landscapes. Our finest temporal time step is monthly resolution, which does not provide information about extreme events at a daily time step, but is nevertheless sufficient for many applications and models that are concerned with longer term analysis of ecological systems to climate variability and climate trends, such as dendroclimatology.

*ClimateNA* generates historical data at high spatial resolution by storing gridded layers of historical monthly anomalies relative to the 1961–1990 normal period at a relatively modest 0.5° resolution, previously sourced from CRU-TS, which are then bilinearly interpolated and added to scale-free climate estimates for the 1961–1990 normal period, as described in detail by Wang et al. (2016). As such, our *ClimateNA* software can integrate any historical time series product. The CRU-TS-product has the longest temporal coverage (1901 to present), but makes use of a limited number of weather stations. Other time series products, such as ERA5, MSWEP, CHELSA and Daymet, cited above, make better use of high-density weather station data for the US and southern portions of Canada, but they are limited in their temporal coverage, starting in the 1950s–1980s.

Here, we test a novel methodological approach to generate a gridded historical time series product for North America, taking full advantage of a large, continuously updated weather station database provided by the Global Historical Climate Network Daily (GHCND) (Menne et al. 2012). Instead of calculating monthly anomalies from weather stations directly as is common practice (e.g., for the CRU-TS data set), we rely on lapse rate-adjusted point estimates from *ClimateNA* to obtain 1961–1990 climate normal estimates for weather station locations. This allows the calculation of anomalies for any weather station record regardless of the length of their coverage. While this approach can utilise all available weather station records, unbiased and precise estimates of monthly historical climate values are not guaranteed because the approach relies on the accuracy of the PRISM-derived *ClimateNA* reference grid.

To test the validity of the approach, we carried out independent validations using a 3° grid size checkerboard approach, where 50% of the data are used for model development (white fields), and the remaining stations are withheld for testing (black fields) and vice versa. This ensures that spatial autocorrelations amongst nearby weather stations are largely removed to avoid overfitting and inflation of statistical accuracies. Lastly, we carried out statistical and visual checks of the final model (using all station data), comparing mapped anomaly grids with other widely used historical time series products after down-scaling to high resolution.

## 2 | Data and Methods

### 2.1 | Weather Station Data

Historical daily data were obtained from the Global Historical Climatology Network—Daily (GHCND) (National Climatic Data Center 2024). The data set was filtered for stations covering North America, comprising 66,282 weather stations (Figure 1). Additional observations from 205 additional weather stations in British Columbia that could fill gaps in the GHCND database (data points in red in Figure 1) were obtained from the Pacific Climate Impact Consortium (PCIC) data portal (http://tools.pacificclimate.org/dataportal/pcds/map/), resulting in a total 66,487 weather stations for interpolation. The variables of interest were monthly average minimum and average maximum temperature (Tmin, Tmax) and total monthly precipitation (Prec), with good coverage from 1950 to 2010, but declining towards the beginning of the century, and also being more limited for recent years (Figure 2).

### 2.2 | Anomalies and Interpolation

Daily station data were aggregated at a monthly time step, requiring at least 20 daily values to calculate a monthly value. Then, monthly anomalies (or change factors) of monthly Tmax, Tmin and Prec variables were calculated by subtracting a 1961–1990 climate normal estimate, obtained from *ClimateNA* for the location and elevation of the weather station. Using a predicted climate normal, instead of calculating the reference value from weather stations, considerably increased the number of climate records that could be utilised. This is because many stations did not have sufficient observations during the 1961–1990 reference period to allow a direct anomaly calculation from station data itself.

To interpolate the anomalies of the stations into a spatial grid for each of the 36 monthly variables, we used Thin Plate Spline regression (TPS), with latitude, longitude and elevation as independent variables. TPS regressions were implemented with the *fastTps* function of the *fields* package (Nychka et al. 2021) for the R programming environment. Because of the large size of the data set, the *fastTps* function was used, optimising the smoothing parameter for each variable of each month and year individually. We used the following steps for the model optimization: (1) built an initial *fastTps* model with starting smoothing parameters (theta for tapering range and lambda for smoothing parameter); (2) generated raster layers at the spatial resolution for the final output ($0.5 \times 0.5°$); (3) extracted the anomaly values for the locations of weather stations; (4) compared the extracted values with the corresponding anomalies calculated from the weather stations; and (5) iterated

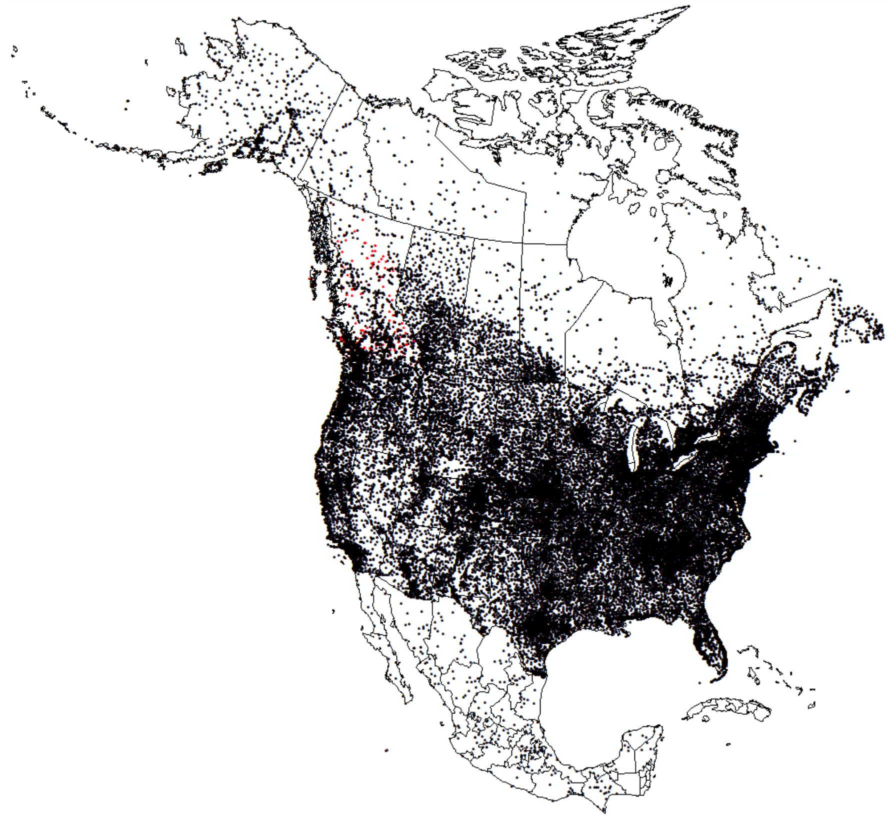

**FIGURE 1** | Distribution of weather stations included in the Global Historical Climatology Network for North America (black) and additional weather stations from the Pacific Climate Impact Consortium database for BC (red).

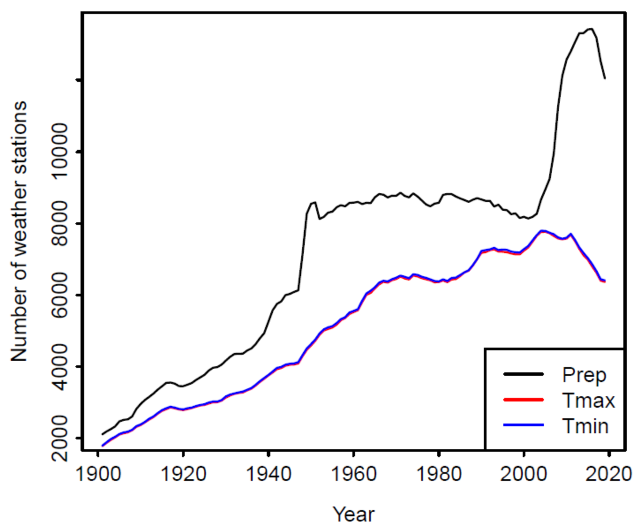


**FIGURE 2** | The number of stations available from 1901 to 2020 with records for monthly precipitation (Prec), mean monthly maximum temperature (Tmax), and mean monthly minimum temperature (Tmin) for generating gridded anomalies.

this process with a varying smoothing parameter until the optimal estimates were achieved at the raster level. We optimised models at the raster level by using the extracted values from the raster layers instead of directly predicted values for weather stations. This was intended to avoid overfitting at the specific locations of weather stations.

## 2.3 | Independent Validation

We conducted independent spatial validation for 20 years from 2001 to 2020 using a checkerboard validation approach according to Fick and Hijmans (2017), in which the study area was divided into 3° grid cells, and half the values (black fields, block A) were used for model training, while the other half (white fields, block B) were used for validation. We then used the weather stations from A blocks to optimise the models and used the stations from B blocks to validate the predictions. This procedure ensured that testing data were generally distanced from training data thereby avoiding overestimating the prediction accuracy due to possible overfitting of the thin-plate spline model. The final model was built based on all available station data with the optimised parameters.

Additionally, we used the same approach to evaluate the effectiveness of utilising predicted grid values for model optimisation (above-mentioned steps 3 and 4) to prevent overfitting, instead of directly using predicted values at the weather station locations. We trained the model with A block station data, and then predicted values for both A and B blocks. The difference in prediction accuracy ($R^2$) between the two blocks was used to represent the level of overfitting. With overfitting defined as the difference in variance explained within (block A to A predictions) versus between (block A to B predictions) of the $3° \times 3°$checkerboard boxes, the amount of overfitting was visualised for raster-level *fastTPS* optimisations versus station-level interpolations.

### 2.4 | Statistical Evaluation and Comparison With Other Products

We evaluated our model predictions against a set of systematically selected stations to ensure spatial and temporal representation. In a first pass, long-term weather stations with a record of at least 80 years were selected and binned into geographic regions of $0.5° \times 0.5°$ and 250 m elevation classes. One station per bin was randomly chosen. The remainder of the stations were then filtered for early-year records with at least 25 years of data for the 1901–1940 period. Again, one qualifying station was selected per bin, and the remainder was subjected to third and fourth selection passes for mid (1941–1980) and recent (1981–2020) data coverage with at least 25 years. The final test database for statistical evaluation of TPS interpolations and for comparison with other data products comprised 4625 stations that had long-term records and that were as balanced as possible in terms of representing the full 1901–2020 period.

Other products included in this comparison included monthly Tmin and Tmax estimates from the re-analysis product ERA5 available since 1940 and ERA5 precipitation estimates available since 1959 at 0.25° resolution (Hersbach et al. 2020). Another multi-source product, utilising weather station interpolation, re-analysis, and remote sensing data was MSWEP, with data availability since 1979 at 0.1° and 0.25° resolution and only available for precipitation (Beck et al. 2019). Another widely used interpolation product that we integrated in earlier versions of *ClimateNA* is CRU-TS (Harris et al. 2020). This data set is available since 1901 at 0.5° resolution for all variables, Tmin, Tmax and Prec. A high-resolution product included in our comparison was Daymet (Thornton et al. 2021), which we aggregated from daily to monthly time steps using the original grid resolution of approximately 1 km resolution. For a fair comparison, all low-resolution products, CRU, ERA5 and MSWEP, were downscaled and adjusted based on local environmental lapse rates with the *ClimateNA* software package (see Wang et al. 2016 for methodology), which reduced error statistics against weather station records by a large margin compared extracting climate values directly from coarse resolution grids. Daymet data, which are already a high-resolution product, did not require this adjustment, and Daymet estimates were evaluated by extracting them directly from the climate grids based on the weather station locations.

Statistics were calculated for monthly, seasonal and annual variables for 120 years time series (1901–2020) with changes in accuracy over this period visualised through line plots of error statistics and summarised numerically by averaging error statistics over the entire period. The prediction accuracy of the data sets was evaluated by the proportion of the total variance explained ($R^2$) in weather station data by the estimates from gridded products. As a second statistic, we chose mean absolute error (MAE), which provides error estimates in original units of°C for temperature and mm precipitation.

## 3 | Results

### 3.1 | Model Development and Validation

In general, the independent cross-validation statistics were not much lower than the statistics for the final model, where no available weather station data was withheld (Table 1). This indicates that the model does not significantly over-parameterise. The model prediction accuracies with regard to the variance explained ($R^2$) were generally higher for temperature variables (Tmax and Tmin) than for precipitation variables (Prec), and mean maximum temperature values could be modelled with slightly higher accuracy than mean minimum temperature values, based on both $R^2$ and Mean absolute errors (MAE) statistics. The MAE statistic was in original variable units and not comparable between temperature and precipitation, but overall, the accuracy of historical climate estimates compared to the original observations at weather stations was satisfactory, with typical errors ranging from 1.0°C to 1.4°C in temperature, and 20–30 mm in precipitation in the independent validation where withheld stations where distanced from training data to minimise spatial autocorrelations with the test data set.

Furthermore, the validation statistics for temperature variables were consistent over time (from 1901 to 2020). Standard deviations of validation statistics over time ranged from 0.006 to 0.015 for $R^2$ and from 0.03°C to 0.17°C for MAE for the different months. In contrast, validation statistics for precipitation over time were an order of magnitude more variable. Standard deviations for $R^2$ ranged from 0.06 to 0.13 for the 1901 to 2020 period and varied with a standard deviation ranging from 9 to 15 mm for MAE for the different months. This indicates that there were historical periods where climate estimates were better than for other periods, which is also visible when the statistics are plotted over time (Figure 3, black line). Generally, model statistics were best for the 1950–1990 period, with errors rising towards the beginning of the century, but also slightly declining towards the most recent decades.

To assess the effect of parameterising thin-plate splines at the grid levels as opposed to fitting weather station values for model optimisation, we used an independent checkerboard validation approach. Grid-level optimisation reduced overfitting for all monthly climate variables (Figure 3), with the effect being more pronounced for precipitation than for temperature. Additionally, the reduction in overfitting was more effective in the summer months for both temperature and precipitation variables.

### 3.2 | Statistical Comparison With Other Data Products

The thin-plate spline estimates from this study generally compared well with other well-regarded and widely used data products that include historical time series estimates. Daymet, when summarised into monthly values from the original daily estimates, had slightly superior error statistics for precipitation and near-identical statistics for temperature variables as our data (Figure 4, red lines). Similarly, MSWEP had very similar or slightly superior error statistics for precipitation, the only

**TABLE 1** | Independent cross-validation statistics and final model evaluation for mean absolute errors (MAE) and variance explained ($R^2$).

| | Independent checkerboard cross-validation | | | | | | Final model evaluation | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Tmax | | Tmin | | Prep | | Tmax | | Tmin | | Prep | |
| Month | $R^2$ | MAE | $R^2$ | MAE | $R^2$ | MAE | $R^2$ | MAE | $R^2$ | MAE | $R^2$ | MAE |
| Jan | 0.976 | 1.3 | 0.958 | 1.6 | 0.853 | 22.0 | 0.982 | 1.1 | 0.964 | 1.5 | 0.891 | 21.1 |
| Feb | 0.979 | 1.2 | 0.965 | 1.6 | 0.829 | 23.4 | 0.986 | 1.0 | 0.972 | 1.4 | 0.871 | 22.3 |
| Mar | 0.977 | 1.2 | 0.960 | 1.5 | 0.813 | 23.1 | 0.984 | 1.0 | 0.969 | 1.3 | 0.865 | 21.8 |
| Apr | 0.976 | 1.1 | 0.959 | 1.3 | 0.747 | 26.6 | 0.982 | 1.0 | 0.966 | 1.1 | 0.815 | 24.6 |
| May | 0.964 | 1.1 | 0.953 | 1.2 | 0.690 | 32.9 | 0.975 | 1.0 | 0.960 | 1.1 | 0.763 | 30.0 |
| Jun | 0.963 | 1.1 | 0.949 | 1.3 | 0.631 | 38.9 | 0.973 | 1.0 | 0.955 | 1.2 | 0.724 | 34.5 |
| Jul | 0.953 | 1.1 | 0.939 | 1.3 | 0.600 | 37.7 | 0.965 | 1.0 | 0.945 | 1.2 | 0.690 | 33.4 |
| Aug | 0.956 | 1.1 | 0.935 | 1.3 | 0.636 | 36.2 | 0.967 | 0.9 | 0.941 | 1.2 | 0.739 | 31.8 |
| Sep | 0.967 | 1.0 | 0.939 | 1.4 | 0.675 | 32.2 | 0.976 | 0.9 | 0.946 | 1.3 | 0.770 | 28.6 |
| Oct | 0.977 | 1.0 | 0.943 | 1.4 | 0.739 | 27.9 | 0.984 | 0.9 | 0.951 | 1.3 | 0.827 | 25.2 |
| Nov | 0.980 | 1.0 | 0.948 | 1.5 | 0.830 | 21.8 | 0.986 | 0.9 | 0.956 | 1.3 | 0.887 | 20.5 |
| Dec | 0.978 | 1.1 | 0.956 | 1.5 | 0.835 | 22.7 | 0.984 | 1.0 | 0.964 | 1.4 | 0.891 | 21.4 |
| Mean | 0.971 | 1.1 | 0.950 | 1.4 | 0.740 | 28.8 | 0.979 | 1.0 | 0.957 | 1.3 | 0.811 | 26.3 |

*Note:* The independent validation is based on a checkerboard approach that ensures that testing data were generally distanced from training data and thereby avoiding estimation of the accuracy of the thin-plate spline model.

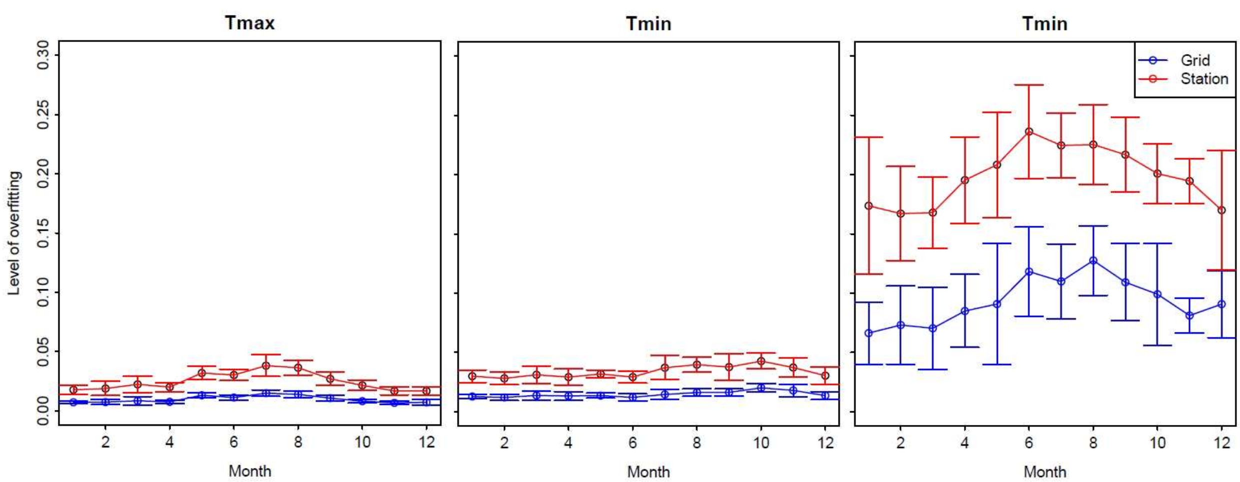


**FIGURE 3** | Reduction in overfitting from optimising thin-plate splines at the 0.5° grid level target resolution of historical time series grids. The level of overfitting is defined as the difference in variance explained within versus between 3° × 3° checkerboard box predictions. Error bars represent the standard deviation across years.

variable that is available for this data product (Figure 4, purple lines in Prep panels). We observed a drop in quality for our own precipitation estimates by approximately 5 mm in MAE for the most recent decade and a general spike in errors in 2011 that affects all products and was driven by highly localised precipitation extreme events in the northeast and mid-west of the United States in that year. The CRU product, which uses a similar interpolation approach as in this study, but based on fewer weather stations, and ERA5, which is a general circulation model-based reanalysis product had generally higher errors, but showed similar trends in how errors develop over time. It appears that ERA5 judiciously restricted their temperature estimates to the 1940s as the earliest temporal coverage, where errors start to increase (Figure 4, blue line).

### 3.3 | Visual Comparisons With Other Data Products

Spatial patterns of the anomalies of both temperature and precipitation were generally similar amongst data products. The data set that appeared to most closely track station data

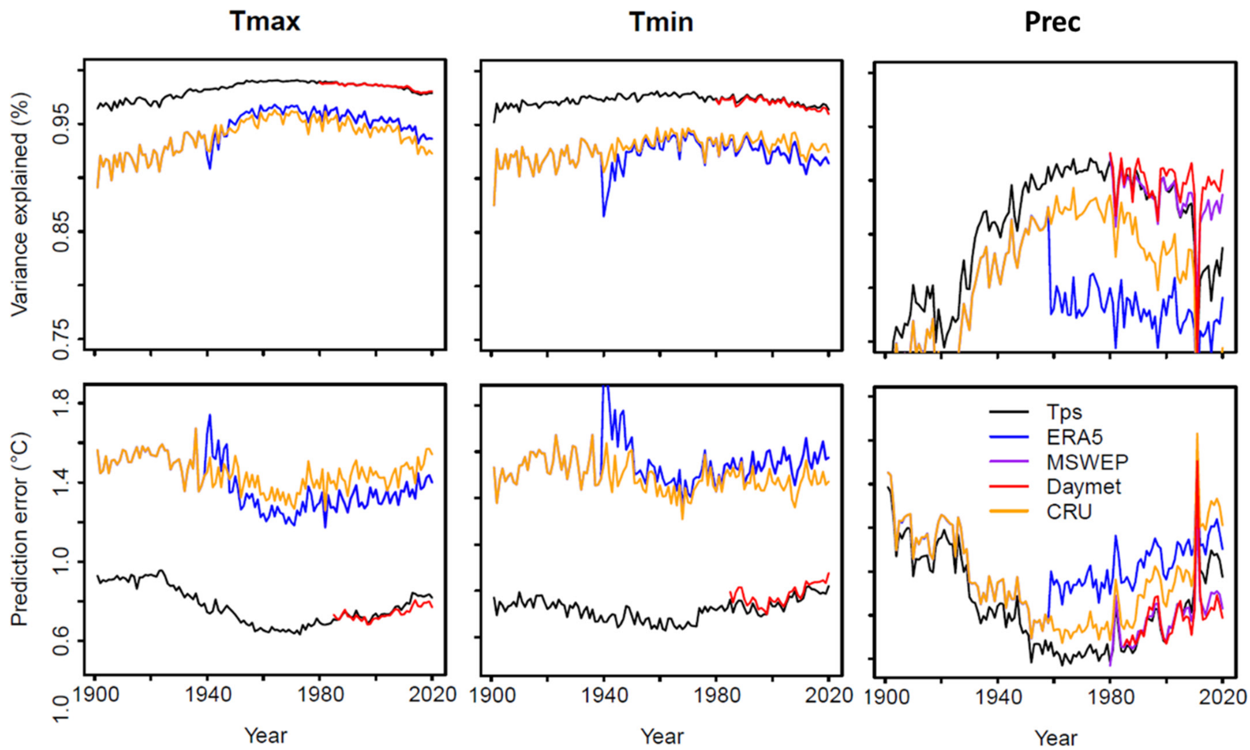


**FIGURE 4** | Comparison of mean absolute errors (MAE) and variance explained ($R^2$) over time from this study (Tps) with other data products. The statistics represent the averages of 12 monthly values for maximum and minimum monthly temperature (Tmin, Tmax) and monthly precipitation (Prec).

with flexible spline (or equivalent) interpolation approach was Daymet, followed by ERA5, then our interpolations (TPS), and with CRU-TS applying the stiffest splines for anomaly grids that appeared smooth across the continent (Figure 5). We noted that Daymet showed anomalies in areas of low weather station coverage that other products did not show, in this example for the year 2020 there were some high-temperature anomalies at the border of British Columbia and the Yukon Territories, and a low temperature anomaly in Mexico not seen in other products. This was a common observation also seen for other years in Daymet data, but only in temperature layers and only where weather station coverage was sparse (data not shown).

For precipitation, the most flexible splines (or equivalent methods underlying interpolations) were observed for MSWEP and Daymet, followed by ERA5, this study (TPS), and CRU again using the stiffest splines to generate interpolated grids (Figure 6). We noted that for precipitation grids we never observed deviations in Daymet data for the Canadian north as in temperature data. The patterns of all products appeared to largely conform.

## 4 | Discussion

Anomaly grids of historical data from this study manage to balance between closely tracking the values of individual weather stations over time, such as Daymet and MSWEP, and using very robust splines, which protects best against over-parameterisation in areas of low weather station coverage, such as CRU. In addition, our anomalies also had the longest coverage of the historical period as CRU. Daymet and MSWEP may provide slightly better estimates of historical climate data in precipitation for areas of very high weather station coverage, such as the lower US states, and CRU-TS may be the superior product with minimal over-parameterisation where weather station coverage is sparse in the Canadian north and other regions of the world and towards the beginning of the century. The independent validation statistics of our model parameterisation procedure and (Table 1) suggest that our anomaly layers (included in *ClimateNA* since version 7.0) strike a good general balance with regard to statistical performance while avoiding over-parameterisation.

Although we used a methodologically similar approach as CRU-TS, namely interpolation of anomalies calculated from weather station data, the higher level of spatial detail and improved statistical accuracies is likely attributable to the full-use of available weather station data, enabled by the use of the 1961–1990 climate reference estimate from *ClimateNA* instead of being calculated from weather stations, as a large number of stations would be excluded as they did not have sufficient observations during the 1961–1990 period. Second, the optimisation of our model predictions at the raster grid level instead of individual stations protected against over-parameterisation. From a visual assessment of the mapped anomalies (Figures 5 and 6), our level of spatial detail from fitting splines with minimal over-parameterisation approximately conforms to those of the re-analysis product ERA5 for temperature and shows somewhat less detail than ERA5 for precipitation. While we may be slightly conservative in allowing a close fit to station data, the approach is justified to strike a compromise between areas

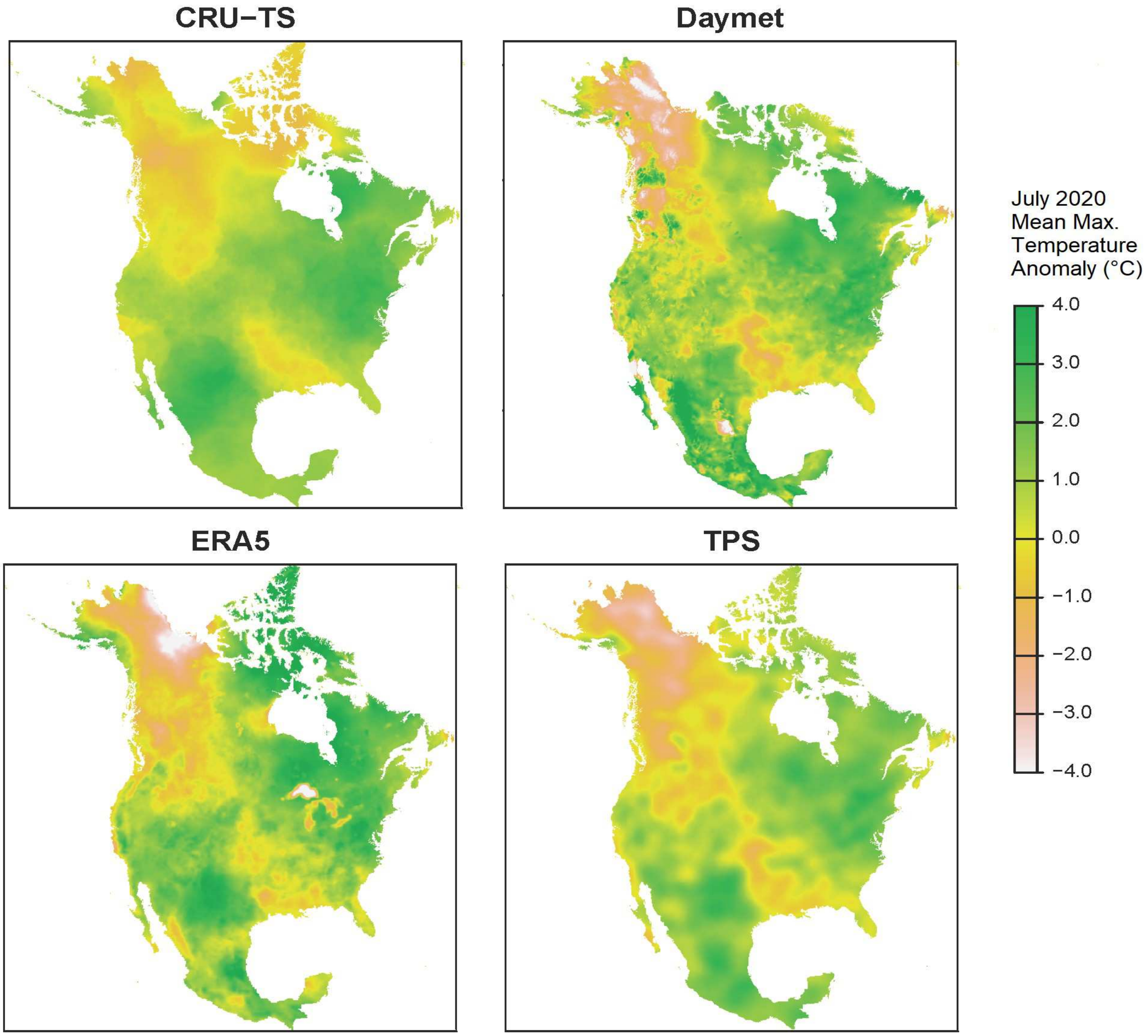


**FIGURE 5** | Visual comparisons of monthly temperature anomalies from three historical time series products (CRU-TS, Daymet and ERA5) with the thin plate spline interpolations (TPS) from this study. The example comparison used here was July mean maximum temperature for the year 2020, with temperature anomalies in°C deviation from the 1991–2020 normal period.

with high density of station data and areas and periods where weather station coverage is sparser.

Generally, a degradation in prediction accuracies over time would be expected towards the early portion of the century, and this was also observed. Prediction accuracy slightly declined for temperature variables towards the early part of the 20th century, with larger declines observed in the north, and the highest declines observed in precipitation, which is a more difficult variable to model without a dense station network. The increase in errors for the early period is consistent with a decline in the number of weather stations shown in Figure 2. The less pronounced worsening of error statistics beyond the 1990s towards the present seems independent of the number of weather stations and affected all data products. A possible explanation is that the most recent weather station records have not yet been subjected to the same quality control procedures as data that has been checked and improved over many decades.

We also note that comparative prediction accuracies were by necessity evaluated against the weather stations that was also used to develop the models. Thus, the prediction accuracies are to some degree an overestimate for all products. The overestimation could be quantified for our model by withholding data, and the effect was surprisingly small (c.f., left and right sections for Table 1). The difference between an independent and

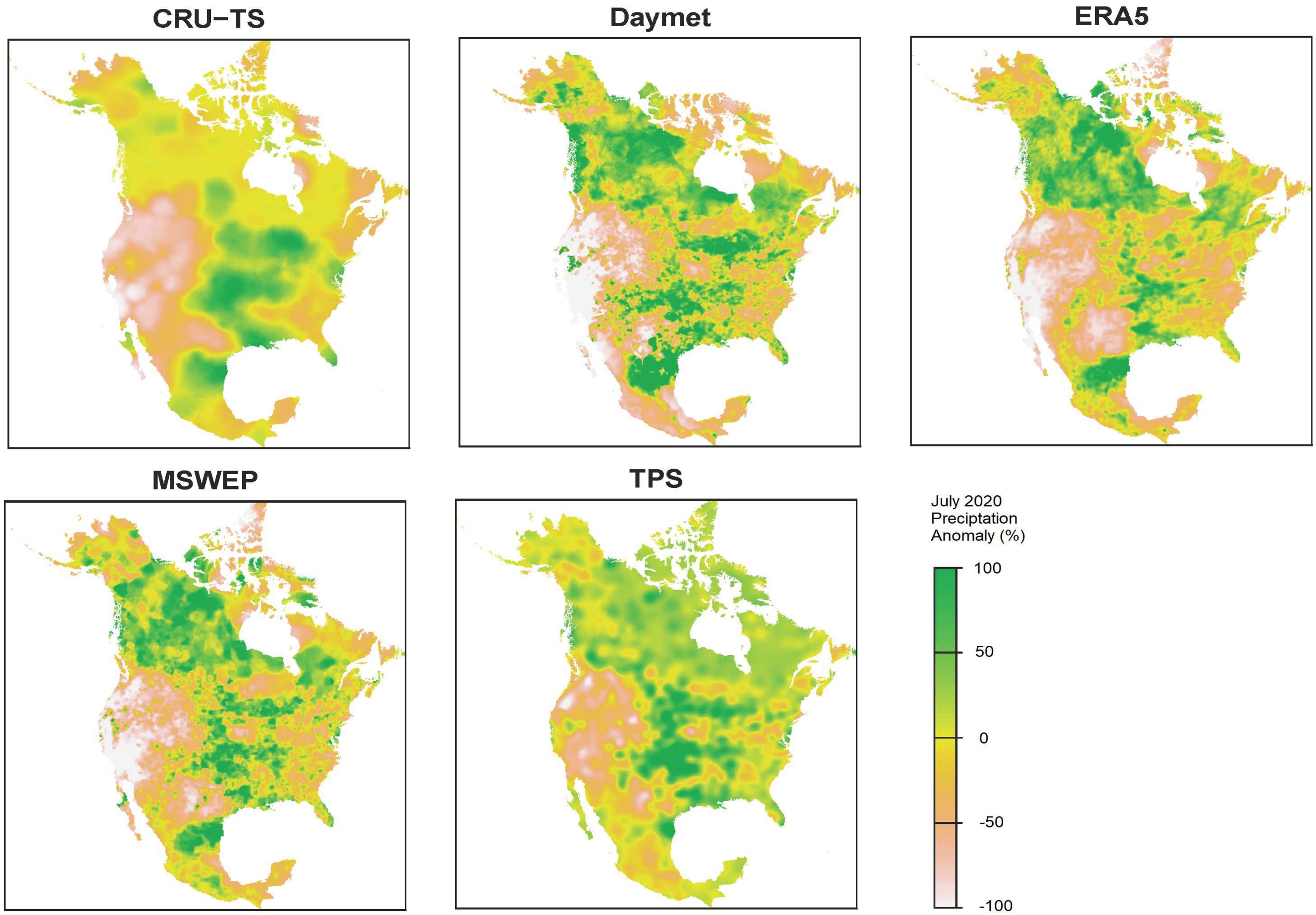


**FIGURE 6** | Visual comparison of precipitation anomalies from four historical time series products (CRU-TS, Daymet ERA5 and MSWEP) with the thin plate spline interpolations (TPS) from this study. The example comparison used here is July precipitation for the year 2020 with precipitation anomalies in % deviation from the 1991–2020 normal period.

non-independent test would likely be even smaller for a product like CRU-TS, which appears to have employed the equivalent of very stiff splines for interpolation (Figures 5 and 6). In contrast, products like Daymet, MSWEP, ERA5 appear to employ the equivalent of flexible splines, and an independent test could potentially reveal a tendency to overparameterise, which might compromise the capability of models to extrapolate far beyond station coverage, in which might therefore be less suitable for areas of the world that do not have dense networks of weather stations. We emphasise, however, that these inferences are speculative as it is generally difficult to organise fully comparable multi-model intercomparisons, where all investigators would need to use the same training and validation data sets.

With regard to usage notes for researchers and practitioners that rely on our ClimateBC/NA software packages (Hamann and Wang 2005; Wang et al. 2016, 2012), the anomaly grids generated in this study are now available by default and are recommended for general usage. However, all other anomaly grids that we tested in this study can also be used in conjunction with our *ClimateNA* software package through a simple file replacement. Monthly anomaly grids derived from Daymet, ERA5, MSWEP and CRU from the start of the respective data coverage to 2020 are available upon request if users need to ensure consistency with previous work or have a data preference for a specific study area.

## Author Contributions

**Tongli Wang:** conceptualization, investigation, funding acquisition, writing – original draft, methodology, validation, visualization, writing – review and editing, formal analysis, data curation, resources. **Andreas Hamann:** conceptualization, investigation, writing – original draft, methodology, validation, visualization, writing – review and editing. **Zihaohan Sang:** visualization, methodology, writing – review and editing, data curation.

## Acknowledgements

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## Conflicts of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

The data that support the findings of this study are available in ClimateNA at https://climatena.ca/. These data were derived from the following resources available in the public domain: Global Historical Climatology Network daily, https://www.ncei.noaa.gov/products/land-based-station/global.

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