Identification of radiative and advective populations in Canadian temperature time series using the Linear Pattern Discrimination algorithm

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Abstract
Long-term high-frequency air temperature time series, typically considered the most authoritative observed records for the detection of climate changes, appear physically heterogeneous by nature. We examine multiple Canadian air temperature records for the presence of physical heterogeneities, using the analysis of their diurnal temperature patterns as the main criterion for the separation of temperature series into ‘homogeneous’ populations. Based on the key differences observed in their diurnal air temperature patterns, two distinct populations of the air temperature sample are identified and assumed to be the result of different heat exchange mechanisms. The Linear Pattern Discrimination (LPD) algorithm, implemented in the R-code, is introduced in this work and applied to 66-year long hourly temperature records of 25 Canadian stations for the separation of the radiative temperature population from the advective temperature population and examination of incidences of specific, advective cases in air temperature data. The LPD analysis reveals a predominance of a remarkably warmer, radiatively driven air temperature regime. In contrast, the significantly colder and geographically controlled advective temperature regime plays a counterbalancing role on the overall magnitude of the midlatitude air temperature signal. Our findings suggest that a substantial temperature increase in annual averages of advective minima amplifies the effect of a positively shifted radiative temperature range, intensifying the overall heating observed in the Canadian North and northwestern regions.

KEYWORDS
analysis, atmosphere, climate, geophysical sphere, geographic/climatic zone, mid-latitude, tools and methods, scale

1 | INTRODUCTION
Apart from inhomogeneities in climatological records, often caused by human errors and measurement inconsistencies, physical heterogeneities in high-frequency air temperature data deserve closer scrutiny. While the elimination of non-physical heterogeneities plays a central role in the preparation of reliable air
temperature time series, analysis of physical heterogeneities caused by the alteration of the diurnal heat exchange process has not yet received proper scientific attention. It is not uncommon to expect that the presence of a subpopulation in data, caused by a disparate physical process, manifests in a distortion of a pattern exhibited by a measured variable. In the case of the measured temperature, weather fronts-associated air temperature changes often deviate from the daily air temperature cycle, creating a subpopulation of days with a non-conforming diurnal temperature pattern. Therefore, the high-frequency air temperature time series can be regarded as continuous records of prevailing atmospheric conditions that control the diurnal air temperature distribution and reflect in characteristic diurnal air temperature patterns. In this work, we introduce the physical heterogeneity of the high-frequency air temperature sample and define it as a presence of more than one physically distinct air temperature population, each one characterized by a specific diurnal air temperature pattern.

Various non-climatic factors are known to affect the shape of air temperature records and the assessment of long-term climate trends. Biases introduced through air temperature observing practices and mean temperature calculation techniques are the most common causes of non-physical heterogeneities in air temperature records (Hartzell, 1919; Trewin, 2004; Vincent et al., 2009; Bonacci et al., 2013; Gough et al., 2020). Hence, meteorological records are routinely subjected to the homogenization process for the improvement of quality and homogeneity of the time series (Peterson et al., 1998; Vincent et al., 2002, 2009, 2012; Aguilar et al., 2003). Yet, despite considerable efforts toward the development of a large number of elaborate techniques for inhomogeneity identification and bias compensation, the quest for the homogeneity of daily air temperature series continues. The adverse effects of unaccounted inhomogeneity sources and adjustments for artificial variations in data are still impacting the long-term temperature observations in various ways (Vincent et al., 2018a; 2018b). The disadvantage of certain homogeneity tests is the impossibility to make a distinction between the inhomogeneity and a regional variation of weather and climate (Pandžič and Likso, 2010). Although typically aimed at rectifying biases caused by non-physical sources in the air temperature observation process, homogenization techniques can potentially indiscriminately treat the physical heterogeneities also.

Discrete search methods for the identification of daily extrema are a hidden, potential source of heterogeneities. Daily temperature observing windows are in general a means for the introduction of biases in measurements of daily extrema since an ideal discretization of time for diurnal temperature recording is difficult to define. Causes of incorrect characterization of air temperature minima related to the widespread cold bias in Canadian minima observations (Vincent et al., 2009) have been related to the systematic effects of the length and the starting point of the observation time frame (Zaknić-Čatović and Gough, 2018, 2019). Prior knowledge of true mathematical extrema has proven necessary for accurate reproduction of daily temperature variability patterns (Zaknić-Čatović et al., 2018). Consequently, correct identification of diurnal extrema is deemed crucial for the classification of diurnal temperature patterns due to the association of the shape of diurnal temperature patterns with physical causes of temperature variability.

A study that compared daily temperature averaging methods found that the daily temperature curve does not typically follow a normal distribution. The spatial, seasonal, and temporal differences in the skewness of the curve are indicated to carry implications for assessments of physical factors influencing the diurnal temperature curve and the magnitude of contemporary climate change (Bernhardt et al., 2018).

Although numerous works examine the mathematical representation of diurnal temperature variation (Parton and Logan, 1981; Floyd and Braddock, 1984; Wann et al., 1985; Reicosky et al., 1989; Linvill, 1990; Schaub, 1991; Bilbao et al., 2002, Chow and Levermore, 2007; Zanknic-Catovic et al., 2018), there has not been an attempt to correlate the diurnal temperature pattern with the atmospheric drivers of air temperature variation. However, an improved representation of daily temperature extrema is necessary for the identification of cases of advective temperature variation (Zaknić-Čatović and Gough, 2018, 2019, 2020).

In this study, we examine usual patterns of air temperature variability to reveal the atmospheric temperature drivers concealed in the spatial configuration of daily temperature extrema points. We further categorize daily temperature patterns as radiative, that is, compliant with the daily solar cycle or as advective, caused by the horizontal transport of cold or warm air.

The definition of the observational window is found to be fundamental to the accuracy of identification of daily temperature extrema points and consequently, a deciding factor for the correct classification of diurnal temperature patterns. Inattention to the heterogeneity of a diurnal sampling unit, consisting of unique daytime and nighttime intervals, is at odds with the fact that the majority of diurnal air temperature variation is predominantly radiatively driven (Figure 1, upper panel). However, diurnal air temperature variation, documented on an hourly or an even smaller time step, commonly displays departures from the assumed radiatively driven pattern (Figure 1 lower panel).
Common occurrences of prolonged, quasi-linear patterns in a predominantly periodic air temperature variation, point to the episodes of cold or warm advection of air, thermally capable of overriding the radiative diurnal air temperature wave. Such distortions of the daily temperature cycle represent indications of abrupt shifts in the atmospheric heat exchange mechanism that dominates the diurnal temperature variability.

The fact that homogenization methods do not routinely discriminate between physically and non-physically caused heterogeneities emphasizes the necessity for the inclusion of the pre-processing steps in the analysis of air temperature data, namely for the separation of air temperature time series into ‘homogeneous’ populations with a common physical denominator. Homogenization of temperature time series, which includes implicit observational biases and lack of information on the timing of diurnal extrema points, potentially leads to a significant loss of relevant climatological information.

If therefore, temperature variation is truly physically heterogeneous, the following questions arise: How reliable are diurnal extrema points, taking a central place in climate analysis, obtained either from diurnal air temperature measurements or derived by discrete search methods from high-frequency air temperature time series? How do diurnal temperature extrema, obtained with current practices, compare to the extrema of the individual and homogeneous air temperature populations? Does separation of air temperature time series provide a deeper insight into the backstage interplay of these contrasting populations, unintentionally obscured by unselective air temperature sampling and data processing?

2 | BACKGROUND

2.1 | Theoretical data pools

In an attempt to explore physically-caused heterogeneity features of Canadian midlatitude air temperature data and examine the partitioning of different air temperature populations within the samples of individual geographical locations, we utilize the Long-Term High-Frequency (LTHF) air temperature time series as theoretical data pools. We take advantage of resampling the LTHF temperature time series by applying two different observing windows to identify daily mathematical extrema from hourly data pools. By doing so we simulate air temperature sampling using different starting points and lengths of the search period.

2.2 | Climatological observing window

Climatological Observing Window (COW) is conceptualized as a time frame over which diurnal air temperature extrema are systematically identified either through min-max thermometers or through a min-max discrete extrema search (Žaknić-Ćatović and Gough, 2018). The COW definition also extends to continuous air temperature series.
temperature sampling. Climatological Observing Window 0–24 (COW_0–24), presently in use, applies to a discrete search of both daily extrema over a common period, extending between two consecutive midnights. Žaknić-Čatović and Gough (2018) examined the effects of the COW on the accuracy of daily extrema points and presented a method that considerably improves the identification of daily minima. Namely, the proposed Climatological Observing Window Night and Day (COWND) imposes a time discretization scale that assigns individual extrema over their corresponding night-and-day search periods.

2.3 | Diurnal temperature sample

The goal of the resampling process is the reduction of the high-frequency air temperature sample to a representative Diurnal Temperature Sample (DTS), conceptualized as a diurnal extrema pair, and defined by two, air temperature and time, coordinates. A DTS pair, intended as an authentic depiction of the diurnal air temperature distribution, captures the diurnal variability of the air temperature–time function based on extrema points obtained using a specific COW. Frequent misidentification of diurnal temperature minima, caused by the extent of the COW_0–24 time frame and the associated cold bias in the identification of the DTS_0–24 pairs, disqualifies, the COW_0–24 temperature–time series from the analysis of sample heterogeneity. Contrarily, a chronologically ordered DTS_{ND} sequence of theoretical COW_{ND} temperature time series provides a suitable platform for the successful reproduction of a continuous temperature–time function and a further separation of temperature time series into the Radiative Temperature Population (RTP), and the Advective Temperature Population (ATP).

2.4 | Diurnal temperature pattern

Diurnal temperature pattern (DTP) represents a visual outline of daily temperature variation, either interpolated between the high-frequency air temperature measurement points or, connected in diurnal extrema by means of a continuous analytical air temperature approximation. Based on the supposition that modification of a DTP indicates a shift in atmospheric heat exchange mechanism, we identify the change in DTP as a ground for the separation of air temperature time series into physically distinct temperature populations. Splitting of the air temperature sample takes place through a systematic examination of each DTP of a temperature extrema sequence by a temperature pattern discriminating algorithm. The development of an analytical tool for the separation of air temperature time series into physically homogeneous air temperature populations is described in Section 3.3.5.

3 | METHODOLOGY

3.1 | Research objective and scope

The primary objective of this study is the identification of physically homogeneous air temperature populations and the evaluation of their temperature trends and degrees of participation in the LTHF Canadian temperature time series. The methodology devised to perform this task requires the development and introduction of multiple research elements with a final goal of creating an analytical tool for an algorithmic splitting of air temperature time series into physically homogeneous populations. The RTP and ATP analyses include the examination of annual population counts, their trends, and the calculation of advective-radiative ratios (Table 2). Presentation of annual averages, trends, and temperature biases of total and radiative and advective samples aim to highlight the implications of COW selection on the accuracy of daily extrema and the outcome of analysis (Tables 2–5). Comparison of the total COW_{ND} sample with its radiative and advective parts reveals the contrasting nature of individual temperature populations and brings to attention a power struggle, evidenced in the resultant temperature regime.

3.2 | Data

High-frequency air temperature series of 25 Canadian climate stations, representing each province and territory, were obtained for the analysis from the Historical Data Archive of Environment and Climate Change Canada (Figure 2). The temperature time series, consisting of original hourly measurements, were recorded at Canadian international and local airports (Environment and Climate Change Canada, 2021). Such hourly temperature measurements were not subjected to homogenization testing or temperature adjustments (Climate Research Division of Environment and Climate Change Canada, personal communication January 5, 2021). In this study, daily minima and maxima were discretely identified from the LTHF data to avoid the use of the adjusted homogenized daily temperature extrema (Environment and Climate Change Canada, 2017) as well as the implications of the observing window on the accuracy of daily extrema points.

Data ranges of climate records are spanning over 65 years in length for all climate stations except for the 63-year long temperature record of Cold Lake in Alberta,
the 62-year long record of Baker Lake from Nunavut, and the 59-year long temperature record of St John’s from Newfoundland (Table 1).

3.3 | Elements of the main theoretical framework

Prior to the presentation of a tool for the separation of temperature time series, it is necessary to specify several research elements involved in LTHF temperature data preprocessing and to lay the theoretical basis for the application of the LPD algorithm. This section introduces the criterion for the separation of air temperature sample, lists the main features of two common diurnal temperature patterns, presents a simplistic description of linear pattern identification procedure, and outlines a process of air temperature resampling of the LTHF temperature time series.

3.3.1 | The criterion for the separation of air temperature sample

We argue that the DTP carries information on the dominant atmospheric heat exchange mechanism in the point of air temperature measurement and that typical midlatitude air temperature time series display physical heterogeneity through the presence of different diurnal temperature patterns. Accordingly, we postulate that occurrences of linear-like distortions of a quasi-sinusoidal DTP, regularly observed in the LTHF temperature time series, signify shifts from a radiatively driven to the advectively driven atmospheric heat-exchange mechanisms. In that context, we qualify a change in the DTP as the main criterion for the separation of air temperature series to its homogeneous populations, the RTP, and the ATP. Separation of the LTHF temperature time series involves an examination of the entire DTSND sequence for four different cases of linear DTP incidences. Each DTP can be identified and classified, based on the knowledge of temperature and time coordinates of diurnal extrema pairs obtained following the COWND extrema search procedure.

3.3.2 | Key features of diurnal air temperature patterns

The RTP population is characterized by radiative temperature changes that induce a sinusoidal diurnal air temperature pattern.
temperature pattern, with maximum air temperature typically occurring during the daytime and the minimum air temperature during the nighttime. In contrast, the ATP, caused by the advection of hot or cold air into the region, is characterized by a quasi-linear diurnal air temperature pattern extending between two consecutive extrema.

### 3.3.3 Linear pattern identification procedure

Simply put, the linear pattern identification procedure involves the following four steps:

1. Identification of diurnal air temperature extrema using the COWND extrema search method.
2. Generation of a chronologically ordered daily extrema sequence and association of each temperature extremum point with its time of occurrence.
3. Application of the LPD algorithm for the identification of four specific quasi-linear cases by testing the occurrence time of each consecutive extrema pair.
4. Confirmation of radiative days and separation of total temperature sample into its radiative and advective populations.

### 3.3.4 Generation of four theoretical air temperature samples

The main task of the theoretical resampling of daily extrema is the reduction of the size of the high-frequency sample to a representative DTS that carries a credible snapshot of the thermal regime of the examined geographical location. Starting from very dense high-frequency temperature data we impose two different observing windows to obtain two chronologically ordered temperature extrema sets. The theoretical expectation is

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**TABLE 1** List of Canadian locations of weather stations with geographic coordinates and data ranges of high-frequency air temperature records used in this study

| Canadian provinces and territories | Locations | Weather stations | Data range | Φ (° N) | λ (° W) |
|-----------------------------------|-----------|------------------|------------|--------|--------|
| Alberta (AB)                      | Calgary   | Calgary Int'l airport | 1953–2018 | 51.11  | 114.02 |
|                                   | Cold Lake | Cold Lake airport  | 1955–2018 | 54.42  | 110.28 |
|                                   | Ft McMurray | Fort McMurray airport | 1953–2018 | 56.65  | 11.22  |
| British Columbia (BC)             | Vancouver | Vancouver Int'l airport | 1953–2018 | 49.19  | 123.18 |
|                                   | Victoria  | Victoria Int'l airport | 1953–2018 | 48.65  | 123.43 |
| Manitoba (MB)                     | Churchill | Churchill airport  | 1953–2018 | 58.74  | 94.07  |
|                                   | Winnipeg  | Winnipeg Richardson Int'l airport | 1953–2018 | 49.92  | 97.23  |
| New Brunswick (NB)                | Fredericton | Fredericton airport | 1953–2018 | 45.88  | 66.53  |
|                                   | Moncton   | Moncton Int'l airport | 1953–2018 | 46.11  | 64.68  |
| Newfoundland and Labrador (NL)    | Goose     | Goose airport     | 1953–2018 | 53.71  | 57.03  |
|                                   | St. John's | St John's airport | 1959–2018 | 47.62  | 52.74  |
| Nova Scotia (NS)                  | Greenwood | Greenwood airport | 1953–2018 | 44.98  | 64.92  |
|                                   | Yarmouth  | Yarmouth airport  | 1953–2018 | 43.83  | 66.09  |
| Ontario (ON)                      | Ottawa    | Ottawa Int'l airport | 1953–2018 | 45.32  | 75.67  |
|                                   | Toronto   | Toronto Pearson Int'l airport | 1953–2018 | 43.68  | 79.63  |
|                                   | Trenton   | Trenton airport  | 1953–2018 | 44.12  | 77.53  |
| Prince Edward Island (PE)         | Charlottetown | Charlottetown airport | 1953–2018 | 46.17  | 63.07  |
| Quebec (QC)                       | Bagotville | Saguenay-Bagotville airport | 1953–2018 | 48.33  | 71.00  |
|                                   | Montreal  | Montreal Int'l airport | 1953–2018 | 45.28  | 73.44  |
| Saskatchewan (SK)                 | Estevan   | Estevan airport  | 1953–2018 | 49.22  | 102.97 |
|                                   | Regina    | Regina Int'l airport | 1953–2018 | 50.43  | 104.67 |
|                                   | Saskatoon | Saskatoon Diefenbaker Int'l airport | 1953–2018 | 52.17  | 106.72 |
| Northwest Territories (NT)        | Yellowknife | Yellowknife airport | 1953–2018 | 62.27  | 114.26 |
| Nunavut (NU)                      | Baker Lake | Baker Lake airport | 1956–2018 | 64.30  | 96.08  |
| Yukon Territory (YT)              | Whitehorse | Whitehorse airport | 1953–2018 | 60.71  | 135.07 |
that the location- and season-specific observing window will enable more accurate identification of true mathematical extrema points on the temperature-time curve. Daily extrema are expected to be the turning points on a quasi-sinusoidal temperature-time curve while discrete search methods can often identify points that do not comply with such expectations. The procedure of air temperature extrema resampling depicted in Figure 3 goes as follows. In the first step, the LTHF theoretical data pool of each weather station is individually subjected to the COW$_{0-24}$ and the COW$_{ND}$ discrete search methods for the identification of diurnal extrema points. Theoretical extrema resampling with COW$_{0-24}$ and COW$_{ND}$ discrete methods identifies extrema points with temperature and time coordinates (T, t). Application of the COW$_{0-24}$ extrema search method yields the daily highest and lowest temperature values obtained over a common 24-hr long search period extending from midnight to midnight (T$_{min}$, t$_{min}$ and T$_{max}$, t$_{max}$). Alternatively, the application of the COW$_{ND}$ discrete search method utilizes a variable staring time and length of the search period determined by the latitude and season of the geographical location. The COW$_{ND}$ method uses exclusive search periods to identify a nocturnal minimum over a sunset to a sunrise period (NT$_{min}$, Nt$_{min}$) and a daytime maximum over a sunrise to a sunset period (DT$_{max}$, Dt$_{max}$). Application of the COW$_{ND}$ correctly identifies the radiatively driven diurnal air temperature extrema. At the same time, the COW$_{ND}$ extrema search method represents a diagnostic tool for the identification of the advective temperature regime by identifying the non-compliant daily extrema pairs. The diagnostic reverse-order extrema pairs, consisting of a nighttime minimum and a daytime maximum, are generally misidentified by the COW$_{0-24}$ extrema search method (Žaknić-Čatović and Gough, 2018, 2019).

The set of all daily extrema points identified using the COW$_{0-24}$ discrete search method forms the total COW$_{0-24}$ temperature extrema sample. Likewise, all daily extrema identified using the COW$_{ND}$ method create the total COW$_{ND}$ temperature extrema sample.

**FIGURE 3** Schematic of the process followed in the generation of four theoretical temperature samples and the separation of the DTS$_{ND}$ to radiative and advective temperature populations. Application of a 0–24 Climatological Observing Window (COW$_{0-24}$) generates a sequence of COW$_{0-24}$ diurnal temperature extrema or a DTS$_{0-24}$ array. In contrast, application of a Night-Day Climatological Observing Window (COW$_{ND}$) generates a chronologically ordered sequence of COW$_{ND}$ nocturnal minima and daytime maxima or a DTS$_{ND}$ array used further in the separation of extrema temperature time series. The Linear Pattern Discrimination (LPD) algorithm implemented in R, splits the DTS$_{ND}$ array into ‘homogeneous’ temperature populations of analogous extrema based on similarity in Diurnal Temperature Pattern (DTP).
Chronologically ordered pairs of daily extrema points, designated as DTS pairs, are denoted in their subscript per the extent of the search method used in their identification (0–24 or ND). As a result, the array of DTS0-24 pairs represents the theoretical output of the COW0-24 search method consisting of daily extrema values obtained over a 0–24 hr range. Likewise, the DTSND array represents a chronologically ordered sequence of diurnal temperature extrema from the assemblage of nocturnal minima and daytime maxima records of the COWND discrete search method. The DTSND extrema array represents the initial extrema series from which the radiative and advective populations are further generated. The subsequent step of theoretical extrema resampling involves the application of the LPD algorithm for examining daily configurations of the DTSND array consisting of radiative and advective DTS pairs with analogous diurnal temperature patterns. The chronological order of radiatively driven extrema forms the Radiative Night-Day (RADND) array while the succession of advective nighttime minima and daytime maxima and, consisting of consecutive advective extrema, forms the Advective Night-Day (ADVND) array.

Temperature pairs of radiative nocturnal minima (RADTmin, RADtmin) and daytime maxima (RADTmax, RADtmax) form the RTP. Likewise, air temperature pairs of advective nocturnal minima (ADVTmin, ADVtmin) and daytime maxima (ADVTmax, ADVtmax) form the ATP.

### 3.3.5 LPD algorithm

Advective days are, as a rule, thermally characterized by the domination of warm and cold air, caused by the warm or cold air advection. The problem of the identification of such days in real air temperature data is practically solved by the application of a temperature pattern recognition algorithm. The LPD algorithm was conceptualized and implemented in the R-programming language as a tool for quasi-linear pattern recognition (R Core Team, 2014). The LPD algorithm is a method of solution, based on the COWND search method, designed for the identification of daily extrema pairs of linearly projected air temperature variability. The only data input required for the application of the LPD algorithm is the sequence of chronologically ordered DTSND pairs. In this process, the LPD algorithm parses through the DTSND extrema sequence and subjects each extrema pair to the criteria for identification of radiative days, as well as different advective quasi-linear cases, as simplified in Figure 4 schematic.

The LPD algorithm relies, in the first place, on the COWND extrema search method for the correct identification of the regularly spaced diurnal mathematical extrema. Such diurnal air temperature extrema, obtained in conformity with the radiative air temperature sequence, indicate a ‘radiative day’. A chronologically ordered succession of radiative days forms the Radiative Night-Day (RADND) array of extrema pairs with specified

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**Figure 4** Linear Pattern Discrimination (LPD) algorithm for identification of advective temperature population and the theoretical basis for identification of advective diurnal air temperature extrema used in the determination of four common cases of warm or cold advective temperature changes.
temperature-time coordinates. The LPD algorithm, further, utilizes an incidental feature of the COWND method, which, proved to be diagnostic and a result of nighttime-daytime period delineation, exposes the non-conforming end-point extrema pairs, and, facilitates the identification of advective DTP.

The LPD algorithm evaluates diurnal extrema pairs at every transition line between the consecutive daytime and nighttime periods using the differences in their timing as main criterion for the evaluation of DTP in sequential order. Once a quasi-linear DTP is positively determined, and a specific advective temperature case is identified, such day is identified as an ‘advective day’ and added in the Advective Night-Day (ADVND) array.

Evaluation of diurnal extrema implies, as first, the verification of the advective air temperature cases from two preliminary groups: the incidences of nearly equal or maximally distanced diurnal extrema starting with the daytime (Figure 4, left) and the incidences of maximally distanced or almost equal extrema occurrences, staring with the nighttime (Figure 4, right panel). The ADVND extrema array is composed of a set of four different cases: Case 11, Case 12, Case 21, and Case 22. The difference in the extrema timing criterion identifies the subsequent extrema with the advective DTP, found to be either close or equal in their occurrence times, or, maximally distanced, by an almost 24-hr period. The Day-Night Case 11, and the Night-Day Case 22, belong to the category of close or equal advective extrema incidences, while the Night-Day Case 12, and the Day-Night Case 21, represent occurrences of maximally distanced advective diurnal extrema pairs. Finally, the LPD algorithm differentiates between the advective extrema cases based on the direction of the diurnal temperature trend as, the ‘warm advective days’ (Case 11, and Case 12) with an upward linear trend, and the ‘cold advective days’ (Case 21, and Case 22) with a downward linear trend.

The base time unit for counting radiative and advective days is a 24-hr period, extending from sunrise to sunrise and consisting of two consecutive periods, a day and a night. The LPD algorithm examines each day-night and night-day configuration of temperature-time extrema
points. In case that the day-night configuration passes the advective criterion, two consecutive days are counted as advective. The 24-hr length of the base unit and extrema criteria for identification of radiative and advective temperature changes does not support the identification of a temperature regime on a shorter time step. Since the advective temperature change is detected on the boundary between two consecutive days and not on the transition between the two periods of 1 day, the tails surrounding the period of advective temperature variation within one base unit are also included. Therefore, the Day-Night Case 11 and Day-Night Case 21 comprise 1-day-long advective temperature transitions while the Night-Day Case 12 and Night-Day Case 22 involve 2 days-long advective temperature passages.

The algorithm in Figure 5 presents a basis for the automation of the recognition of advective cases in the LTHF temperature time series. The R-code, which implements the LPD algorithm, takes the chronologically ordered sequence of diurnal time-temperature pairs, previously obtained by the COW\textsubscript{ND} extrema identification method, as a single input. Upon setting the tolerance limit of the timing difference between two consecutive extrema points, a maximum of 4 hr, the algorithm automatically identifies whether the processed day classifies as one of the four advective extrema cases or instead as a radiative day. The outputs of the LPD algorithm are two chronologically ordered extrema sequences, a population representing all advective days and, the larger population of radiative days (Figure 6).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{map.png}
\caption{A map of Canadian climate regions showing Atlantic Canada, Great Lakes/St. Lawrence Lowlands, Northeastern Forest, Northwestern Forest, Prairies, South British Columbia Mountains, Pacific Coast, North British Columbia Mountains/Yukon, Mackenzie District, Arctic Tundra, and Arctic Mountains and Fiords. \textit{Source: Environment Canada, Atmospheric Environment Service, Climate Research Branch, 1998, Climate Trends and Variation Bulletin for Canada, Ottawa}}
\end{figure}
3.3.6 | COWND climatological day for LPD results reporting

The main cause of the imprecision within the LPD algorithm relates to the coarseness of the time step used in the recording of the frequency of the advective air temperature change. The problem of the association of the advective air temperature change with a 24-hr interval lies in the inconsistency between the duration of advective air temperature episodes and a fixed, 24-hr time frame for their reporting. The erratic nature of hot or cold advective air temperature changes introduces a difficulty in defining the time frame for their reporting and creates additional uncertainty in the quantification of such a population. The duration of radiative air temperature cycles, caused by the diurnal motion, implicitly determines the time standard for the reporting of the radiatively driven RTP. On the contrary, the variability in the time duration of air temperature advection occurrences presents a source of imprecision within the LPD algorithm and largely complicates the quantification of the ATP. Nevertheless, to maintain the RTP and ATP results reporting consistency, if the LPD conditions for advective day identifications are met, we associate the duration of the advective air temperature change with the length of a climatological day, initially selected for the reporting of radiatively driven days, as well as primarily applied for the identification of diurnal extrema using the COWND method.

3.3.7 | Unique advective-radiative ratio

The ratio of participation of the ATP to the RTP of the LTHF temperature time series, for a geographic location, can be expressed as a unique radiative to advective air temperature population ratio. The Adveative-Radiative (AR) ratio, denoted as ARrr, is simply the ratio of the advective to the radiative air temperature population, obtained using the COWND discrete search method for diurnal extrema identification and the LPD algorithm for the separation of LTHF air temperature populations, as explained in the previous section. The AR ratios are intended for the characterization of local air temperature samples and regional specifications of similar temperature time series sharing common climate drivers and resulting in the comparability of their long-term air temperature variation.

4 | RESULTS

This chapter presents the results of the assessment of radiative and advective counts in Section 4.1 followed by a general assessment of the main regional features of participating climatic regions (Figure 6) in Section 4.2. Lastly, Section 4.3 summarizes the radiative and advective temperature changes in COWND populations accrued over the range of the study.

The LPD algorithm for the identification of physical heterogeneities in the LTHF air temperature time series was successfully applied to determine radiative and advective participation counts in the total COWND sample (Table 2). The RTP and ATP counts discussed in Subsection 4.1.1 are presented in Figure 8. The rates of change in the RTP and ATP counts are discussed in Section 4.1.2, while Canadian AR ratios are briefly commented on in Subsection 4.1.3. The overall means of daily extrema are presented in Table 3 to offer a glimpse into the extrema ranges of different temperature samples examined across the Canadian wide latitudinal span. Air temperature biases between total COW0-24 and COWND samples presented in Table 4 point to the implication of COW on the accuracy of extrema identification. At the same time, temperature biases between the COWND, and its RADND, and ADVND populations highlight the temperature differences between the total sample and homogeneous populations. Visual comparisons of minima and maxima annual averages of all theoretical samples are presented in Figure 9. Centennial trends of annually-averaged extrema, from Table 5, provide insights into the magnitude of long-term temperature changes in total and individual, homogeneous air temperature populations. Following a general introduction of common temperature population features, Subsection 4.2.1 reviews only the unique aspects of individual climate regions. Annually averaged regional increases in diurnal extrema are commented in Subsection 4.2.2 and the observed temperature changes accrued over the length of the study range are reported in Table 6. Figures 10–12 illustrate the individual temperature changes in COWND, RADND, and ADVND, extrema populations while Section 4.3 provides a brief recapitulation of main observations.

4.1 | Assessment of Canadian radiative and advective counts

4.1.1 | Averages of RTP and ATP counts

The Pacific Coast locations, Vancouver and Victoria, stand out by the predominance of the RTP in their LTHF air temperature time series on the map of RTP and ATP participation (Figure 7). Other western Canadian locations, mostly from the Northeastern Forest and the Prairies, similarly exhibit high participation of the radiative population in temperature–time series (Table 2). In
TABLE 2  Participation of Radiative Temperature Population (RTP) and Advective Temperature Population (ATP) in Canadian individual and regional temperature samples, the RTP and ATP annual trends expressed as changes in count per century, and dimensionless Advective-Radiative (AR) ratios

| Canadian climate regions and station locations          | Radiative Temperature | Advective Temperature | Ratio |
|--------------------------------------------------------|------------------------|------------------------|-------|
|                                                        | Annual Count RTP (%)   | m #/c. DN              | Annual count ATP (%) | m #/c. DN | ARr DN |
| Atlantic Canada                                        | 81.6                   | −1 >.05                | 18.4                          | 1 >.05           | 0.23            |
| Charlottetown, PE                                      | 18,801                 | 78.0                   | 5,305                          | 22.0               | 0.28            |
| Fredericton, NB                                        | 21,201                 | 87.9                   | 2,905                          | 12.1               | 0.14            |
| Greenwood, NS                                          | 20,269                 | 84.1                   | 3,837                          | 15.9               | 0.19            |
| Moncton, NB                                            | 20,567                 | 85.3                   | 3,539                          | 14.7               | 0.17            |
| St. John’s, NL                                         | 16,436                 | 75.0                   | 5,479                          | 25.0               | 0.33            |
| Yarmouth, NS                                           | 19,158                 | 79.5                   | 4,947                          | 20.5               | 0.26            |
| Arctic Tundra                                          | 70.5                   |                        | 29.5                           |                   | 0.42            |
| Baker Lake, NU                                         | 16,990                 | 4 >.05                 | 7,116                          | −4 >.05           |                   |
| Great Lakes/St. Lawrence Lowlands                      | 85.2                   |                        | 14.8                           |                   | 0.17            |
| Montreal, QC                                           | 20,126                 | 83.5                   | 3,980                          | 16.5               | 0.20            |
| Ottawa, ON                                             | 20,725                 | 86.0                   | 3,381                          | 14.0               | 0.16            |
| Toronto, ON                                            | 20,644                 | 85.6                   | 3,462                          | 14.4               | 0.17            |
| Trenton, ON                                            | 20,656                 | 85.7                   | 3,450                          | 14.3               | 0.17            |
| Mackenzie District                                     | 76.9                   |                        | 23.1                           |                   | 0.30            |
| Yellowknife, NT                                        | 18,532                 | 17 <.05                | 5,574                          | −17 <.05          |                   |
| North British Columbia Mts/Yukon                       | 82.1                   |                        | 17.9                           |                   | 0.22            |
| Whitehorse, YT                                         | 19,792                 | 17 <.05                | 4,314                          | −17 <.05          |                   |
| Northeastern Forest                                    | 78.4                   |                        | 21.6                           |                   | 0.28            |
| Bagotville, QC                                         | 19,597                 | 81.3                   | 4,509                          | 18.7               | 0.23            |
| Churchill, MB                                          | 17,182                 | 71.3                   | 6,924                          | 28.7               | 0.40            |
| Goose Bay, NL                                          | 19,944                 | 82.7                   | 4,162                          | 17.3               | 0.21            |
| Northwestern Forest                                    | 88.3                   |                        | 11.7                           |                   | 0.13            |
| Cold Lake, AB                                          | 20,812                 | 89.0                   | 2,564                          | 11.0               | 0.12            |
| Fort McMurray, AB                                      | 21,119                 | 87.6                   | 2,987                          | 12.4               | 0.14            |
| Pacific Coast                                          | 90.1                   |                        | 9.9                            |                   | 0.11            |
| Vancouver, BC                                          | 21,635                 | 89.7                   | 2,471                          | 10.3               | 0.11            |
| Victoria, BC                                           | 21,808                 | 90.5                   | 2,298                          | 9.5                | 0.11            |
| Prairies                                                | 87.3                   |                        | 12.7                           |                   | 0.15            |
| Calgary, AB                                            | 21,563                 | 89.5                   | 2,543                          | 10.5               | 0.12            |
| Estevan, SK                                            | 21,161                 | 87.8                   | 2,945                          | 12.2               | 0.14            |
| Regina, SK                                             | 21,037                 | 87.3                   | 3,069                          | 12.7               | 0.15            |
| Saskatoon, SK                                          | 21,079                 | 87.4                   | 3,027                          | 12.6               | 0.14            |
| Winnipeg, MB                                           | 20,287                 | 84.2                   | 3,819                          | 15.8               | 0.19            |
| Canadian average                                        | 82.3                   | 11                     | 17.7                           | −11                | 0.22            |

Note: The ARr is a dimensionless (DN) and the characteristic ratio of the temperature sample. The range of the AR ratio extends between zero and one. The ARr of 0 signifies a fully radiative endmember, while ARr of 1 stands for equal participation of radiative and advective endmembers. Small ARr ratios signify low participation of the ATP in the LTHF temperature time series.
comparison to western locations, the eastern rim of the Prairies, the Northwestern Forest, and the Great Lakes with St. Lawrence Lowlands display a smaller range of the RTP. Higher participation of the ATP is common in LTHF samples of Atlantic Canada. Charlottetown, Prince Edward Island station, situated within the Gulf of St. Lawrence, as well as Greenwood, Nova Scotia station, on the Bay of Fundy, show higher participation of the RTP, rather typical of continental locations. The highest ATP participation between the studied LTHF air temperature time series is identified in Arctic Tundra at the northernmost Baker Lake location. Although regionally classified as a Northeastern Forest climate station, Churchill stands out by displaying a high ATP participation.

| Canadian climate regions and station locations | COW_{0-24} | COW_{N-D} | RAD_{N-D} | ADV_{N-D} |
|-----------------------------------------------|------------|-----------|-----------|-----------|
| Atlantic Canada                               |            |           |           |           |
| Charlottetown, PE                            | 1.9        | 9.6       | 2.7       | 9.1       |
| Fredericton, NB                               | 0.6        | 11.1      | 1.5       | 10.8      |
| Greenwood, NS                                 | 2.5        | 12.0      | 3.3       | 11.6      |
| Moncton, NB                                   | 0.7        | 10.3      | 1.6       | 9.9       |
| St. John’s, NL                                | 1.5        | 8.5       | 2.2       | 8.1       |
| Yarmouth, NS                                  | 3.7        | 10.7      | 4.3       | 10.2      |
| Charlottetown, PE                            | 1.9        | 9.6       | 2.7       | 9.1       |
| Fredericton, NB                               | 0.6        | 11.1      | 1.5       | 10.8      |
| Greenwood, NS                                 | 2.5        | 12.0      | 3.3       | 11.6      |
| Moncton, NB                                   | 0.7        | 10.3      | 1.6       | 9.9       |
| St. John’s, NL                                | 1.5        | 8.5       | 2.2       | 8.1       |
| Yarmouth, NS                                  | 3.7        | 10.7      | 4.3       | 10.2      |
| Arctic Tundra                                | −14.9      | −8.0      | −14.2     | −8.7      |
| Baker Lake, NU                                | −10.3      | −4.4      | −23.1     | −19.4     |
| Great Lakes/St. Lawrence Lowlands             | 0.4        | 9.2       | 1.1       | 8.7       |
| Montreal, QC                                  | 2.5        | 11.0      | 3.2       | 10.6      |
| Ottawa, ON                                    | 1.7        | 10.9      | 2.4       | 10.5      |
| Toronto, ON                                   | 3.5        | 12.4      | 4.3       | 12.1      |
| Trenton, ON                                   | 2.9        | 12.0      | 3.6       | 11.6      |
| Mackenzie District                            | −8.6       | −0.6      | −7.8      | −1.1      |
| Yellowknife, NT                               | −4.6       | 2.5       | −18.5     | −14.1     |
| North British Columbia Mts/Yukon              | −5.3       | 4.1       | −4.5      | 3.7       |
| Whitehorse, YT                                | −2.5       | 9.7       | −1.6      | 8.4       |
| Northeastern Forest                           | −5.5       | 3.2       | −4.7      | 2.6       |
| Bagotville, QC                                | −2.0       | 7.6       | −1.1      | 7.1       |
| Churchill, MB                                 | −10.4      | −2.8      | −9.5      | −3.5      |
| Goose Bay, NL                                 | −4.2       | 4.7       | −3.4      | 4.2       |
| Northern Forest                               | −4.2       | 6.5       | −3.4      | 6.2       |
| Cold Lake, AB                                 | −3.4       | 6.9       | −2.7      | 6.5       |
| Fort McMurray, AB                             | −5.0       | 6.2       | −4.2      | 5.9       |
| Pacific Coast                                 | 6.5        | 13.6      | 6.8       | 13.5      |
| Vancouver, BC                                 | 7.0        | 13.3      | 7.2       | 13.2      |
| Victoria, BC                                  | 6.0        | 13.8      | 6.4       | 13.7      |
| Prairies                                      | −2.5       | 8.7       | −1.6      | 8.4       |
| Calgary, AB                                   | −1.5       | 9.9       | −0.8      | 9.5       |
| Estevan, SK                                   | −2.1       | 9.5       | −1.2      | 9.1       |
| Regina, SK                                    | −3.1       | 8.6       | −2.1      | 8.2       |
| Saskatoon, SK                                 | −3.3       | 7.8       | −2.4      | 7.5       |
| Winnipeg, MB                                  | −2.5       | 8.0       | −1.5      | 7.5       |
| Canadian average                              | −1.3       | 7.9       | −0.5      | 7.5       |

TABLE 3 Air temperature population means of COW_{0-24}, COW_{N-D}, RAD_{N-D}, and ADV_{N-D} air temperature samples reported in °C.
### TABLE 4 Differences between annual means in daily minima, maxima, and the diurnal temperature range between the COW_{0.24} - COW_{ND}, RAD_{ND}, and ADV_{ND} temperature samples reported in °C

| Canadian climate regions and station locations | COW_{0.24} - COW_{ND} | RAD_{ND} - COW_{ND} | ADV_{ND} - COW_{ND} |
|-----------------------------------------------|------------------------|---------------------|---------------------|
|                                              | Δ1 \( mT_{min} \) (°C) | Δ2 \( mT_{max} \) (°C) | ΔΔDTR \( T_{max} - T_{min} \) (°C) |
| Atlantic Canada                              | 0.7                    | 0.4                 | 0.12                |
| Charlottetown, PE                            | 0.8                    | 0.5                 | 0.13                |
| Fredericton, NB                              | 0.8                    | 0.3                 | 0.11                |
| Greenwood, NS                                | 0.8                    | 0.4                 | 0.12                |
| Moncton, NB                                  | 0.8                    | 0.4                 | 0.12                |
| St. John’s, NL                               | 0.7                    | 0.5                 | 0.12                |
| Yarmouth, NS                                 | 0.6                    | 0.5                 | 0.11                |
| Arctic Tundra                                | 0.7                    | 0.7                 | 0.14                |
| Baker Lake, NU                               | 0.7                    | 0.4                 | 0.11                |
| Great Lakes/St. Lawrence Lowlands            | 0.7                    | 0.4                 | 0.11                |
| Montreal, QC                                 | 0.7                    | 0.4                 | 0.11                |
| Ottawa, ON                                   | 0.7                    | 0.4                 | 0.11                |
| Toronto, ON                                  | 0.8                    | 0.3                 | 0.11                |
| Trenton, ON                                  | 0.8                    | 0.4                 | 0.12                |
| Mackenzie District                           | 0.8                    | 0.6                 | 0.14                |
| Yellowknife, NT                              | 0.8                    | 0.6                 | 0.14                |
| North British Columbia Mts/ Yukon            | 0.8                    | 0.4                 | 0.12                |
| Whitehorse, YT                               | 0.8                    | 0.4                 | 0.12                |
| Northeastern Forest                          | 0.9                    | 0.6                 | 0.15                |
| Bagotville, QC                               | 1.0                    | 0.5                 | 0.15                |
| Churchill, MB                                | 0.9                    | 0.7                 | 0.16                |
| Goose Bay, NL                                | 0.8                    | 0.5                 | 0.13                |
| Northwestern Forest                          | 0.8                    | 0.3                 | 0.11                |
| Cold Lake, AB                                | 0.7                    | 0.3                 | 0.10                |
| Fort McMurray, AB                            | 0.9                    | 0.4                 | 0.12                |
| Pacific Coast                                | 0.3                    | 0.1                 | 0.04                |
| Vancouver, BC                                | 0.3                    | 0.1                 | 0.04                |
| Victoria, BC                                 | 0.4                    | 0.1                 | 0.05                |
| Prairies                                     | 0.9                    | 0.4                 | 0.13                |
| Calgary, AB                                  | 0.7                    | 0.4                 | 0.11                |
| Estevan, SK                                  | 0.9                    | 0.4                 | 0.13                |
| Regina, SK                                   | 1.0                    | 0.4                 | 0.14                |
| Saskatoon, SK                                | 0.9                    | 0.4                 | 0.13                |
| Winnipeg, MB                                 | 1.0                    | 0.4                 | 0.14                |
| Canadian average                             | 0.8                    | 0.4                 | 0.12                |

Note: Differences in annual minima and maxima temperatures between COW_{0.24} and COW_{ND} total samples (Δ1 and Δ2), the total COW_{ND} sample and the RAD_{ND} (Δ3 and Δ4), and the total COW_{ND} and the ADV_{ND} sample (Δ5 and Δ6).
Table 5: Slopes (m) of annually averaged minima ($T_{min}$) and maxima ($T_{max}$) temperature trends of different theoretical samples (COW_{0-24}, COWN-D, RADN-D, and ADVN-D) reported in degrees Celsius per century ($^\circ$/C/c.)

| Canadian climate regions and station locations | COW_{0-24} | COWN-D | RADN-D | ADVN-D |
|-----------------------------------------------|------------|--------|--------|--------|
| | $mT_{min}$ (°C/c.) | $mT_{max}$ (°C/c.) | $mT_{min}$ (°C/c.) | $mT_{max}$ (°C/c.) | $mT_{min}$ (°C/c.) | $mT_{max}$ (°C/c.) |
| Atlantic Canada | 1.6 | 1.8 | 1.7 | 1.8 | 1.6 | 1.7 | 1.4 | 1.8 |
| Charlottetown, PE | 1.4 | 2.0 | 1.5 | 1.8 | 1.4 | 1.9 | 1.9 | 2.2 |
| Fredericton, NB | 1.5 | 1.4 | 1.7 | 1.3 | 1.4 | 1.1 | 3.3 | 3.4 |
| Greenwood, NS | 2.1 | 1.8 | 2.1 | 1.7 | 2.0 | 1.4 | 0.6 | 1.1 |
| Moncton, NB | 1.7 | 1.7 | 1.7 | 1.7 | 1.4 | 1.3 | 1.5 | 2.2 |
| St. John’s, NL | 1.5 | 2.2 | 1.6 | 2.2 | 1.8 | 2.5 | 0.4 | 0.7 |
| Yarmouth, NS | 1.6 | 1.9 | 1.6 | 1.8 | 1.8 | 2.0 | 0.9 | 1.2 |
| Arctic Tundra | 3.8 | 4.8 | 3.7 | 4.8 | 3.2 | 4.7 | 4.1 | 4.3 |
| Baker Lake, NU | 2.7 | 1.8 | 2.6 | 1.8 | 2.5 | 1.6 | 2.5 | 2.6 |
| Great Lakes/St. Lawrence Lowlands | 2.8 | 1.9 | 2.7 | 1.9 | 2.8 | 1.9 | 1.8 | 1.6 |
| Montreal, QC | 1.8 | 1.9 | 1.8 | 2.0 | 1.5 | 1.6 | 1.8 | 2.0 |
| Ottawa, ON | 4.5 | 1.9 | 4.3 | 1.9 | 4.4 | 1.8 | 4.3 | 3.4 |
| Toronto, ON | 1.5 | 1.4 | 1.6 | 1.5 | 1.1 | 1.1 | 1.9 | 3.5 |
| Mackenzie District | 4.0 | 3.7 | 3.9 | 3.8 | 2.7 | 2.8 | 4.9 | 4.3 |
| Yellowknife, NT | 3.2 | 2.8 | 3.4 | 2.8 | 2.2 | 1.7 | 6.5 | 4.9 |
| Northwestern Forest | 3.5 | 3.0 | 3.5 | 3.1 | 2.8 | 2.3 | 3.7 | 2.8 |
| Cold Lake, AB | 3.2 | 2.6 | 3.1 | 2.7 | 2.4 | 1.9 | 4.5 | 3.2 |
| Fort McMurray, AB | 3.8 | 3.3 | 3.8 | 3.4 | 3.2 | 2.7 | 2.8 | 2.3 |
| Pacific Coast | 1.9 | 1.6 | 1.8 | 1.6 | 1.7 | 1.4 | 1.7 | 1.3 |
| Vancouver, BC | 2.2 | 1.4 | 2.1 | 1.4 | 2.0 | 1.2 | 1.9 | 1.2 |
| Victoria, BC | 1.5 | 1.8 | 1.5 | 1.8 | 1.4 | 1.6 | 1.4 | 1.3 |
| Prairies | 1.5 | 1.7 | 1.7 | 1.7 | 1.3 | 1.3 | 2.3 | 1.5 |
| Calgary, AB | 2.9 | 2.4 | 2.8 | 2.6 | 2.3 | 2.0 | 3.6 | 2.7 |
| Estevan, SK | −0.2 | 0.4 | −0.2 | 0.5 | −0.3 | 0.4 | −0.6 | −0.8 |
| Regina, SK | 1.7 | 1.6 | 2.2 | 1.4 | 1.7 | 0.8 | 2.9 | 1.8 |
| Saskatoon, SK | 1.4 | 2.1 | 1.9 | 2.1 | 1.2 | 1.4 | 4.0 | 2.9 |
| Winnipeg, MB | 1.7 | 2.0 | 1.7 | 2.1 | 1.4 | 1.8 | 1.4 | 0.8 |
| Canadian average | 2.2 | 2.1 | 2.3 | 2.1 | 1.9 | 1.8 | 2.4 | 2.2 |
4.1.2 Rate of change in annual RTP and ATP counts

The RTP and ATP annual trends (m), presented in Table 2, expressed as changes in the RTP and ATP counts per century (#/c.) have been tested for the statistical significance using the Mann Kendall Trend Test in R language (R Core Team, 2014). The increasing count of the RTP at the expense of the ATP (Figure 8) has been observed at all stations apart from two cases of decreasing counts recorded at Trenton (ON), and Charlottetown (PE), and one case of a neutral count at Toronto (ON).

| Canadian climate regions                     | COW0-24 |          |          |          | COWN-D |          |          |          | RADN-D |          |          | ADVN-D |
|----------------------------------------------|---------|----------|----------|----------|---------|----------|----------|----------|---------|----------|----------|--------|
|                                              | mTmin   | mTmax    | mTmin    | mTmax    | mTmin   | mTmax    | mTmin    | mTmax    | mTmin   | mTmax    | mTmin   | mTmax  |
| Atlantic Canada                              | 1.3     | 1.2      | 1.3      | 1.2      | 1.2     | 1.1      | 1.2      | 1.2      | 1.2     | 1.2      |          |        |
| Arctic Tundra                                | 2.5     | 3.2      | 2.4      | 3.2      | 2.1     | 3.1      | 2.7      | 2.8      |          |          |          |        |
| Great Lakes/St. Lawrence Lowlands            | 1.7     | 1.2      | 1.7      | 1.2      | 1.6     | 1.1      | 1.6      | 1.7      |          |          |          |        |
| Mackenzie District                           | 2.6     | 2.4      | 2.6      | 2.5      | 1.8     | 1.8      | 3.2      | 2.8      |          |          |          |        |
| North British Columbia Mts/Yukon             | 2.1     | 1.8      | 2.2      | 1.8      | 1.5     | 1.1      | 4.3      | 3.2      |          |          |          |        |
| Northeastern Forest                          | 1.3     | 1.4      | 1.3      | 1.4      | 1.1     | 1.2      | 0.7      | 1.0      |          |          |          |        |
| Northwestern Forest                          | 2.3     | 1.9      | 2.3      | 2.0      | 1.8     | 1.5      | 2.4      | 1.8      |          |          |          |        |
| Pacific Coast                                | 1.2     | 1.1      | 1.2      | 1.1      | 1.1     | 0.9      | 1.1      | 0.8      |          |          |          |        |
| Prairies                                     | 1.0     | 1.1      | 1.1      | 1.1      | 0.8     | 0.8      | 1.5      | 1.0      |          |          |          |        |
| Canadian average                             | 1.8     | 1.7      | 1.8      | 1.7      | 1.5     | 1.4      | 2.1      | 1.8      |          |          |          |        |

Figure 7 Participation of the ATP (magenta) to the RTP (turquoise) in Long-Term High-Frequency (LTHF) air temperature time series of studied Canadian locations.
Statistically significant positive rates of change in the RTP are consistently observed within northern Canadian climate regions, with the highest positive rate recorded at Churchill (MB). An interesting observation on the time evolution of the RTP and ATP counts is that the northernmost station Baker Lake (NU) has maintained stable populations without significant changes observed in annual counts. Western Canadian Pacific Coast stations and the westernmost Prairie location Calgary (AB) also exhibit statistically significant positive rates of change in the RTP. The rest of the Prairie, Atlantic, and Great Lakes/St. Lawrence Lowlands stations exhibit positive and statistically non-significant trends in their RTP counts.

4.1.3 Canadian advective-radiative ratios

The ratio of the participation of the ATP to the RTP of the LTHF temperature time series, for each geographic location, is expressed as a unique advective to the radiative air temperature population ratio (Table 2). The highest regional AR ratios are observed in the Arctic Tundra, Mackenzie District, and Hudson Bay area of the Northeastern Forest. St. John’s (NL) station displays the highest AR ratio in the Atlantic Coast followed by Charlottetown (PE) and Yarmouth (NS) stations. These high AR ratios are hypothesized to be related to seasonally strong diurnality in fog-prone areas (Gough and He, 2015). The lowest regional AR ratios are identified in the Pacific Coast and Northwestern Forest regions. The Prairies climate region is characterized with lower AR ratios apart from Winnipeg (MB) that exhibits AR values closer to the Great Lakes/St. Lawrence Lowlands region.

4.2 Regional characteristics of air temperature populations

Figure 9 presents the annually-averaged daily extrema of different air temperature populations. The common characteristics of total \( \text{COW}_{0-24} \) and \( \text{COW}_{\text{ND}} \) samples and
individual RADND and ADVND temperature populations in each Canadian climate region are as follows. Annual minima of the total COW0-24 sample (Figure 9, dark blue line) are systematically lower than the minima of COWND (green line) and RADND (turquoise line) populations. The significantly colder annual averages of
diurnal minima identified by the COW_{0-24} extrema search method are the result of a systematic cold bias introduced by the length and the starting point of the observing window. A closer agreement between the COWND and the RADND annual temperature minima is attributable to a high incidence of correctly identified diurnal temperature minima, achieved by the COWND extrema identification method. Temperature indices of the radiative population display the highest average in both minima (turquoise line) and maxima (orange line) and are noticeably warmer than indices of total COW_{0-24} and COW_{ND} samples. Advective temperature indices (ADV_{ND} minima – purple line and ADV_{ND} maxima – pink line) are, on the other hand, substantially colder than the corresponding indices of other temperature populations. Differences between the individual temperature samples within a climate region are the least noticeable on the west coast, where the participation of the ATP is the lowest across Canada. Canadian climate regions except for the South British Columbia Mountains, and the Arctic Mountains and Fiords, are characterized by one representative station, each associated with the eastern, central and western, or northern geographic division.

4.2.1 Analysis of counts and trends of air temperature populations

Atlantic Canada
The main characteristics of the Atlantic Canada climate region are the highest advective extrema means of both minima and maxima (Table 3, Figure 9). Additionally, distinctly small ADV_{ND} extrema trends, particularly pronounced in annual minima, are identified in St John’s (NL), Greenwood (NS), and Yarmouth (NS) temperature data (Table 5).

Great Lakes/St. Lawrence Lowlands
Despite the annual variability in the number of radiative and advective days, the resulting trends of radiative and advective counts of the Great Lakes/St. Lawrence Lowlands region display very small rates of the RTP counts (Figure 8) except for the Ottawa (ON) station (Table 2). Furthermore, Toronto populations of COW_{ND} and RAD_{ND} minima exhibit up to three times larger slope averages than Trenton temperature minima (Table 5).

Northeastern Forest
The analysed LTHF temperature time series within this vast climate region do not show many commonalities between the features of their temperature populations. Although Churchill (MB) station belongs to the Northeastern Forest according to the classification of Canadian Climate Regions presented in Figure 6, Churchill’s latitude (58.74 N) includes it in the northern Canadian region likewise. The most peculiar feature of the Churchill data set is the largest statistically significant increase in the RTP count observed across all Canadian data (+34/c). While Churchill (MB) and Bagotville (QC) temperature data show some similarity in their COW_{ND} and RAD_{ND} minima range, they greatly differ in their maxima range and the time evolution of the RTP counts (Table 2, Figure 8). The Goose Bay (NL) temperature data even more prominently stands out with very low COW_{ND}, RAD_{ND}, and ADV_{ND} temperature extrema slopes (Table 5).

Northwestern Forest
In addition to a large variability observed in their year-to-year temperature population counts, the Northwestern Forest data display large, statistically significant trends of increase in the RTP and a consequential decrease in the ATC counts (Table 2, Figure 8). The Northwestern Forest climate region is characterized by the largest differences between the annual means of COW_{ND} and the advective temperature maxima (Table 4). Other important characteristics of this climate region are large trends in the COW_{ND}, RAD_{ND}, and ADV_{ND} indices (Table 5).

Pacific Coast
The main feature of the Pacific Coast climate region is the high presence of radiatively driven days in the total COW_{ND} sample and the highest average indices of all temperature populations. Consequently, the Pacific Coast climate is also characterized by the lowest AR ratio and smallest temperature differences between the total sample and the individual temperature populations. The main feature of the Pacific Coast climate region is the high presence of radiatively driven days in the total COW_{ND} sample and consequently the lowest AR ratio (Table 2). The Pacific Coast climate is also characterized by the highest average indices of all temperature populations (Table 3) and the smallest temperature differences between the total sample and the individual temperature populations (Table 4).

Prairies
The smallest increase in the number of radiative days is observed at Estevan. All Prairie locations show positive slopes of annually-averaged temperature indices, except for the Estevan data set in which COW_{0-24}, COW_{ND}, RAD_{ND}, and ADV_{ND} minima populations display a small negative slope. Furthermore, the unusual occurrence of a declining trend in ADV_{ND} maxima has a counteracting
effect on the $\text{RAD}_{\text{ND}}$ temperature population, causing a cooling of the total $\text{COWND}_{\text{ND}}$ temperature sample.

**Climate regions of northern Canada**

Canadian climate regions covering most of the Canadian North include the following climate regions: North British Columbia Mountains with Yukon Territory, Mackenzie District, Arctic Tundra, and parts of the Northeastern Forest. Baker Lake (NU) temperature time series, representing the Arctic Tundra climate region, display the lowest Canadian RTP participation and the highest AR ratio due to a large number of advective days (7,116) identified over the length of the study period (Table 2). Unlike the other northern stations, the Baker Lake LTHF data have preserved stable radiative to advective count ratios through time. A small increase in the RTP count at this station stands out in comparison to other northern/northwestern Canadian locations that are characterized by large and statistically significant changes in RTP counts. All northern stations exhibit significant temperature increases in $\text{COWND}_{\text{ND}}$, $\text{RAD}_{\text{ND}}$, and $\text{ADV}_{\text{ND}}$ extrema populations (Table 5). The most significant increase in northern $\text{COWND}_{\text{ND}}$ maxima (4.8°C) is recorded at Baker Lake (NU) while the most significant temperature increase in $\text{COWND}_{\text{ND}}$ minima (3.9°C) is identified at Yellowknife (NT) in Mackenzie District. Baker Lake (NU) temperature data display the largest radiative temperature increase in radiative maxima (4.7°C) while Whitehorse (YU) representing the North British Columbia Mountains/Yukon climate region exhibits the largest observed temperature increase in advective maxima (6.5°C).

### 4.2.2 Regional averages of observed temperature changes

Regionally averaged temperature increases in means of diurnal minima and maxima of $\text{COW}_{0-24}$, $\text{COWND}_{\text{ND}}$, $\text{RAD}_{\text{ND}}$, and $\text{ADV}_{\text{ND}}$ samples presented in Table 6 are
estimated as temperature increments (°C) gained over the length of the study period (1953–2018). Canadian averages of the overall temperature growth do not differ between the COW_{0-24} and COW_{ND} estimates. Regional radiative temperature increases are smaller on average than the corresponding increments in the total COW_{ND} sample. Despite the significant variability between the advective temperature gains of the Canadian northwest and the rest of the climate regions, the average advective temperature change is still the largest among all populations.

### 4.3 Summary of results

Assessment of the RTP and ATP participation in LTHF Canadian temperature time series reveals the highest ATP participation in all northern, high latitudes. The temperature time series of the Pacific Coast and Prairies climate regions are, to the contrary, showing high participation of the RTP. Figures 10–12 illustrate individual temperature changes in COW_{ND}, RAD_{ND}, and ADV_{ND}, extrema populations gained over the study period from the year 1953 to 2018. Figure 10 shows a map of increases in COW_{ND} minimum and maximum daily temperatures accrued over the time range of the study. It can be observed that the highest temperature increase is associated with Canadian Northwest locations. Temperature increases are more prominent in COW_{ND} air temperature maxima than in the minima of the total COW_{ND} sample except for a few highly urbanized locations. Figure 11 shows a map of radiative minima and maxima temperature increases gained over the study time range. The highest temperature increase in the RAD_{ND} population is observable in minima and maxima of northern locations. A larger temperature increase in annual RAD_{ND} minima, when compared with the maxima, is most noticeable in highly urbanized areas. Large temperature increases in the ADV_{ND} population are identified in Canadian Territories and the Northwestern Forest region (Figure 12). Small-to-moderate temperature changes are identified in South Prairies, Atlantic Canada, and the Northeastern Forest climate region.

Even though the RAD_{ND} minima and maxima temperature increases are slightly smaller than the...
corresponding increases of the COWND total sample, it should be noted that the annual RADND extrema averages are, to begin with, systematically shifted toward the warmer temperatures. The combination of these two, RADND temperature augmenting conditions, added to substantial increases observed in the counteracting ADVND extrema averages set the scenes for an even faster future rate of temperature change anticipated in Canadian northern regions (Zhang et al., 2019).

5 | DISCUSSION

The presence of physical heterogeneities in temperature–time series, or the existence of air temperature populations with characteristic diurnal features, represents the evidence of common disturbances enforced upon the dominant, atmospheric heat exchange mechanism. Physical heterogeneity of long-term high-frequency air temperature time series manifests as a coexistence of physically distinct air temperature populations, present at the ratios visibly controlled by the geographical factors.

The study of physical heterogeneities in Canadian temperature records approached through the systematic discrimination of diurnal temperature patterns addresses several critical areas necessary for the understanding of diurnal temperature variability:

1. correct identification of true or mathematical diurnal extrema points,
2. identification of the timing of occurrence of diurnal extrema points,
3. conceptualization of a diurnal temperature sample,
4. assembling of a chronological sequence of diurnal extrema points,
5. connection of temperature approximating functions in consecutive extrema points,
6. identification of spatial configuration of diurnal extrema pairs for pattern recognition,
7. identification of specific advective case scenarios,
8. assessment of a degree of physical heterogeneity in a temperature sample,
9. assessment of systematic differences between temperature populations, and
10. analysis of homogeneous annually-averaged air temperature populations.

Based on the list of critical areas, it is evident that the most important element for the assessment of physical heterogeneity is knowledge of the temporal distribution of daily extrema pairs. The success of this assessment lies entirely in the domain of the accuracy of diurnal extrema points and therefore requires information on their exact position in the temperature-time space. The initial selection of a time frame for identification of temperature extrema exerts the largest influence on the accuracy of diurnal extrema timing and consequently on the analysis of radiative and advective days, the examination of the time evolution of population counts and air temperature trends associated with these populations.

Characteristics of the radiative temperature population, and its positively shifted temperature extrema range, sheds light on the magnitude of this principal air temperature regime, exposed here without the counteracting effect of the advective temperature regime. The annual averages of the RADND extrema rank the highest among all temperature populations and display a non-uniform heating pattern throughout Canadian midlatitudes. The largest radiative temperature changes are seen in extrema averages of Arctic Tundra, Hudson Bay area, and Northwestern Forest regions, while the opposite is observed in the eastern Prairies and northern Atlantic Canada regions.

The degree of advective regime participation, the ADVND temperature range, and the rate of temperature change appears to keep in balance the magnitude of the radiative temperature regime and, in that way, control the resultant temperature of the total COWND sample. However, the effectiveness of this counteracting effect is, to a degree, compromised in Canadian north and northwestern regions. The largest ADVND temperature change is observed in the annual minima of the North British Columbia Mountains/Yukon climate region and the Canadian Territories in general. The importance of this finding is in the offered explanation for the intensified heating rate observed in the Canadian North that appears to be related to the time evolution of advective temperature changes. Warming of ADVND temperature minima in north and northwest regions affects the total COWND sample averages in several ways. Although the annual counts of the radiative population generally increase at the expense of the advective days, the participation of the advective temperature population in high-latitude temperature samples is considerable. Larger participation of the ADVND temperature population in Canadian north and northwest regions gives weight to the effect of the advective regime on the overall temperature of the sample. The typically cooling effect of the advective temperature regime is rapidly weakening over the study range. This phenomenon, in addition to not providing a strong temperature counterweight to the warmer radiative regime, rather increases the temperature of the total COWND temperature sample. The weakening of the advective cooling effect on the total air temperature sample appears to be related to the changes in populations of air masses type typically dominating the region (Leung and Gough, 2016). The resulting rates of change in advective air temperature minima are theorized to accelerate the observed process of permafrost thawing and ice melting rates in the Canadian North.

6 | CONCLUSION

We examine multiple Canadian temperature records for the presence of climatic heterogeneities and propose a method for an algorithmic separation of temperature–time series into physically distinct homogeneous air temperature populations. This work highlights an obscured research area in the field of air temperature variability and points to the direction of the knowledge gap in diurnal air temperature extrema identification as the main obstacle to the detection of physical heterogeneities in temperature time series. Our findings suggest that inattention to the physical make-up of the temperature sample leads to an overall loss of identity of homogeneous temperature signals. Research results, reported in this article, caution against the indiscriminate use of diurnal temperature extrema without the consideration of their heterogeneous nature and previous attention to the frequent mischaracterization of diurnal minima caused by the present observing window. Thus, the physically heterogeneous nature of the total temperature sample requires attention in the early stages of data processing and ideally, prior to the application of homogenization techniques.

Finally, the annual analysis of radiative and advective air temperature population averages only superficially addresses the problem of physical heterogeneity in long-term high-frequency air temperature samples of northern Canadian midlatitudes. In-depth seasonal analysis of all air temperature population averages, and the extension of the LPD algorithm to improve the representation of the duration of advective episodes, is advised.
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