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Comparisons of fire weather indices using Canadian raw and homogenized weather data

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ABSTRACT

Modifications to the environment around a weather station or changes in instrument result in discontinuities or shift in weather data. This paper asks the often ignored questions such as, “what are the impacts of inhomogenized data?” and “does using homogenized weather data affect the conclusions of environmental research?” To answer these questions, we used the Canadian Forest Fire Weather Index (CFFWI) System for our studies. Weather station data are used to calculate wildfire danger indices. The homogenized data and raw (inhomogenized) observations for sixteen weather stations spread across Canada were used to calculate the CFFWI indices. The sixteen weather stations were further divided into three subset of stations based on the length of the accessible data during the fire season (April to end of September). The first set included stations that covered just 27 years of data and the second data sets had 49 years of data, while the third set included only five stations with the longest time period of 66 years. The majority of the stations, as measured by the Wilcoxon signed-rank test, rejected the null hypothesis (difference between the pairs follows a symmetric distribution around zero). The rejection rate increases to 100% as the length of data record increases from 27 to 66 years. Homogenization of 66 years data reduced the indices values approximately 0.7–8.4% and also reversed the long-term trend in some stations such as Kapuskasing.

1. Introduction

Historical (climate) surface weather data have several shortcomings that affect the quality of studies using such data. The two most well-known problems are missing data and data inhomogeneity. The first problem is usually looked after by estimating missing data points from nearby stations (Hasanpour Kashani and Dinpashoh, 2012; Kornelsen and Coulibaly, 2014), eliminating missing observations (eliminating periods with missing data), or a combination of the two approaches. The second problem of data inhomogeneity is often overlooked (Tsinko, 2016); it includes any rearrangement to the weather station site such as landscape modification, urbanization, irrigation, change in instrumentation, observation procedure, and station relocations as well as alterations of the environment (Aguilar et al., 2003; Trewin, 2010) around a weather station. While some changes only affect one station and may be averaged out by spatial interpolation or at least identified in comparison with other stations, others have a nationwide effect. Some examples of nationwide changes in Canada include the relocation of weather stations to airports in the 1940s (Vincent et al., 2012), new definition of a climatological day in 1961 (Hopkinson et al., 2011), a switch from imperial to metric units in 1977–1978 (Mekis and Vincent, 2011), as well as nation-wide phase-ins of new measuring instruments (van Wijngaarden and Vincent, 2005; Devine and Mekis, 2008; Wan et al., 2010).

Overall, station relocations are the most disruptive type of change (Peterson, 2006; Trewin, 2010) and can cause variation in temperature of 2 °C on average or up to 10 °C if a sharp gradient of temperature is involved, differences of 7 km/h in wind speed (Wan et al., 2010) and 40% for seasonal precipitation (Heino, 1999). Even though station relocations in Canada are supposed to be accompanied with an assignment of a new station number, smaller movements, displacement of 1.5 km, can remain undocumented (Whitfield, 2014).

It is important to recognize the extensive non-climate signals in long-term weather time series and their feedbacks to weather variables. Vincent et al. (2012) found that a third of the 338 Canadian station temperature time series had non-climatic shifts for the 1950-2010 time period. Mekis and Vincent (2011) found that all 464 Canadian second generation stations’ rainfall and snowfall amounts need to be adjusted

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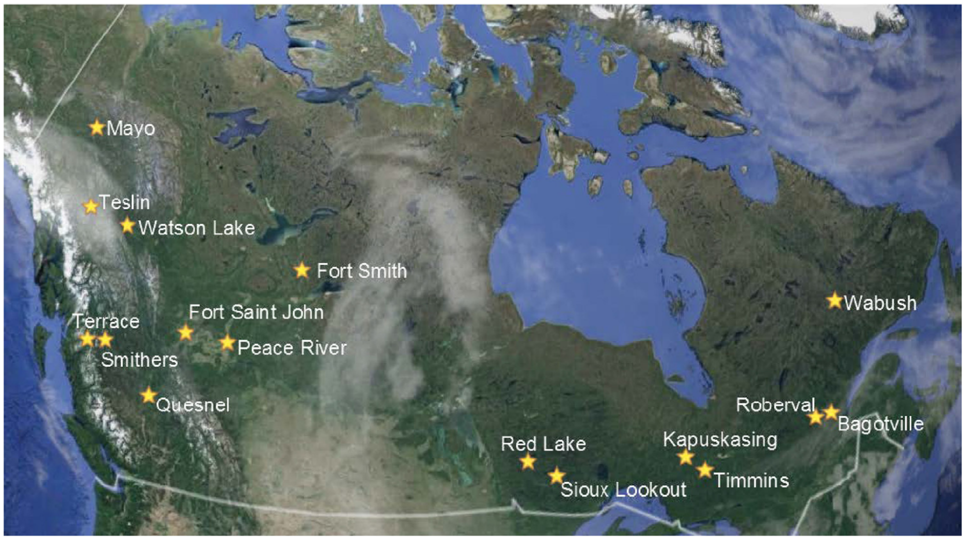

Fig. 1. Locations of the 16 meteorological stations in Table 1.

for trend analysis. 97% of stations analyzed by Wan et al. (2010) experienced at least one type of discontinuity in wind speed records during 1953 – 2006 and 96% of 75 stations changed their instrumentation for measuring relative humidity during 1953 – 2003 (van Wijngaarden and Vincent, 2005). We focused on Canadian stations as our domain of study, but the problem is global, e.g. in USA (Arguez et al., 2012) and Europe (Venema et al., 2012).

The data inhomogeneity and data limitation in general, lead to bias in climate frequencies and ecological disturbances (Bakhshaii and Johnson, 2017). The main question is how a study will be affected by such inconsistency in the data? The objective herein is to determine the effect of homogenization on inhomogenized data and the Canadian Forest Fire Weather Index (CFFWI) System. The paper compares the CFFWI system codes with two different data sets, raw observation (inhomogenized) and homogenized data, to investigate the impact of data inhomogeneity on the CFFWI system.

World Meteorological Organization (WMO) homogenization guidelines do not provide a recommendations of a specific homogenization procedures but present a variety of methods that may be suitable in different situations (Aguilar et al., 2003). Performance of various homogenization approaches varies widely, especially in non-gaussian variables such as precipitation data (Ducré-Robitaille et al., 2003; Venema et al., 2012). As a result, disclosure of the method is crucial for reproducibility of the research.

There are two types of weather data homogenization: relative and absolute. The absolute method applies statistical tests to the station data itself, while the most popular relative homogenization procedure compares data series under consideration to a reference data series, i.e. another station, in order to reveal any breaks or trends in correlation between the two stations (Costa and Soares, 2009; Venema et al., 2012). Both methods include break point identification and data adjustment, but the relative method involves an additional step of creating a reference series.

The most common approach to create a reference time series is either to use a nearby homogeneous station that is highly correlated to the station of interest or, if such station is not available, to create a complex reference series. To create such a reference series, a simple averaging of the neighboring stations or extracting principal components from the whole network (Aguilar et al., 2003) have been used. However, it is important to keep in mind that nearby stations are not always the best choice for a reference series for all weather variables.

Although temperature data show a high degree of correlation between records from nearby stations, other highly localized variables such as precipitation and wind speed do not show such correlations (Wang et al., 2010). In this case, other alternatives may provide a reference series, such as a geostrophic wind time series (Wang, 2008).

Moreover, homogenization of these variables is further complicated by non-gaussian distributions of these variables. While algorithms dealing with monthly and annual data can circumvent this problem due to increasing convergence to a normal distribution with an increase of samples that follows a decrease in resolution (Wilks, 2011), such a solution is not possible for data with daily resolution.

Metadata are essential in breakpoint identification for both relative and absolute approaches. However, such data are often incomplete or missing, especially for the earlier records, and thus statistical tests are an unavoidable step (Peterson et al., 1998; Trewin, 2010; Wan et al., 2010; Vincent et al., 2012). There is a variety of statistical tests available including the Standard Normal Homogeneity Test (Alexandersson, 1986), Two-Phase regression (Easterling and Peterson, 1995), Wilcoxon's non parametric test, a percentiles approach (Štěpánek et al., 2009), genetic algorithm and hidden Markov models (Toreti et al., 2012) and a wavelet-based method (Li et al., 2014). Reeves et al. (2007) and Costa and Soares (2009) provide reviews of current breakpoint identification techniques. Data adjustment methods range from uniform annual adjustment (Torok and Nicholls, 1996) to quantile matching (Wang et al., 2010). Several automated homogenization algorithms, such as MASH (Szentimrey, 1998), RHTest (Wang, 2008; Wang et al., 2010) and AnClim (Štěpánek et al., 2009), combine breakpoint identification and data adjustment.

The COST (European Cooperation in Science and Technology) Action ES0601 implemented a comparison of monthly, yearly and decadal homogenization algorithms using realistic surrogate benchmark data in a blind test and found that manual algorithms did not show any superior performance over automated ones (Venema et al., 2012). Most of these algorithms cannot handle data with daily resolution and require a presence of a reliable reference series or at least a number of highly correlated time series from nearby stations (Venema et al., 2012).

We compared homogenized data set against raw weather data, and then we used both data sets as input to Canadian Forest Fire Weather Index System. We demonstrated that the homogenization produces discrepancies in Fire Weather Indices. The differences is large enough to be considered important.

2. Methods

We selected sixteen weather stations across Canada for this study (Fig. 1, Table 1). The selection criteria for weather stations were as

Table 1
Description of the sixteen Canadian weather stations used in the study. T&P Start denotes the beginning of temperature and precipitation records which were used for a separate long DC dataset.

Station	Climate ID	Short name	Latitude (degrees)	Longitude (degrees)	Elevation (m)	Population[a]	Start-end	T&P Start
Kapuskasing	6073960, 6073975[b]	Kap	49.414	−82.468	227	8196	1953–2012	1919
Roberval	7066685	Rob	48.517	−72.267	179	8440	1958–2005	–
Wabush	8504175	Wab	52.927	−66.874	551	1861	1961–2007	–
Bagotville	7060400	Bag	48.333	−71.000	159	N/A[c]	1953–2012	–
Timmins	6078285	Tim	48.570	−81.377	295	30,614	1955–2009	–
Sioux Lookout	6037775	SLo	50.117	−91.900	383	3047	1953–2011	–
Red Lake	6016975	RLa	51.067	−93.793	386	1274	1965–2011	–
Fort Smith	2202196, 202198, 2202200[b]	FSm	60.020	−111.962	205	2093	1915–2012	1915
Peace River	3075040	PRi	56.227	−117.447	571	4252	1959–2007	–
Teslin	6078285	Tes	60.174	−132.736	705	122	1953–2005	–
Watson Lake	2101200	WaL	60.117	−128.822	687	802	1953–2011	–
Mayo	2100700	May	63.617	−135.867	504	226	1953–2011	1926
Quesnel	1096600, 1096630[b]	Que	53.026	−122.510	545	13,566	1953–2005	1907
Smithers	1077500	Smi	54.825	−127.183	522	5473	1953–2009	–
Terrace	1068100, 1068130[b]	Ter	54.466	−128.577	217	15,569	1956–2011	1913
Fort Saint John	1183000	FSJ	56.238	−120.740	695	18,699	1953-2012	–

[a] Population numbers are provided from census 2011 (Statistics Canada, 2012).
[b] Terrace stations were combined on April 1st, 1953. For Fort Smith, the transition between 2202196 and 202198 occurs on Dec 31, 1928 and the transition from 202198 to 2202200 occurs on Dec 31, 1944. Quesnel stations were joined on March 1, 1946. For Kapuskasing, 6073975 is used for short Datasets 1 and 2 and 6073960 is used for the long Dataset 3.
[c] Canadian Forces Base Airport.

follows. The first criterion was a long record of hourly data and homogenized daily (at least 50 years), including temperature, precipitation, wind and relative humidity that are the minimum requirement for CFFWI system code calculation. The second criterion was minimization of the urbanization (Balchin and Pye, 1947) heat island effect by choosing small towns with < 30,000 population. The paved surfaces and buildings in cities absorb more incoming shortwave radiation than the ground does. The released long wave radiation is trapped by the surrounding high rise buildings, further raising the temperature. Other sources of urban heat include a change in albedo and an anthropogenic heat flux, such as heat coming from building heating/cooling, transportation, industrial production and similar (Atkinson, 2003; Shahmohamadi et al., 2011). The urban heat island influence is even more noticeable at night, in the cloudless calm conditions, while overcast windy days may not be noticeably affected (Ackerman, 1985; Parker, 2010). The third criterion was the availability of homogenized records for precipitation (*P*), temperature (*T*) and wind speed (*W*). While some concurrent temperature and precipitation records extended back to the beginning of the 20th century, there were no wind and relative humidity data before the 1950s in the Environment and Climate Change Canada data archive.

The sixteen weather stations were further divided into three sub sets of stations (Table 2) based on the length of the accessible data during the fire season (April to end of September). The first set included stations that covered just 27 years of data and the second data sets had 49 years of data, while the third included only five stations with the longest time period of 66 years.

The inhomogenized raw observation data set provided by Environment and Climate Change Canada (EC) included daily accumulated precipitation, daily temperature statistics, hourly wind speed and relative humidity. The daily homogenized temperature and precipitation data set were also provided by EC. However, since they did not have daily homogenized relative humidity and wind data, we homogenized the raw data for those two variables using the same homogenization approach that has been employed by EC, which is the RHTest (Wang, 2008; Wang et al., 2010). RHTest V4 (Wang and Feng, 2013), was used for daily homogenization of wind and relative humidity. RHTest uses regression based break point detection and quantile matching for data adjustment on both monthly and daily time scales. Its breakpoint detection algorithms are based on a penalized maximum T test, which relies on a reference time series, and a penalized maximal *F* test, which applies Box-Cox transformation to non-Gaussian time series and only incorporates the series itself and is modified to account for autocorrelation (Wang et al., 2010; Vincent et al., 2012). Although hourly raw data were available from EC, we used the daily values from inhomogenized raw observation as well, simply because the homogenized data were only available via EC in daily values.

2.1. Missing values estimation

The relative number of missing events was a small percentage of the

Table 2
Description of the three data sub-sets used in the analysis including number of stations, the stations include in each subset, the number of years of data available for each subset, and the years available. The time period for each dataset is not continuous due to availability.

	Dataset 1	Dataset 2	Dataset 3
Number of stations	16	10	5
Stations	Wab, Bag, Rob, Kap, Tim, SLo, RLa, FSm, PRi, FSJ, May, Tes, WaL, Ter, Smi, Que	Bag, Kap, Tim, SLo, FSm, FSJ, May, WaL, Ter, Smi	Kap, FSm, May, Ter, Que
Number of years	27	49	66
Years	1965–1969, 1971, 1973–1978, 1985–1988, 1990–1993, 1996–2001, 2005	1956–1971, 1973–1988, 1990–1993, 1996–2008	1926–1928, 1930, 1932–1935, 1938–1941, 1943–1952, 1956–1988, 1990–1994, 1996–2001

Table 3
Pearson correlation coefficients between the paired stations' corresponding daily weather records. The stations were paired by proximity. All available years were used to calculate the correlation coefficients.

Station pairs	Distance (km)	Correlation coefficients			
		T_{mean}	P	RH	W
Bag/Rob	95	0.99	0.67	0.69	0.44
Kap/Tim	125	0.99	0.62	0.82	0.63
SLo/RLa	170	0.99	0.52	0.80	0.55
PRi/FSJ	205	0.98	0.51	0.70	0.51
Tes/WaL	215	0.97	0.43	0.69	0.40
Ter/Smi	99	0.97	0.50	0.70	0.16

entire database. A multilinear regression approach was chosen to recover the missing values (Hasanpour Kashani and Dinpashoh, 2012; Kornelsen and Coulibaly, 2014). For a given station, regressions were carried out on all the available variables and the missing variable from the nearby paired station. Whenever the nearby station records, which assume that nearby stations are exposed to almost the same climate signal, were not available and the amount of missing precipitation data exceeded two days in any month of fire season, the entire year was removed from analysis. The nearby stations are located more than 90 km apart. Table 3 is summarized the paired-stations. Similarly, if any other variable was missing more than 5 days with no reference records in any month of the fire season, the given year was omitted from the analysis. And finally, if more than 60 days of a variable in a fire season were missing, the full year was removed, regardless of the presence of a reference station's records. Relative humidity was converted to dew point temperature (Lawrence, 2005) and after estimating missing values, it was converted back to relative humidity.

2.2. Homogenization

The inhomogenized and homogenized weather records from Environment and Climate Change Canada were used for this study. Precipitation (Mekis and Vincent, 2011) and temperature (Vincent et al., 2012) records were homogenized on a daily scale and wind records were homogenized by EC on a monthly scale (Wan et al., 2010). As indicated previously, the station choice was bound by the availability of homogenized records for precipitation (*P*), temperature (*T*) and wind speed (*W*). The daily precipitation and temperature and monthly wind datasets were homogenized by EC with the RHTest software; for continuity the same software, RHTest V4 (Wang and Feng, 2013), was used for daily homogenization of W and RH data. RHTest uses regression based break point detection and quantile matching for data adjustment on both monthly and daily time scales. Its breakpoint detection algorithms are based on a penalized maximal *t* test (PMTred), which relies on a reference time series, and a penalized maximal *F* test (PMFred), which applies Box-Cox transformation to non-Gaussian time series and only incorporates the series itself and is modified to account for autocorrelation (Wang et al., 2010; Vincent et al., 2012).

Since correlation coefficients between nearby stations for W are poor (Table 3), approximate breakpoint dates were first roughly identified by using PMTred with the monthly homogenized wind dataset (Wan et al., 2010) as a reference and then compared with the station metadata from the homogenized dataset description (Wan et al., 2010). This is partly due to large distance between paired stations. Afterwards, the analysis was re-run on a daily scale using PMFred with no reference, and the dates closest to the ones identified in the first run were picked and used for final homogenization. As a quality control, the monthly averages of the resultant EC homogenized series were compared to the homogenized monthly wind dataset.

As opposed to other time series, most relative humidity records did not have more than one break point. The RH breakpoints mostly occurred in 1970–1990s and corresponded to the years of instrumentation switch to dewcel for stations with available metadata (van Wijngaarden and Vincent, 2005). PMFred was used for breakpoint identification.

2.3. Canadian Forest Fire Weather Index System

The Canadian Forest Fire Weather Index (CFFWI) System has been used to measure long term fire weather trends, climate variability and possible future fire behavior under climate change (Girardin and Wotton, 2009; Wallenius et al., 2011; Shabbar et al., 2011; Johnson et al., 2013; Mori and Johnson, 2013; de Groot et al., 2013; Whitman et al., 2015). The wide usage and its dependency to weather stations data made the CFFWI system a good example to see the effects of inhomogenized versus homogenized data.

Weather inputs to CFFWI system consist of four basic surface weather station observation variables: temperature (*T* in °C, screen-level air temperature), precipitation (*P* in mm, 24-h accumulated precipitation), relative humidity (RH, the ratio of the partial pressure of water vapor in ambient air) and wind speed (*W* in m/s, wind speed at 10 m above ground level) (Van Wagner, 1987). The four weather measurements are generally taken daily at noon local standard time (LST) or 1300 local daylight time (LDT). The CFFWI components are numerical indices of fire-weather potential that have been used by Canadian fire management agencies for more than forty years (Girardin and Wotton, 2009), as well as in other countries, such as southern European countries (Bedia et al., 2015; Viegas et al., 1999; Good et al., 2008), South Africa (Kraaij et al., 2013), Australia (Dowdy et al., 2010) and China (Tian et al., 2011).

Calculation of CFFWI is divided into two sections. The first three components are called fuel moisture codes and consist of Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC) and Drought Code (DC). The second three components are relative fire behavior indices representing the rate of fire spread, Initial Spread Index (ISI), available fuel, Buildup Index (BUI), and finally, frontal fire intensity, Fire Weather Index (FWI) and daily severity rating (DSR). Except for FFMC that varies between 0 and 101, the other CFFWI components have a bottom level of zero with an unlimited top. FFMC indicates the moisture content of the smallest forest fuels (surface litter, leaves, needles and small twigs). It is estimated from the previous day's FFMC, local noon temperature, relative humidity, wind speed, and 24-h precipitation. It also takes about 2–3 days to equilibrate under constant conditions. DMC represents the moisture content of the medium-sized surface fuels and represents duff layers (approximately 2–10 cm beneath the surface). The DMC code's variables are the previous day's DMC, local noon temperature, relative humidity and 24-h precipitation; it requires about 12 days to equilibrate. DC indicates the moisture content of the largest surface fuels and deep duff layers (deeper than approximately 10 cm). It is also estimated from the previous day's DC, local noon temperature and 24-h precipitation with a longer period to lose its moisture, about 52 days (Van Wagner, 1987).

At the second level of CFFWI components, the fuel moisture codes are further combined with wind speed values to calculate the Initial Spread Index (ISI) and the Buildup Index (BUI) that represent relative fire growth behavior (Van Wagner, 1987). Although Van Wagner explained that FWI should represent 'intensity of the spreading fire' (Van Wagner, 1987), it is now understood (Wotton, 2009) that weather indices cannot accurately represent fire intensity alone without considering fuel structure and loading. A more modern interpretation is what Wotton (2009) wrote: "The FWI provides a general summary of fire weather and fuel moisture in a region". The third and final level components are the Fire Weather Index (FWI) is 'is an index of overall fire weather, correlated with fire intensity and calculated using the ISI and BUI (Van Wagner, 1987), and the Daily Severity Rating (DSR) which is a power transformation of FWI that emphasizes higher FWI values (Shabbar et al., 2011).

In addition to the final FWI and DSR codes that are commonly used for assessing fire weather behavior trends (Stocks et al., 1998; Flannigan et al., 2001; Shabbar et al., 2011; Krawchuk et al., 2009; de Groot et al., 2013; Bedia et al., 2015; Wang et al., 2015; Whitman et al., 2015), upper forest floor (duff) layers (Duff Moisture Code, DMC) and deep organic soils (Drought Code, DC) are routinely analyzed on a decadal scale (Girardin and Wotton, 2009; Wallenius et al., 2011; Waddington et al., 2012; Mori and Johnson, 2013). Shabbar et al. (2011) identified soil moisture and drought estimates as being crucial to improving the climate-based fire forecast models, as fuel moisture state is not only important in fire initiation but also plays a role in fire spread and extinction (Girardin and Wotton, 2009; Macias Fauria et al., 2011).

2.4. CFFWI system codes

We applied the original equations and FORTRAN code (Van Wagner and Pickett, 1985) to calculate CFFWI system codes. The six components of the CFFWI system and DSR were calculated for the fire season. The fire season was assumed to start on April 1st and end on September 31st (Johnson and Wowchuk, 1993; Wotton et al., 2003). The Drought Code (DC) must be overwintered when winter precipitation is insufficient to recharge soil moisture (Lawson and Armitage, 2008). The DC tracks long-term moisture deficit then will be influenced by the value of the DC at the end of the previous season and the amount of precipitation received overwinter (Lawson and Armitage, 2008). Due to a number of non-consecutive years in the datasets, we assumed that DC layer moisture is fully recharged in spring and the DC in boreal forests with considerable overwinter precipitation and spring snow melt was considered saturated with an assigned value of 15 for startup (Lawson and Armitage, 2008). Then, we assumed that DC layer moisture was fully recharged in spring and has a starting value of 15 (Girardin and Wotton, 2009; Lawson and Armitage, 2008). This assumption was found to be reasonable in Canada, with an exception for certain locations in western and northern Canada, where total precipitation from November to April is lower than 200 mm (Girardin and Wotton, 2009). Any overwintering assumption might change DCs for both data sets (homogenized and inhomogenized data) equally. The impact of homogenization would be valid even though the DC values are equally reduced.

The CFFWI system requires weather variables that are observed at noon. General practice considers weather at the exact hour (1200 LST or 1300 LDT), without correcting for local noon. Originally, noon was chosen as the basic observation time to ensure that weather readings were taken late enough in the day to indicate conditions during the period of afternoon peak fire activity but early enough that the system was available for planning and operational purposes.

All four weather variables (temperature, 24 h accumulated precipitation, relative humidity and wind speed at noon) were needed to calculate the moisture codes of the CFFWI system for the weather stations of interest (Van Wagner and Pickett, 1985). However, the homogenized data, provided by Environment and Climate Change Canada, does not include noon values. Therefore, the mean temperature, which is an average between the maximum and minimum values was considered instead. The mean temperature was closer to the noon temperature than the maximum temperature (Table 4). The average difference between mean and noon temperature was about 0.4 − 2.0 °C, while the maximum temperature showed an average difference around 3.0 − 5.0 °C in the raw observations. Furthermore, the accumulated precipitation at noon was not available for the majority of the stations and the daily precipitation was aggregated for a climatological day. The above assumptions do not have an impact on the objective of our research; we used the mean temperature and daily precipitation for both data sets (homogenized and inhomogenized data) as we were interested in the impact of homogenized data versus raw observation, not the exact operational value of CFFWI system.

Table 4
The mean and median differences between the recorded daily noon temperature and the recorded maximum/mean daily temperatures for each station. All available years for each station were used to calculate the differences.

Station	T_{noon}–T_{max}, mean (°C)	T_{noon}–T_{max}, median (°C)	T_{noon}–T_{mean}, mean (°C)	T_{noon}–T_{mean}, median (°C)
Bag	−3.516	−3.200	1.881	1.650
FSJ	−3.672	−3.300	1.210	1.250
FSm	−3.907	−3.600	1.705	1.450
Kap	−4.277	−3.900	1.725	1.450
May	−4.690	−4.100	1.253	1.150
PRi	−4.541	−4.200	1.376	1.350
Que	−4.213	−3.900	1.779	1.600
RLa	−3.794	−3.500	1.627	1.400
Rob	−3.366	−2.800	1.729	1.650
SLo	−3.539	−3.300	1.767	1.600
Smi	−3.918	−3.700	1.301	1.100
Ter	−3.148	−2.800	0.437	0.300
Tes	−4.207	−3.800	1.360	1.400
Tim	−4.132	−3.900	1.968	1.700
WaL	−4.208	−3.600	1.659	1.650
Wab	−3.668	−3.200	1.515	1.150

3. Results and discussion

To determine the effects of using the inhomogenized data for fire weather analysis, the linear trend and distribution analysis, which are commonly performed with CFFWIS codes (Girardin and Wotton, 2009; Bedia et al., 2012; Kraaij et al., 2013), were carried out using the FFMC, DMC, DC, FWI and DSR, derived from both the homogenized and inhomogenized Canadian weather data. Further, weather variables were assessed by correlation analysis and the sensitivity of the codes to the weather variables was assessed with the percentiles method (Bedia et al., 2012). The common fire season statistics including median, 90th percentile and inner quartile range, trend analysis (Wilcoxon rank significance test, Kolmogorov–Smirnov, Mann–Kendall/Linear regression, Kendall's Tau correlation coefficients), and weather variable sensitivity test for all 3 data sets provided in Tsinko's dissertation (Tsinko, 2016). We provided a selection of the graphs and analysis here. The complete analysis including tables and graphs for individual stations are available online via Tsinko (2016).

Two sets of homogenized and inhomogenized time series for all stations were compared by scatter plots. Figs. 2 and 3 illustrate all weather variables and fire weather indices. The difference (inhomogenized − homogenized) of paired variables and indices were calculated and the difference distribution is demonstrated by histograms. Figs. 4, 5 are the residual distribution of on indices (FWI and DSR) for two stations selected to present hear. The standard statistical scores for the difference values such as mean, root mean square, median, minimum, and maximum of the differences were calculated (Table 5). The correlation coefficient of paired indices were also estimated (Table 6). The central tendency (median), dispersion (interquartile range or IQR) and the extreme values (90th percentile) of a fire season's indices changed after the homogenization(not provided here, see Tsinko (2016)). The majority of the stations, as measured by the Wilcoxon signed-rank test (not provided here, see Tsinko, 2016), rejected the null hypothesis (difference between the pairs follows a symmetric distribution around zero). The rejection rate increases to 100% as the length of data record increases from 27 to 66 years. The trend of annual statistical scores of indices such as annual mean, standard deviation and median also are plotted for individual stations (Tsinko, 2016). Mann Kendall and linear regression trend analysis tests demonstrated that homogenization changes the linear trend of the CFFWIS codes, up to 60% of the stations affected in some codes (Tsinko, 2016). An example is provided in Fig. 6 which presented the median of FWI and DC for fire season and months of August. The results showed a mismatch between two trends driven from homogenized and

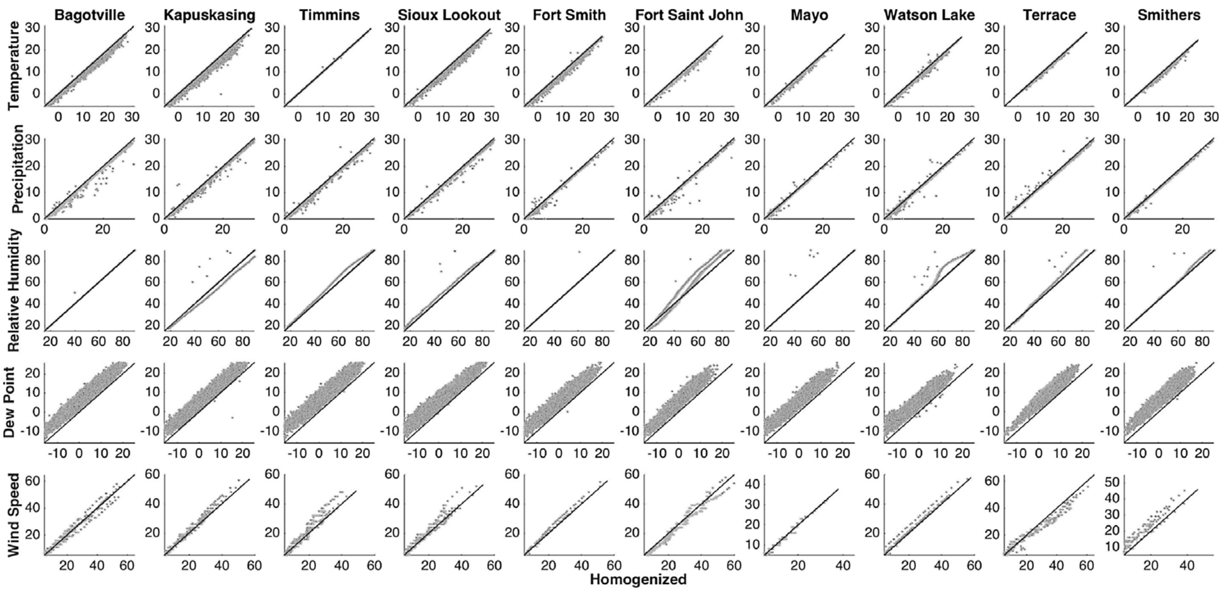

Fig. 2. Scatter plots for 10 stations with 49 years of data. Each row presents the same weather variables. Temperature and dew-point in °C, 24-h accumulated precipitation in mm, relative humidity in %, and wind speed in m/s. The solid black line shows when the homogenized and raw weather data are the same. Vertical axis represents the raw observation. For further detail see Tsinko (2016).

inhomogenized data.

Table 5 is a selection of statistical scores for dataset number 2 with 49 years of data. Mean values of temperature and precipitation differences are negative. The negative mean value confirms the warmer temperature and higher precipitation in the general trend of homogenized data. The root mean square (RMS) of differences are persistently larger (2 − 3 times) than absolute mean values of differences. The higher RMS indicates that extreme values are affected as homogenization evens out the outliers.

Fig. 2 demonstrates that there are discrepancies between the homogenized and raw weather data. The results show a warmer temperature and higher precipitation at all stations, except Timmins, in the homogenized series. Although the humidity and windspeed vary between the two series, they don't follow the same shift everywhere. Table 6 presents the correlation coefficient between homogenized CFFWI system codes and inhomogenized CFFWI system codes. All the low values in precipitation and relative humidity are perhaps due to the time series of precipitation with many zeros and its hybrid discrete-continuous frequency distribution. The skewed distribution of precipitation makes it more sensitive to any statistical processing or analysis (Bakhshaii and Stull, 2009).

Fig. 3 demonstrates indices for 10 stations. The scatter plots of fire indices indicate an impact for all 10 stations. Table 5 demonstrates a persistent positive value of mean difference ($\text{index}_{\text{raw}} - \text{index}_{\text{homogenized}}$) for DSR and FWI indices. The root mean square scores are considerably larger as they are more responsive to extreme values. Overall, CFFWI indices driven by homogenized data are lower than the inhomogenized indices (Table 5). The majority of stations have similar to identical results. We chose two stations, Fort Smith, NWT and Kapuskasing, ON, for our further discussion. The FWI (Fire weather Index) and DSR (Daily Severity Rating) difference are calculated for two stations. Histograms (Figs. 4 and 5) show a skewed distribution of differences. To emphasize the lower frequencies of tails, the vertical axis is presented in log scale. Although the frequency of

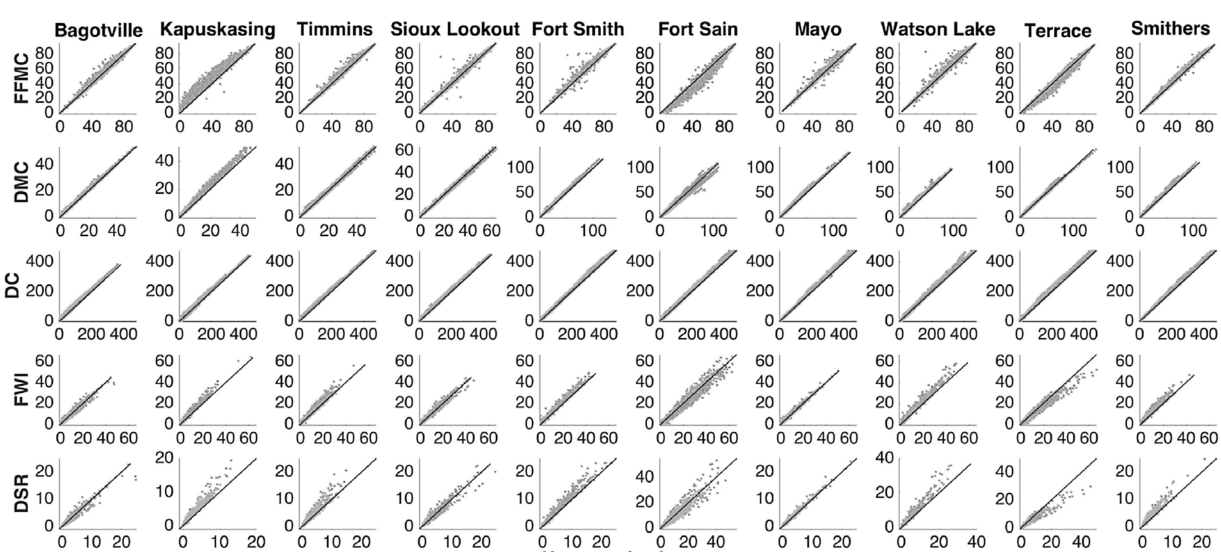

Fig. 3. Scatter plots for 10 stations with 49 years data. Each row presents the same fire index. The solid black line shows when the indices estimated with homogenized and raw data are the same. Vertical axis represents the raw observation. Note scale differences between plots for DMC and DSR.

Table 5
Mean, root mean square (RMS), maximum and minimum values of The difference (inhomogenized − Homogenized) of paired variables temperature, precipitation and indices of CFFWIS codes for datasets 2, which includes 49 years of data.

		Residuals statistical scores									
Stations		Bag	Kap	Tim	SLo	FSm	FSJ	May	WaL	Ter	Smi
Dataset 2	T_{mean}°C	−0.33	−0.38	−0.01	−0.28	−0.28	−0.12	−0.19	−0.14	−0.07	−0.11
	T_{RMS}°C	0.80	0.94	0.90	0.80	1.08	0.45	1.55	1.04	0.25	0.47
	T_{min}°C	−9.98	−17.70	−3.53	−12.57	−29.95	−11.95	−27.56	−17.55	−8.55	−6.91
	T_{max}°C	6.35	2.61	2.29	12.0	6.23	10.10	28.67	21.02	2.82	5.35
	T_{median}°C	0	0	0	0	0	0	0	0	0	0
	P_{mean}(mm)	−0.42	−0.33	−0.37	−0.27	−0.20	−0.20	−0.15	−0.19	−0.16	−0.16
	P_{RMS}(mm)	0.99	0.76	0.86	0.70	0.47	0.60	0.46	0.77	1.15	0.58
	P_{min}(mm)	−21.36	−13.38	−13.96	−56.3	−14.41	−15.53	−14.10	−61.35	−42.0	−25.22
	P_{max}(mm)	7.10	8.88	10.69	8.98	4.64	19.8	3.79	29.2	47.51	−2.84
	P_{median}(mm)	−0.21	−0.21	−0.21	−0.20	−0.15	−0.01	0	−0.11	−0.15	−0.14
	$FFMC_{mean}$	0.47	4.05	0.56	0.46	0.75	−1.58	0.75	0.99	−0.22	1.396
	$FFMC_{RMS}$	1.5	5.4	1.4	1.7	1.8	3.3	2.2	2.5	2.1	2.5
	DMC_{mean}	0.28	1.41	0.31	0.10	1.07	−0.03	2.32	1.10	0.42	1.05
	DMC_{RMS}	0.57	1.9	0.8	0.8	1.8	2.1	9.9	2.7	1.1	2.2
	DC_{mean}	6.99	6.31	8.12	6.55	7.58	8.29	8.42	9.65	6.06	10.6
	DC_{RMS}	10.1	9.3	10.7	9.5	10.7	11.2	18.0	17.9	12.4	21.6
	FWI_{mean}	0.13	0.79	0.32	0.20	0.64	−0.64	0.34	0.88	−0.15	0.79
	FWI_{RMS}	0.7	1.3	0.9	0.9	1.1	1.8	1.1	1.7	1.1	1.4
	DSR_{mean}	0.02	0.18	0.09	0.04	0.21	−0.18	0.09	0.28	−0.08	0.19
	DSR_{RMS}	0.3	0.5	0.4	0.3	0.5	1.1	0.4	0.6	0.7	0.5

DSR differences > 3 is less than 0.8% of the entire series at Fort Smith, it can be very significant in fire studies as it could correspond to two fire-days per year. For instance, on August 31st, 2009, the FWI of 13.914 and DSR of 2.874 put Fort Smith in moderate class. The FWI and DSR driven from homogenized data are 16.469 and 3.8713 respectively for the same date. These changes have implications regarding the expected fire behaviour in areas affected. The homogenization changed the DSR from moderate to high class.

Kapuskasing is another similar example with a time dependency pattern in differences. The time series in Fig. 4 shows a harmonic shape which the magnitude of FWI residual increases and decreases with about a decadal frequency. It can be a weather driven shape that deserves more investigation in future. Fig. 6 presents a change in the trends. The inhomogenized observations show a decreasing trend at Kapuskasing, while the homogenized trend increases for DC and FWI indices.

Recent studies (Flannigan et al., 2016) suggest that for every degree of warming, precipitation has to increase by more than 15% for FFMC, about 10% for DMC and about 5% for DC to compensate for the drying caused by warmer temperatures. Our study showed homogenization increases the temperature around 0.1 − 0.4°C on average. Using homogenized precipitation in the CFFWI increases the overall moisture in the data set and therefore reduces the effect of dryness. Homogenization also reduces the CFFWI system indices. The DSR from homogenized data has a mean value around 3 and the mean value of DSR difference varies about 0.14 on average. The 4% is only the

Table 6
Correlation coefficients (Kendall's tau) for the CFFWIS codes and weather variables of Datasets 1, 2 and 3. Correlation coefficients below 0.9 are in bold.

		Stations															
		Wab	Bag	Rob	Kap	Tim	SLo	RLa	FSm	PRi	FSJ	May	Tes	WaL	Ter	Smi	Que
Dataset 1	T	1.00	0.95	0.95	0.95	1.00	0.97	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	P	0.93	0.93	0.93	0.93	0.91	0.92	0.91	**0.87**	**0.89**	**0.89**	**0.88**	**0.89**	**0.87**	0.93	**0.89**	0.91
	W	0.92	0.92	0.92	0.93	0.91	**0.86**	**0.80**	0.96	0.94	0.94	0.98	0.90	0.95	0.94	**0.83**	**0.86**
	RH	0.93	1.00	0.93	0.99	0.98	0.96	0.96	1.00	0.95	0.90	1.00	1.00	0.98	0.97	0.99	0.93
	FFMC	0.94	0.97	0.95	0.95	0.97	0.96	0.95	0.97	0.95	0.91	0.97	0.96	0.96	0.96	0.96	0.96
	DMC	0.92	0.96	0.94	0.94	0.96	0.96	0.95	0.95	0.94	0.93	0.95	0.94	0.95	0.97	0.96	0.96
	DC	0.94	0.95	0.96	0.96	0.96	0.96	0.95	0.98	0.98	0.97	0.98	0.98	0.98	0.98	0.98	0.98
	FWI	0.93	0.95	0.93	0.94	0.96	0.94	0.92	0.95	0.94	0.93	0.96	0.94	0.95	0.94	0.93	0.94
	DSR	0.93	0.95	0.93	0.94	0.96	0.94	0.92	0.95	0.94	0.93	0.96	0.94	0.95	0.94	0.93	0.94
Dataset 2	T	–	0.96	–	0.96	1.00	0.97	–	0.98	–	0.99	0.99	–	0.99	0.99	0.99	–
	P	–	0.93	–	0.92	0.91	0.91	–	**0.86**	–	**0.88**	**0.88**	–	**0.87**	0.92	**0.89**	–
	W	–	0.93	–	0.93	0.90	**0.86**	–	0.96	–	0.93	0.97	–	0.91	0.94	**0.84**	–
	RH	–	1.00	–	0.98	0.96	0.96	–	1.00	–	0.90	1.00	–	0.97	0.95	0.99	–
	FFMC	–	0.96	–	0.95	0.97	0.96	–	0.97	–	0.92	0.97	–	0.96	0.95	0.96	–
	DMC	–	0.96	–	0.93	0.96	0.96	–	0.96	–	0.93	0.95	–	0.95	0.96	0.96	–
	DC	–	0.94	–	0.96	0.96	0.96	–	0.97	–	0.97	0.98	–	0.97	0.97	0.98	–
	FWI	–	0.95	–	0.93	0.96	0.94	–	0.95	–	0.93	0.96	–	0.94	0.93	0.93	–
	DSR	–	0.95	–	0.93	0.96	0.94	–	0.95	–	0.93	0.96	–	0.94	0.93	0.93	–
Dataset 3	T	–	–	–	0.94	–	–	–	0.98	–	–	0.99	–	–	0.97	–	0.99
	P	–	–	–	**0.71**	–	–	–	**0.86**	–	–	**0.88**	–	–	0.93	–	0.92
	DC	–	–	–	**0.83**	–	–	–	0.97	–	–	0.97	–	–	0.97	–	0.96

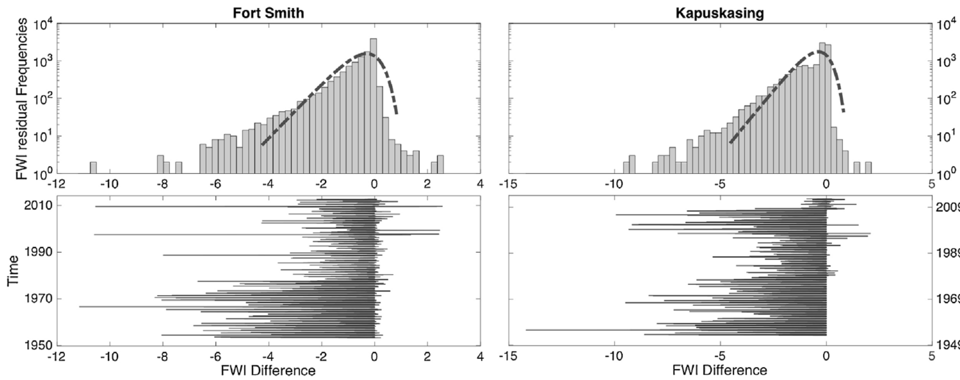

Fig. 4. Histograms and time-series for two stations with 49 years data. First row exhibits the histograms of residual of homogenized and raw data. The solid black line is extreme value fit curve. The second row graphs are time series of residuals. The residual is the $FWI_{Homogenized}$–FWI. The horizontal axis are residuals.

reduction of average DSR, while the considerably higher RMS score indicates that the change can be 10 times larger for outliers and possible extreme events. The rest of the indices are reduced from 0.7% to 8.4%, with the lowest changes in FFMC and highest changes in DC.

Overall results demonstrated that (1) Homogenization did not impact the normality and auto-correlation of 2 data sets (2) the central tendency (median), dispersion (interquartile range or IQR) and the extreme values (90th percentile) of a fire season's values for all codes changed after the homogenization for the majority of the stations, as measured by the Wilcoxon signed-rank test (see Tsinko, 2016). DC had the largest number of affected stations (100% for all Datasets), and DMC had the least number of affected stations (60–80%). The proportion of the affected stations increased as the time period increased. (3) Mann Kendall and linear regression trend analysis tests demonstrated that homogenization changes the linear trend depend on the CFFWIS code, up to 60% of the stations affected in some codes.

4. Conclusion

The data homogenization methods propose statistical techniques to reduce the inhomogeneity in weather station data. In this paper we explored the impact of data homogeneity on CFFWI system as an example.

Our study demonstrates that data homogenization on the CFFWI system reduces the indices 0.7–8.4% and also reverses the long-term trend in some stations. The small, but perhaps significant, discrepancies in FWI indices identified by this study and the implications for long term climatology (including fire climatology), fire history, and continued use of empirical fire moisture models in the research and operational realms. Our results show some striking pattern differences between weather variables in homogenized and inhomogenized data. Homogenization of older records (pre-1960) appears a more significant impact (likely biased), compared to newer records. Also, the largest discrepancies in more recent years seem to be in extreme years (FWI or DC), where homogenized values frequently miss the peak values. Overall trends appear subtle, and may be insignificant, though a difference from negative trend to positive is possibly meaningful. Removing the non-climate signal via homogenization can remove partly or entirely the extreme heat wave events. Researchers might prefer to used inhomogenized data or Numerical Weather Prediction (NWP) and then use a sensitivity analysis to measure the impact of homogenization.

Homogenization is one of many methods that have been in use to overcome the lack of continuous and uniform quality of weather data. Alternatives to homogenized and raw surface observations is to develop individual data sets by aid of a professional meteorologist at regional stations, using higher quality and smaller data sets in length using upper level observed variables and a combination of surface observations, or a combination of NWP model outputs and satellite data for the high grid resolution data.

Wildland fire researchers have developed coupled atmospheric-fire simulations (Koo et al., 2012; Coen et al., 2013; M et al., 2014). Even though these models do not function as operational weather-fire systems for forecasting, the interactive dynamics that connect weather and

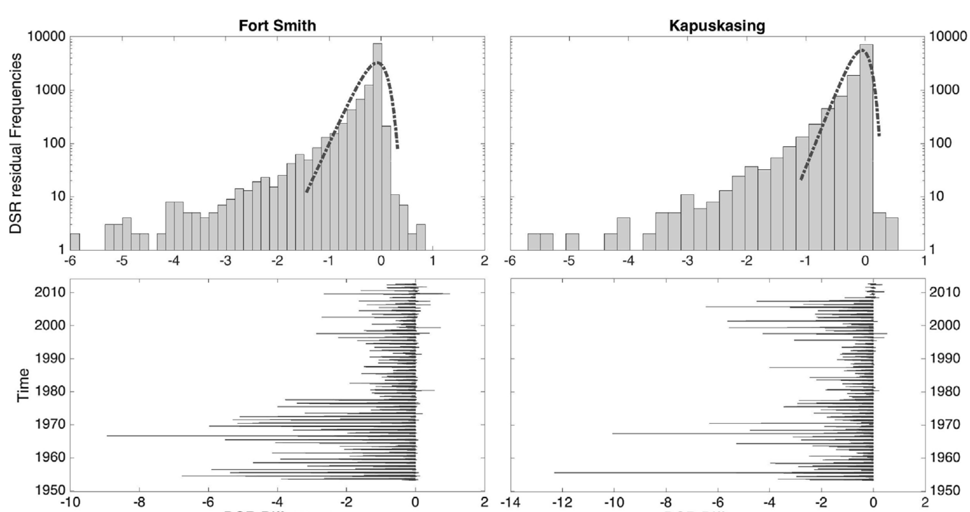

Fig. 5. Histograms and time-series for two stations with 49 years data. First row exhibits the histograms of residual of homogenized and raw data. The solid black line is extreme value fit curve. The second row graphs are time series of residuals. The residual is the $DSR_{Homogenized}$–DSR. The horizontal axes are residuals.

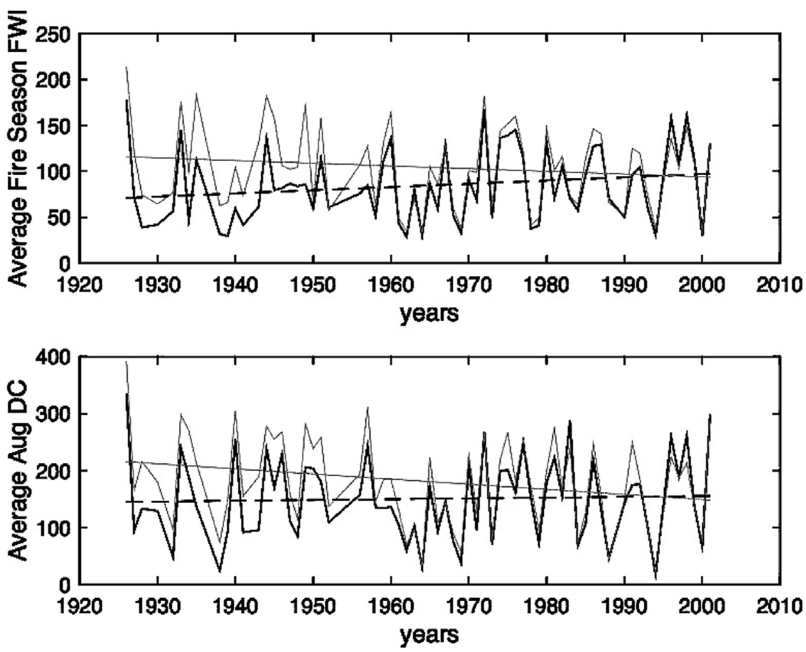

Fig. 6. Plots of the 1918–1998 average DC values for Kapuskasing for the month of August and for the whole fire season. The gray line shows the inhomogenized data and the black line – homogenized. The solid gray and the dashed black lines show the linear trends for the period for the unhomogenized and homogenized datasets respectively. Years with missing data were omitted.

fire helps to improve our understanding of fire behavior. Future models will not only help to bridge the limits of weather station measurements, but also guide the advancement of spread and fuel models.

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