Climate Variability and the Frequency of Extreme Temperature Events for Nine Sites across Canada: Implications for Power Usage

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ABSTRACT

To study the impact of incremental climatic warming on summer extreme temperature event frequency, the historical record of daily maximum June, July, and August temperatures was analyzed for nine sites across Canada. It was found that all of these sites are well modeled by a first-order autoregressive process using three parameters: the mean, variance, and first-order autocorrelation coefficient. For slight changes in the mean or variance there are increases in the frequency of both single days and runs of 2–5 consecutive days with daily maximum temperatures over a threshold value. For example, for a 3°C increase in the mean daily maximum temperature at Toronto, the frequency of a 5-day consecutive run over 30°C rose by over a factor of 8 to 7.1%. Sites with less variability are more sensitive to an increase in the mean summer temperature than sites with higher variability. Analysis of simulated series indicates that when two parameter values change simultaneously the change in the frequency of a given event is usually greater than the sum of the individual changes. Output from the Canadian Climate Centre GCMII model for the nine sites for both the current and 2 × CO_2 atmosphere indicate an average increase in the daily maximum temperature of 4.2°C. Changes in the standard deviation and autocorrelation were usually less pronounced.

For Toronto, a positive correlation ($R^2 = 0.718$) between daily peak power demand and the cube of the current and previous 2 days daily maximum temperature was found. A sensitivity analysis was performed on daily peak power demand by first generating temperature time series and then using the derived regression relationship. Results follow a predictable pattern and indicate that the standard deviation of the peak power series increases proportionally more than the mean for increases in the mean daily maximum temperature. For example, for a 3°C increase in mean daily maximum temperature, the increase in mean peak power demand was 7% (1200 MW) while the increase in the standard deviation of peak power demand was 22%. Changes in the autocorrelation of the temperature time series do not lead to significant changes in the mean or standard deviation of daily peak power demand. These results indicate that, while the average peak power demand is not moved drastically, the number of high energy consumption days may increase appreciably due to higher variability, placing stress on the provincial power utility to meet this higher demand.

1. Introduction

In the past few decades there has been increasing concern over anthropogenically induced climate change and how the enhanced greenhouse effect will impact the quality of life. The influence of climate on virtually all human activities implies the need for adaptive strategies in order to minimize disruption to economic, social, technical, and other institutions. One could effectively argue that there is already a basic failure to adapt to the best of our ability to the current level of natural variability (e.g., damage to homes built improperly in flood plains or on hurricane prone coastlines). While it is difficult to predict precisely how climate change will manifest itself, there is a scientific consensus that doubling atmospheric CO_2 will increase the global mean temperature by 1.5°–4.5°C (IPCC 1996), possibly by the end of the next century. Of greater concern may be the possible increase in the frequency of extreme events (Wigley 1988). Many systems may be able to cope with

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an increase in average temperature, but may fail under the stress of more frequent higher temperature perturbations.

Huff and Neill (1982) acknowledged this concern in their attempt to model the effect of changes in mean temperature on the growing season and individual crop productivity in the U.S. cornbelt. Motivated by this concern for crop integrity, McQuigg (1981) studied the relationship between the number of days with maximum temperatures greater than 37.8°C in July 1980 and the damage to the year's corn crop. Mearns et al. (1984) studied the changing frequency of extreme heat events for the U.S. corn belt and found that for Des Moines, the probability of five consecutive days over 35°C tripled with only a 1.7°C increase in the mean daily maximum temperature. In a similar fashion Hennessy and Pittock (1995) found nonlinear sensitivities to changes in the mean for heat waves at several sites in Victoria, Australia. For some sites the probability of 5 consecutive days over 35°C doubled for a 1°C increase in mean temperature, while for an increase of 3°C some sites experienced a five-fold increase in this probability. Conversely, the probability of 5 consecutive days below 0°C was reduced by a factor of three in some cases.

The fact that these studies were conducted for highly productive agricultural regions underscores possible risks to food security if climate change is felt through changes in the magnitude, frequency, or distribution of extreme events. An increased frequency of high temperature events, especially runs of consecutive days, will have an impact on health and comfort as evident by such incidents as the 1995 Chicago heat wave and other events in other parts of the world. The stress placed on energy supply systems during summer months is expected to be greater with increased air conditioner use during extreme temperature events, thus requiring the power utilities to consider climate change scenarios in their planning.

An attempt to quantitatively describe the change in the distribution and frequency of extreme temperature events is made by employing stochastic time series modeling, specifically the first order autoregressive [AR(1)] model. The results of Canadian Climate Centre second generation GCM (McFarlane et al. 1992; Boer et al. 1992) model simulations for the sites studied support the use of this model. Correlation between daily peak power demand and daily maximum temperature is made using regression techniques. The resulting relationship is then used in conjunction with the AR(1) model in order to obtain a quantitative description of how summer energy consumption might change if the pattern of occurrence of extreme temperature events changes as predicted by the AR(1) model.

2. Methodology

a. Event definitions

There are two types of extreme temperature events considered here: 1) The single day event in which the maximum temperature of a given day equals or exceeds a specified temperature threshold, and 2) a run event for which the daily maximum temperature of 2–5 consecutive days equals or exceeds a specified temperature threshold on each day. The first event type can be considered as a subset of the second (i.e., a run length of 1 day). Temperature thresholds range from 25° to 35°C, except for the milder coastal sites where the threshold ranges from 20° to 30°C.

FIG. 1. Map of Canada showing the nine monitoring sites.

The probability of any event is determined by performing a run analysis on the daily maximum temperature time series and counting the number of occurrences of that event within the sample space (the total number of possible occurrences of that event). Thus, for a series of 920 observations (10 concatenated June–August summers), there are 916 possible five consecutive day runs (sample size − run length + 1). If there are four 5-day runs satisfying a given event's criteria for a consecutive 10 summer series the probability of that event is simply 4/916 = 0.0044. This moving window analysis approach is patterned on that used in hydrology for intensity-duration-frequency curves of rainfall events. Thus, 4 consecutive days above a given threshold implies that there are two 3-day run events for the same threshold.

b. Series selection

Nine monitoring stations across Canada were chosen for study (Fig. 1) according to three criteria: 1) sites having a relatively long (90–120 yr) historical record are favored, 2) the sites should reflect the major climatic regions of the well-inhabited portions of Canada, and 3) the sites should have no, or few, changes in their location, elevation, and other physical characteristics. Nicholls (1995) explains several of the factors that should be considered for accurate meteorological data collection. The length of the historical record is of obvious importance in reducing sampling error in the evaluation of empirical event probabilities and for better assessment of the probability distribution defining daily maximum temperatures. By including sites from diverse regions around the country, it is possible to examine spatial variations of sensitivity to perturbations in climatic parameters. For example, prairie sites such as Indian Head, Saskatchewan, and Morden, Manitoba lie in an important agricultural region for which the effect of extreme temperature events on agriculture has already been acknowledged (Huff and Neill 1982; Mearns et al. 1984; Hennessy and Pittock 1995). Large population centers such as Toronto, Montreal, and Ottawa are important from an energy consumption perspective as these sites include many residences and office places with air conditioning. Of particular concern was the potential influence of heat islands from large urban centers on temperature records. For this reason, sites were carefully chosen to avoid this problem. For example, the Toronto record is taken from the airport monitoring station, which is located over 20 km from the downtown core, where the urban heat island effect does not noticeably affect temperature readings.

Mearns et al. (1984) studied the month of July for four Midwestern sites by stringing consecutive July months end-to-end to form a single time series. Hennessy and Pittock (1995) pursued a similar approach for Victoria, Australia, by taking December, January, and February data from each year and joining them to form a single summer daily maximum temperature time series for each site. After examining the correlation structure of the complete empirical series (all months included) for the different sites, it was found that stacking the three summer months end-to-end into a continuous sequence yielded a more stationary and manageable time series than using the continuous empirical series with every observation from all 12 months of the year. In this study, the summer daily maximum temperature time series is constructed by joining the June–August months of each year in chronological order. For example, the value of the daily maximum temperature of 31 August 1967 is immediately succeeded by the daily maximum temperature value of 1 June 1968. The result is that the sample size becomes 92 days multiplied by the number of years of record. Sample sizes ranged in length from about 7000 temperature observations to just over 11 000. Table 1 lists the nine sites and presents the basic descriptive statistics and first three sample moments from the consecutive summer time series.

The hottest summer sites in the country are in the prairies and the Great Lakes. The sites with the three highest mean daily maximum temperatures are Welland, Toronto, and Morden at 26.1, 25.6, and 25.4°C, respectively. The highest variances can be found at Indian Head, Morden, and Lacombe (27.8, 26.3, and 24.5°C, respectively). The combination of a high mean and variance makes Morden the most extreme of the sites, however, for very low probability events, frequencies may be higher at Indian Head because the larger variance will dominate on the tail of the distribution. Not surprisingly, the mildest sites are the two coastal sites: Victoria Gonzales and Charlottetown. The skewness of the daily maximum temperature distributions ranges from −0.1 at Morden to 1.8 at Victoria Gonzales. The sites with the most symmetrical distributions are the three prairie locations, while sites in close proximity to large bodies of water exhibit greater skewness in their empirical distributions.

c. Modeling of daily maximum temperature time series

Mearns et al. (1984) and Hennessy and Pittock (1995) used AR(1) models to represent the daily maximum temperatures of the stations in their studies. While the applicability of this model is wide in scope, its validity was determined for each site in this study. Employing a statistical package (SYSTAT v. 6.0, SPSS Inc.), the autocorrelation function (ACF) and partial autocorrelation function (PACF) for the historical series at each site were examined. Generally, the ACF and PACF plots for all the sites closely resemble those for Morden presented in Figs. 2 and 3, which in turn closely resemble the theoretical plots for a pure AR(1) process. The very distinct spike at lag-1 in the PACF denotes the importance of the correlation with the first lag relative to the larger lags, while the sample ACF exhibits exponential decay for the first five lags similar to that which occurs in a theoretical ACF plot for a pure AR(1) process. After the fifth lag there is a departure from the exponential pattern of decay predicted by the model and the ACF

TABLE 1. Descriptive statistics of each consecutive summertime series for daily maximum temperature (°C).

Station	Number of cases	Min	Max	Mean	Standard deviation	Skewness	Auto-correlation
Victoria, BC	8481	8.9	35.0	19.36	3.27	1.81	0.60
Lacombe, AB	7911	4.4	38.3	22.24	4.95	−0.18	0.61
Indian Head, SK	9748	1.7	42.8	24.11	5.27	−0.11	0.62
Morden, MB	7165	6.7	43.9	25.37	5.13	−0.10	0.61
Welland, ON	10 462	8.9	37.8	26.00	3.88	−0.39	0.64
Toronto, ON	5336	9.4	38.3	25.65	4.25	−0.21	0.60
Ottawa, ON	9751	10.0	37.8	25.31	4.25	−0.15	0.61
Montreal, PQ	11 123	11.1	36.1	24.57	3.93	−0.24	0.67
Charlottetown, PEI	7513	6.7	36.7	22.10	4.10	0.40	0.62

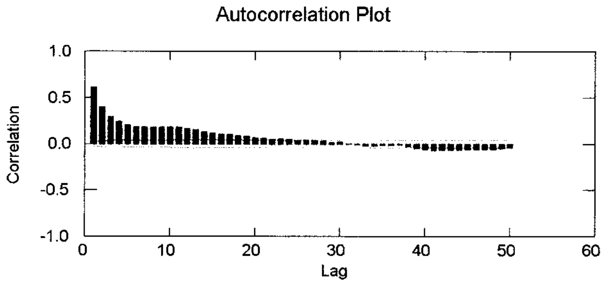

FIG. 2. Empirical ACF plot for Morden, Manitoba.

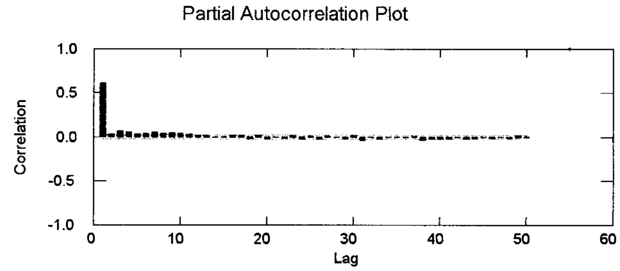

FIG. 3. Empirical PACF plot for Morden, Manitoba.

attenuates more slowly. This lack of perfect agreement is not surprising and can be attributed to a finite empirical sample size and the fact that the AR(1) model simply cannot describe all of the variability in daily maximum temperature at this site or any other.

Use of the AR(1) model for the representation of summer daily maximum temperature time series is supported by the results of nearest gridpoint simulations of the Canadian Climate Centre GCMII model for the sites being studied. The correlation structures of 20-yr stacked July and August series for both the $1 \times CO_2$ and $2 \times CO_2$ atmospheres were examined. The ACF and PACF of these series reveal them to be well approximated by the AR(1) process as typified by the $1 \times CO_2$ series for the nearest grid point to Indian Head, Saskatchewan (Fig. 4), which shows a strong correlation with the first lag and only a very slight transgression of the white noise 95% confidence limits at the third lag.

Parameter values for several tentative models {including the AR(2), first-order auto regressive moving average [ARMA(1, 1)], first-order moving average [MA(1)], and a few higher-order AR models} were estimated and then used in order to narrow down model selection by applying the more objective Bayesian information criterion (BIC; Hipel and McLeod 1994; Katz and Skaggs 1981). The BIC aims at optimizing the trade-off between goodness of fit and model parsimony according to more objective criteria than visual inspection of correlation plots. It consists of two logarithmic terms: the first represents goodness of fit and the second represents model parsimony and assumes the form

$$\text{BIC} = \ln \text{MSE} + (p + q + 1) \ln n, \tag{1}$$

where n is the sample size of the series, MSE is the mean squared error of the ARIMA model fit to the series, p is the number of AR parameters, and q is the number of MA parameters. Thus, for the AR(1) model, $p = 1$ and $q = 0$. As the model better fits the data the first term decreases; however, if this is achieved by using a more elaborate model the second term will increase. The objective is to minimize the BIC so that, when comparing several tentative models, it is the one that yields the lowest BIC, which should generally be accepted.

For Morden the BIC for the AR(1), AR(2), ARMA(1, 1) and MA(1) models is 20 107, 20 110.5, 20 109, and 21 010, respectively. The difference in the BIC among the AR(1), AR(2), and ARMA(1, 1) models are minimal (less than 0.1%), but do indicate the slight superiority of the AR(1) model. Thus, the improvement in fit obtained from using these other models is not sufficient to undermine the parsimony of the AR(1) model. The MA(1) model is clearly inappropriate due to its higher BIC and the lack of agreement between the empirical correlation plots with those of a pure MA(1) process. However, the BIC was minimized to a value of 20 070 for an AR(4) model with the second-order parameter, ϕ_2, constrained to zero. This slight improvement in the BIC with fourth- and fifth-order constrained AR models was observed for Welland and Toronto as well, thus suggesting that higher-order models describe daily maximum temperatures slightly better. Despite this marginal improvement in the BIC, it is equally valid and far easier to simulate and draw inferences from AR(1) models.

Analysis of the residuals obtained from fitting the AR(1) model to the historical record of each site was conducted by plotting their residual ACF and normal probability plots. For every station, the residuals closely approximated white noise, indicating that the AR(1) model accounts for much of the variability when describing daily maximum temperatures at several sites in Canada and also supporting the model choice of Mearns et al. (1984) and Hennessy and Pittock (1995). As a further check on model validity, temperature time series for current climate conditions (i.e., no parameter changes for μ, σ, and ϕ) were simulated and run analyses were performed for a range of temperature thresholds

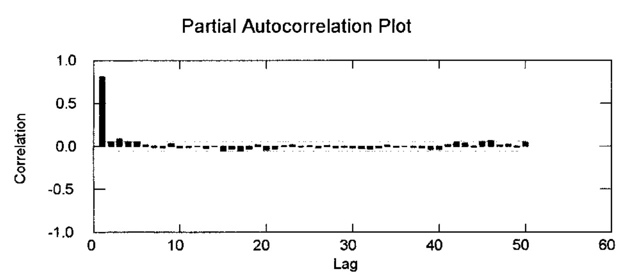

FIG. 4. PACF plot for Indian Head, Saskatchewan, for the $1 \times CO_2$ GCM simulated series.

TABLE 2. Model calibration for Morden, Manitoba. Event probabilities for the day, 3-day and 5-day events.

Threshold temperature °C	5-day run		3-day run		Day event		
	Empirical	Simulated	Empirical	Simulated	Empirical	Theoretical	Simulated
35	0.001	0.000	0.003	0.003	0.030	0.032	0.030
34	0.001	0.001	0.005	0.005	0.047	0.043	0.046
33	0.002	0.001	0.009	0.009	0.068	0.067	0.068
32	0.005	0.003	0.019	0.016	0.099	0.103	0.097
31	0.009	0.007	0.032	0.028	0.136	0.143	0.136
30	0.017	0.013	0.053	0.046	0.184	0.193	0.183
29	0.024	0.023	0.071	0.070	0.239	0.229	0.238
28	0.044	0.042	0.110	0.107	0.305	0.301	0.304
27	0.080	0.069	0.168	0.155	0.375	0.384	0.376
26	0.132	0.109	0.238	0.216	0.452	0.474	0.452
25	0.201	0.166	0.318	0.289	0.528	0.558	0.529

and run lengths in order to compare event frequencies with historical frequencies. In general, agreement was quite good. For single-day events, good agreement between the empirical and simulated series indicates the validity of the normal approximation of the distribution of daily maximum temperatures, while good agreement for run lengths greater than 1 day indicates the general validity of both the normal approximation and the AR(1) model. Table 2 presents the model calibration for Morden for the single-day, 3-day, and 5-day events at various temperature thresholds. Figure 5 depicts the close agreement between the simulated and empirical series for the single-day and 5-day run probabilities at Morden.

Agreement between the simulated probabilities and those obtained directly from a normal distribution probability table (theoretical) implies that the random number generator of the simulator is efficient. The probabilities for the simulated run events are also quite good indicating that the AR(1) model is appropriate. Although Morden has the smallest skewness of the sites,

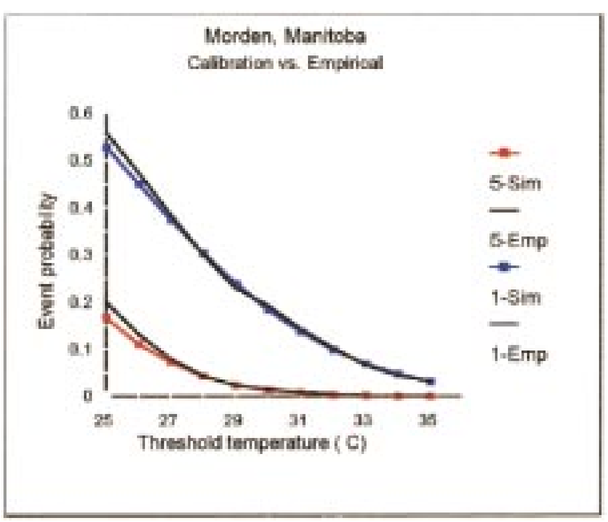

FIG. 5. Comparison of the simulated (Sim; parameters unchanged) 1-day and 5-day run event probabilities with the corresponding empirical (Emp) probabilities at Morden, Manitoba.

the same comparisons were made for each site and found to provide similar matches. A summary of the model parameters is given in Table 1.

d. Simulation algorithm

Synthetic temperature time series were generated by employing the method of Mearns et al. (1984). The algorithm first generates an initial value for the series from an $N(\mu, \sigma_x)$ distribution using a Box–Muller random number generator with the polar modification. Independent random shocks, a_t, are then generated from a $N(0, \sigma_a)$ distribution, where the shock standard deviation is determined by $\sigma_a^2 = (1 - \phi^2)\sigma_x^2$. The temperature values are then determined according to the following AR(1) recursion formula

$$X_t = \mu + \phi(X_{t-1} - \mu) + a_t, \qquad (2)$$

where X_t is the individual generated temperature at time step t, μ is the mean daily maximum temperature, ϕ is the first-order autocorrelation coefficient, and a_t is the independent and normally distributed random shock at time step t.

For each synthetic series, 50 000 daily maximum temperature values were generated corresponding to a realization of 543 yr. At this length most of the sampling variability was eliminated. Following series generation, a run analysis routine counted the frequency of events for a range of specified threshold temperatures and run lengths.

e. Sensitivity analysis

As in previous studies (Mearns et al. 1984; Hennessy and Pittock 1995), univariate sensitivity analyses were performed on the mean, standard deviation, and autocorrelation. The mean and standard deviation were perturbed by incrementing their values by 1°, 2°, and 3°C while the autocorrelation was altered by moving from 0.3 through to 0.9 at 0.1 increments, except where the actual value (near 0.6) was encountered. Of the three parameters, increases in the mean are the most certain to occur in a climate warming scenario. Assessment of σ and ϕ is difficult, and substantial uncertainty exists about how climate change should affect these parameters.

Mearns et al. (1984) rightly attempted to model the effects of feedback by perturbing the values of two parameters simultaneously. Feedback in climatic systems is known to exist, for example, in radiation interactions with the ground and atmosphere, and it is possible that an increase in the mean daily maximum temperature will be accompanied by changes in variability and/or persistence. Mearns et al. (1984) attempted to determine the direction in which the mean and standard deviation might change simultaneously by performing a simple linear regression on coupled empirical means and standard deviations at four sites for three different months, and found an inverse relationship between the mean and variance. A similar approach was pursued here, except that the mean and standard deviations for approximate 10-yr blocks were plotted for each site individually (generally about eight points of data per site). Figures 6a–d present plots of the variance against the mean for Lacombe, Indian Head, Montreal, and Charlottetown, respectively.

The R^2 for the Lacombe plot (Fig. 6a) is 0.88, suggesting that as the mean increases so too will the variance. The R^2 for Indian Head, Montreal, and Charlottetown are 0.14, 0.11, and 0.14, respectively. For Indian Head and Montreal (Figs. 6b and 6c) there is not any discernable trend, while at Charlottetown (Fig. 6d) there is an inverse relationship between the mean daily maximum temperature and its variance. Victoria Gonzales and Morden also depicted positive relationships between the mean and variance with R^2 of 0.61 and 0.77, respectively. These figures suggest that changes in the mean and standard deviation of daily maximum temperature may not occur independently in some parts of Canada, though extrapolation of these historical relationships to a future climate cannot be made. Plots for the relationship between the standard deviation–autocorrelation and mean–autocorrelation were even less informative. Consequently, feedback relationships are chosen in a simple linear, but arbitrary fashion, so as to conduct bivariate sensitivity analyses that are intended to show what synergies might exist without necessarily stating the direction or actual magnitude they may manifest themselves.

f. Correlations with peak power demand

Extreme temperature events have an impact on daily peak power demands primarily through increased air conditioner use, as people attempt to maintain an expected level of comfort. Thus, as extreme temperature events become more common, both air conditioner use and power demand are expected to increase. Power utilities may have to adopt new strategies in order to meet these increased demands. Furthermore, the extra demand coupled with hot temperatures can cause transmission lines to sag, thus simultaneously stressing the integrity of the distribution system.

To assess how daily peak power demand might change, it has to be correlated with daily maximum temperature. Once a correlation is made, the probability of equalling or exceeding certain peak power demand thresholds can be obtained directly from the sensitivity analysis results. Data from five summers (1991–95) for the 60-Hz East System was provided by Ontario Hydro. The 60-Hz East System comprises about 80% of Ontario energy demand excluding some of the more remote regions in the northwest where power demand derives from climatically insensitive industrial operations. Included in the system are the climate stations of Toronto, Welland, and Ottawa. The data contain the daily power demand in megawatts (MW) and values for several climatic variables at Toronto, including daily maximum temperature. Because several of the highly populated sites have similar statistics to Toronto (see Table 1), provincial peak power demand is correlated with Toronto temperatures. Figure 7 shows a plot of daily peak power demand (MW) with daily maximum temperature (°C) (weekends and holidays excluded). The plot suggests that after 23°C there is a linear relationship between daily peak power demand and daily maximum temperature, however, after examining several sectional relationships, it was found that a regression of peak power demand against the cube of current daily maximum temperature and the cube of the previous two days' maximum temperature yielded the highest correlation ($R^2 = 0.718$). The following relationship for peak power demand and daily maximum temperature was obtained:

$$\text{power} = 13\,760 + 0.134\,\text{temp}^3 + 0.036\,\text{temp}^3_{-1} + 0.014\,\text{temp}^3_{-2}. \quad (3)$$

Using (3), peak power demand figures corresponding to threshold temperatures used in the sensitivity analysis are easily computed. The correlation between daily peak power demand and daily maximum temperature is quite pronounced considering that some of the variability is explained by other climatic variables such as wind speed, humidity, and dewpoint, which are not included in the regression. Thus, if the probability of a 5-day run equalling or exceeding 30°C is 0.05 then the probability of having 5 days consecutively where the peak power demand is equal to or greater than 18 586 MW is approximately 5%. Naturally, since R^2 is less than unity, the correlation with threshold temperatures does not give completely reliable peak power figures.

Using the regression relationship (3), daily peak power demand (MW) time series were generated for Toronto by simultaneously generating a temperature time series with the AR(1) simulator. The resulting series were analyzed to determine how changes in the mean, standard deviation, and autocorrelation of the temperature time series affected the mean and standard deviation of the

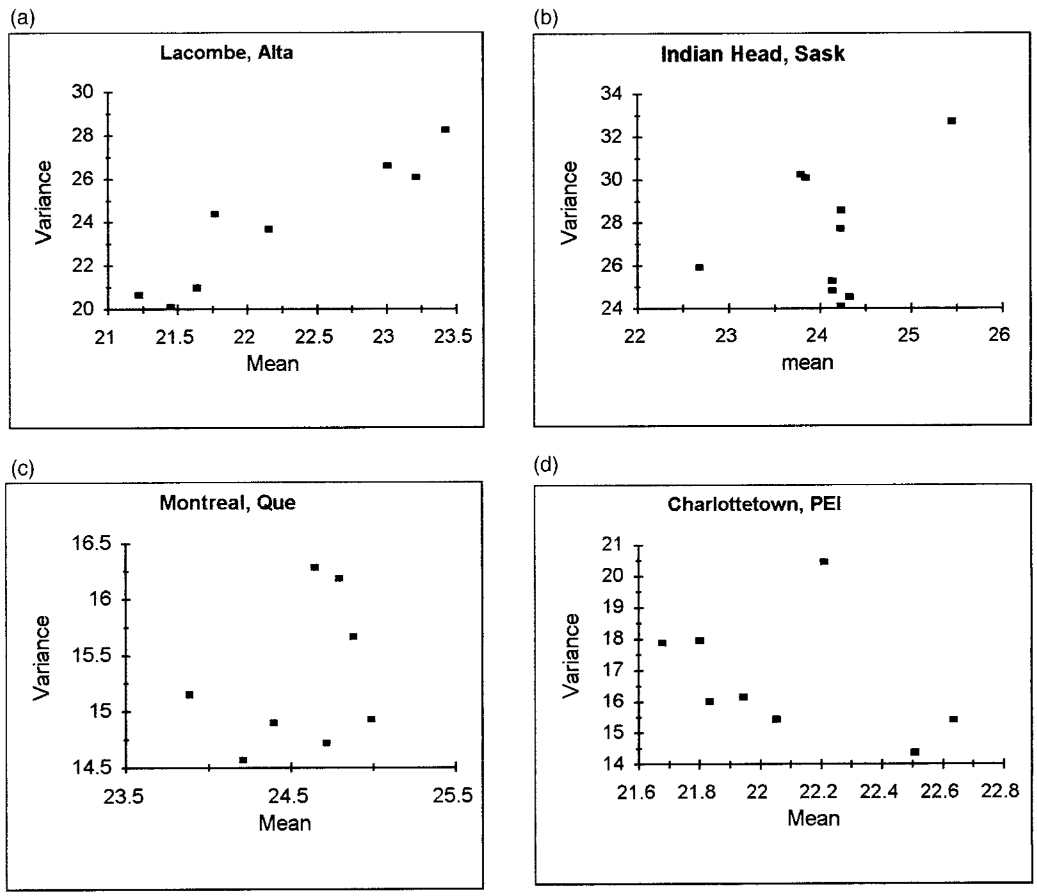

FIG. 6. Mean vs variance at (a) Lacombe, (b) Indian Head, (c) Montreal, and (d) Charlottetown.

peak power demand series. Also a bivariate sensitivity analysis was conducted whereby the mean/standard deviation and the mean/autocorrelation were varied simultaneously in order to determine the magnitude of synergistic effects.

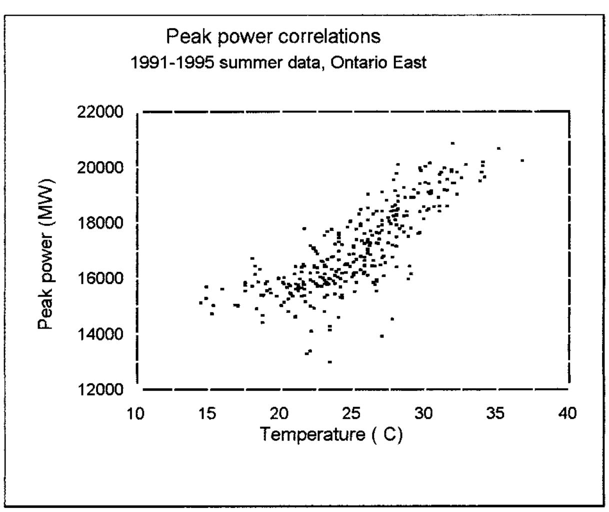

FIG. 7. Daily peak power demand (MW) vs daily maximum temperature (°C) (weekends and holidays excluded).

While warming during the winter months may reduce energy needs during that season, this is not as important from the perspective of Ontario Hydro as summer heat waves, since the majority of the province relies on the oil and gas utilities for winter heating energy. Sites in Southern Ontario are generally too warm in the summer months to require heating at night and, therefore, there are no energy savings due to climate warming to be realized. This may not be true for prairie sites where even daily maximum temperatures can be sufficiently low to require heating on at least some of the days during these months.

3. Results

a. Univariate sensitivity analysis

1) CHANGES IN THE MEAN

Increases in the mean of the daily maximum temperature time series were carried out for 1°, 2°, and 3°C increments. As expected, the probability of all events increased with positive changes in the mean, and gen-

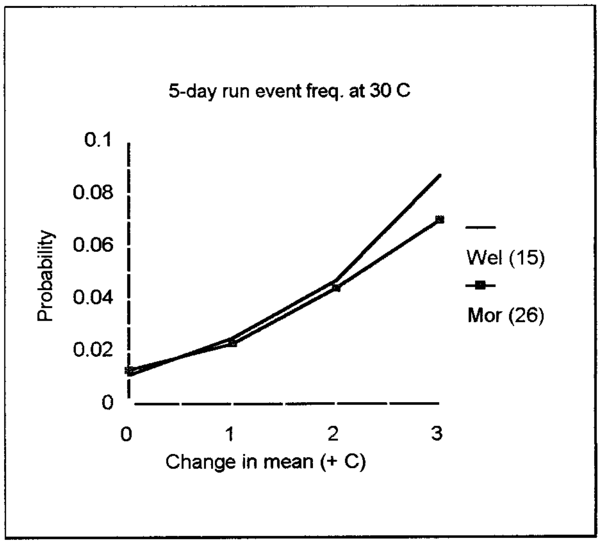

FIG. 8. Comparison of event probabilities for the 5-day run at a threshold of 30°C for changes in the mean summer daily maximum temperature at Morden and Welland.

erally at an increasing rate. This nonlinearity is observed in Fig. 8, which presents the change in the probability of 5 consecutive days above or equal to 30°C at Morden and Welland. One important pattern that Mearns et al. (1984) detected can be seen in Fig. 8. The rate of change of the increase in probability with increasing mean for Welland is larger than the rate for Morden. This results from Welland's lower variability (its variance is 11.3°C^2 less than Morden's). As the distribution of daily maximum temperatures has more spread, the responsiveness of event probabilities to changes in the mean becomes less pronounced. Table 3 presents the results of the mean sensitivity analysis for all stations at the 30°C threshold for the day, 3-day, and 5-day events. The hottest summer sites in the country continue to be Welland, Morden, and Toronto while the sites that respond most drastically are Victoria Gonzales, Lacombe, and Charlottetown. In some cases, events that have not appeared in the historical record begin to occur, such as with the 5-day run at Charlottetown.

Katz and Brown (1992) underscore the importance of considering the variability of climate for the adequate representation of possible scenarios. By using statistical theory, they demonstrated that the frequency of extreme events is more sensitive to changes in the variance rather than changes in the mean, and that this sensitivity is relatively greater as the event becomes more extreme (i.e., the threshold increases). Table 4 presents the 3-day run probabilities at Indian Head for changes in the mean and standard deviation at three different threshold temperatures. At 30°C changes in the mean of 1°C lead to greater changes in the probability than do equal changes in the standard deviation, whereas at 32°C the relative increases in probability are comparable, if not equal, for the same increases in the mean and standard deviation. At 34°C the greater relative sensitivity to changes in variability, as compared to increases in the mean, is evident.

2) CHANGES IN THE STANDARD DEVIATION

As with the mean sensitivity analysis, results for the standard deviation, σ, sensitivity analysis follow a predictable pattern. As σ is increased, the event probability also increases. Victoria Gonzales, Lacombe, and Charlottetown are the most responsive stations for increases in σ suggesting that the sites with lower means will have greater proportionate increases in event probabilities over a given threshold than sites with high means. This property is explicable by considering the theoretical properties of the normal distribution. Although Morden, Welland, and Toronto are the least sensitive to perturbations in σ, they are consistently the hottest sites. Thus, as the tail of the distribution is farther from (or covers less of) the threshold region, altering the location (μ) or scale (σ) of the distribution leads to greater percentage changes in event probabilities because the events are already quite rare. Figure 9 shows event probabilities for both Indian Head and Charlottetown for the 5-day run at 25°C. These curves are typical of the shape of such curves for other sites. Both stations have identical autocorrelations, but differ in their means for any common σ. Table 5 presents the results of the standard

TABLE 3. Site comparison of event probabilities for sensitivity to changes in the mean daily maximum temperature at a temperature threshold of 30°C.

	1-day run Change in mean (°C)				3-day run Change in mean (°C)				5-day run Change in mean (°C)			
Site	0	+1	+2	+3	0	+1	+2	+3	0	+1	+2	+3
Victoria	0.001	0.002	0.004	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lacombe	0.056	0.087	0.123	0.166	0.006	0.014	0.023	0.038	0.001	0.002	0.006	0.010
Indian Head	0.132	0.177	0.231	0.292	0.028	0.045	0.068	0.102	0.007	0.013	0.023	0.039
Morden	0.183	0.233	0.306	0.379	0.046	0.070	0.112	0.158	0.013	0.023	0.044	0.070
Welland	0.153	0.220	0.296	0.390	0.039	0.069	0.113	0.177	0.011	0.025	0.047	0.087
Toronto	0.155	0.219	0.291	0.378	0.034	0.062	0.100	0.158	0.008	0.020	0.037	0.071
Ottawa	0.133	0.192	0.256	0.345	0.027	0.052	0.083	0.139	0.007	0.015	0.029	0.061
Montreal	0.082	0.127	0.190	0.266	0.013	0.026	0.051	0.088	0.003	0.006	0.016	0.032
Charlottetown	0.025	0.047	0.079	0.120	0.002	0.005	0.013	0.023	0.000	0.001	0.002	0.005

TABLE 4. Event probabilities and relative changes in probability (3-day run) for incremental changes in mean and standard deviation for three different thresholds at Indian Head.

Change in parameter °C	Threshold probability of event (relative change) 30°C		32°C		34°C	
	μ	σ	μ	σ	μ	σ
0	0.028	0.028	0.010	0.010	0.003	0.003
+1	0.045 (61%)	0.045 (61%)	0.016 (60%)	0.019 (90%)	0.005 (67%)	0.007 (133%)
+2	0.068 (143%)	0.061 (118%)	0.028 (180%)	0.031 (210%)	0.010 (233%)	0.014 (367%)
+3	0.102 (264%)	0.078 (179%)	0.045 (350%)	0.045 (350%)	0.016 (433%)	0.024 (700%)

deviation sensitivity analysis at 30°C for the day, 3-day, and 5-day events at each station. Consistently the most extreme sites remain Morden, Welland, and Toronto, while the proportionate increases in event probability are greater at the milder sites.

3) CHANGES IN AUTOCORRELATION

Changing the first autocorrelation coefficient necessarily alters the probabilities of the run events, though it should theoretically not affect one-day probabilities since these are determined by the normal distribution. Values of the autocorrelation were varied from 0.3 to 0.9 in increments of 0.1 for each site and Fig. 10 presents the change in the 5-day run probability for a threshold of 30°C at Ottawa and Morden. These curves are also typical of other sites. The nonlinearity is apparent with an increasing rate of increase of the event probability for increasing ϕ. Although the curves are quite similar, the probabilities at Morden are higher due to its higher variability (both sites have an almost identical mean). It should be noted that autocorrelations for midlatitude sites are typically near 0.6, and that there is no evidence to suggest that large changes are likely in the future.

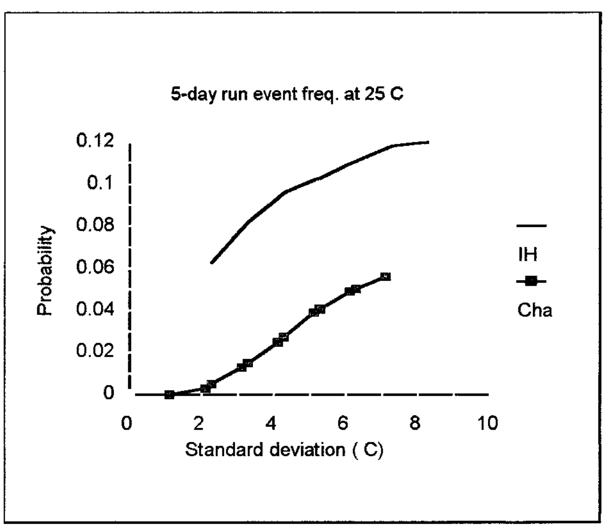

FIG. 9. Standard deviation sensitivity analysis for Indian Head (IH) (μ = 24.1°C) and Charlottetown (Cha) (μ = 22.1°C), two sites with equal autocorrelation, but different means.

b. Bivariate sensitivity analyses

The difficulty in determining feedback relationships has already been mentioned. The complexities of the interactions between climatic variables are such that statistical empirical methods are well suited for the determination of parameter relationships. While at some stations (especially in the west) the correlation between the mean and variance is good, the correlation between ϕ and σ and between μ and ϕ is generally poor. Thus, the bivariate sensitivity analyses were performed for selected levels of two variables at a time. Excerpts from the results are presented in Tables 6 and 7. Table 6 presents the probabilities for the 3-day run at a 30°C threshold for Montreal for changes in μ and σ and Ottawa for combined changes in σ and ϕ. Table 7 presents the probabilities of the 5-day run at 30°C threshold for Lacombe for combined changes in σ and ϕ and for Morden for combined changes in μ and σ.

Considering the 3-day run at Montreal, if μ is increased by 3°C without any other changes, then the probability increases by a factor of 6.8, from 0.013 to 0.088. If an isolated change of 3°C in σ occurs, the increase in probability is 0.049 (a factor of 4.8). If the above changes occur simultaneously, the increase in probability is 0.140 (a factor of 11.8), which is greater than the sum of the individual isolated changes, 0.124. Thus, the effect of the combined increases in mean and standard deviation is greater than the individual effects. This synergy is apparent for several simultaneous parameter changes and can be conveniently expressed as

$$\Delta P(\mu + \delta_m) + \Delta P(\sigma + \delta_{sd}) < \Delta P(\mu + \delta_m, \sigma + \delta_{sd}), \tag{4}$$

where P is the event probability, μ is the mean, σ is the standard deviation, and δ_m and δ_{sd} are the increments to the mean and standard deviation, respectively. Simple

TABLE 5. Site comparison of event probabilities for sensitivity to changes in the standard deviation (threshold of 30°C).

Site	1-day Change in standard deviation (°C) 0	+1	+2	+3	3-day Change in standard deviation (°C) 0	+1	+2	+3	5-day Change in standard deviation (°C) 0	+1	+2	+3
Victoria	0.001	0.008	0.022	0.044	0.000	0.000	0.001	0.004	0.000	0.000	0.000	0.000
Lacombe	0.056	0.097	0.131	0.163	0.006	0.016	0.027	0.038	0.001	0.003	0.006	0.010
Indian Head	0.132	0.178	0.212	0.244	0.028	0.045	0.061	0.078	0.007	0.012	0.020	0.028
Morden	0.183	0.226	0.257	0.287	0.046	0.065	0.084	0.100	0.013	0.021	0.030	0.038
Welland	0.153	0.202	0.243	0.276	0.039	0.059	0.080	0.097	0.011	0.019	0.030	0.037
Toronto	0.155	0.205	0.244	0.266	0.034	0.055	0.075	0.084	0.008	0.016	0.026	0.029
Ottawa	0.133	0.185	0.224	0.262	0.027	0.046	0.065	0.085	0.007	0.013	0.021	0.031
Montreal	0.082	0.131	0.183	0.213	0.013	0.028	0.049	0.062	0.003	0.007	0.015	0.021
Charlottetown	0.025	0.062	0.097	0.132	0.002	0.008	0.016	0.028	0.000	0.001	0.003	0.007

modification of (4) will represent the synergy that exists for mean–autocorrelation and standard deviation–autocorrelation interactions. Thus, if the variance and mean increase simultaneously, as some regression analyses suggest is a more likely relationship than others, then the increases in probability will be more than suggested by single parameter value increases.

c. *Comparison with GCM results for the doubling of atmospheric CO_2 concentration*

Analysis of the output of the Canadian Climate Centre GCMII model for equilibrium $2 \times CO_2$ simulations of 20 yr (July and August concatenated series extracted) for the nearest grid points to the sites studied was also undertaken to compare with the historical series. According to the area covered per grid, Welland and Toronto fall within the same grid as do Ottawa and Montreal. Table 8 presents the minimum, maximum, and mean daily maximum temperatures as well as the standard deviation and autocorrelation of the current and $2 \times CO_2$ simulated climates. In general, the GCM underestimates historical means for the summer months by about 4°C and standard deviations by about 1°–2°C. Autocorrelations for these months are higher than observed showing that the model does not account for all the factors leading to daily maximum temperature variability. This tendency to underestimate the first two moments and overestimate persistence is preserved, however, in the $2 \times CO_2$ simulation, indicating that bias is consistent.

For the $2 \times CO_2$ scenario, the average increase in mean daily maximum temperatures for all seven grid points is 4.2°C. The average increase in minimum and maximum daily maximum temperature is 5° and 4.8°C, respectively. There is no clear pattern for changes in the standard deviation, which increases at some sites, but decreases at others (the magnitude of changes being less than 1°C in every case). The same holds true for autocorrelation, which increases at Victoria Gonzales, Indian Head, Morden, and Toronto/Welland, but decreases on the east coast, at Ottawa/Montreal and Lacombe. Despite the lack of discernable trend in these parameters, the GCM does show that an increase in mean is likely based on increasing CO_2 concentrations, a fact that may have considerable significance for power demand.

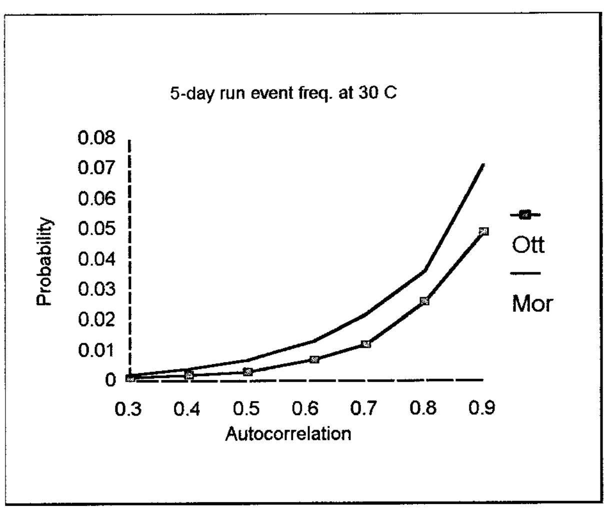

FIG. 10. Run event probability curves as a function of autocorrelation, at Morden (Mor) (σ = 5.13°C) and Ottawa (Ott) (σ = 4.25°C).

d. *Daily peak power demand sensitivity analysis*

The results of the peak power demand sensitivity analysis for changes in the mean and standard deviation (μ_t and σ_t) of daily maximum temperature at Toronto are presented in Table 9. Trends in the power series are

TABLE 6. Bivariate changes for the 3-day run event probability at Montreal and Ottawa for a 30°C threshold.

$\Delta\sigma$	Montreal 3-day run $\Delta\mu$ 0	+1	+3	Ottawa 3-day run ϕ 0.613	0.7	0.8
0	0.013	0.026	0.088	0.027	0.036	0.056
+1	0.028	0.047	0.119	0.052	0.060	0.082
+3	0.062	0.092	0.153	0.139	0.159	0.188

TABLE 7. Bivariate changes for the 5-day run event probability at Morden and Lacombe for a 30°C threshold.

	Morden 5-day run $\Delta\mu$			Lacombe 5-day run ϕ		
$\Delta\sigma$	0	+1	+3	0.4	0.605	0.8
0	0.013	0.023	0.070	0.000	0.001	0.006
+1	0.021	0.033	0.082	0.001	0.003	0.014
+3	0.038	0.052	0.095	0.003	0.010	0.032

completely predictable from trends in the temperature series because Eq. (3) is deterministic; however, the analysis gives an idea of the magnitude of changes in terms of megawatts. Increases in both the mean and standard deviation of the peak power demand series occur for univariate increases in the mean daily maximum temperature. While the mean of the peak power series (μ_p) increases only 2% for a 1° increase in mean daily maximum temperature, this increase becomes 7% for a 3° increase. The spread of the peak power distribution (σ_p) is more responsive proportionally with increases of 6% and 22% for 1° and 3° increases, respectively, in μ_t. Thus, as μ_t increases, more extreme power demand days could occur despite a relatively modest increase in the mean daily peak power demand. This would result in more potential brownouts and similar reduced-capacity phenomena. If the mean daily maximum temperature increases 4.5°C as the GCM simulation calls for, these changes in peak power demand will obviously be more exaggerated.

The mean daily peak power demand changes only slightly with increasing spread of the daily maximum temperature distribution (only a 2% increase for a 3°C increase in σ_t). Consistent with the deterministic relationship relating peak power demand to maximum temperature, σ_p increases substantially with increasing σ_t. For a 1°C increase in σ_t there is a 25% increase in σ_p; however, this becomes an increase of 88% for a 3°C increase in σ_t. The magnitude of synergy for combined increases in μ_t and σ_t is barely significant. For example, a simultaneous 2°C increase in both μ_t and σ_t yields a μ_p only 2.4% greater than the μ_p that results from the addition of the independent increases in temperature parameters. Simulations were carried out for temperature series with autocorrelations of 0.5, 0.7, and 0.603 (the empirically derived autocorrelation for Toronto) at different 1° increments of μ_t (25.4°–28.4°C). Changes in μ_p and σ_p did not seem to follow any trend with changing ϕ_t. Increases in either one or both peak power parameters were sometimes followed by decreases in either one or both parameters as ϕ was increased from 0.5 to 0.603 and then to 0.7. The magnitude of changes in μ_p were generally less than 0.5% while changes in σ_p were less than 2.5%, suggesting that changes in ϕ_t alone do not yield substantial changes in the peak power demand series governed by (3). Simultaneous changes in the autocorrelation of the temperature series with either μ_t or σ_t are, thus, not expected to yield any perceptible synergy in the peak power demand parameters.

4. Concluding remarks

The historical time series of daily maximum temperatures for several sites in Canada are well represented by an AR(1) model. Simulations of the AR(1) model with current empirical parameters for each site produces time series with closely matching extreme event frequencies to the empirical record for most of the sites. Furthermore, examination of the correlation structure of GCM output for current and 2 × CO_2 atmospheres supports the use of the AR(1) model. None of the sites is well modeled by a pure moving average process. Daily maximum temperatures are approximately normally distributed. This approximation is especially good for continental sites.

Increases in the mean are more significant for sites with less variability (smaller σ) than for sites with larger variability, for given thresholds. Also, as the event becomes more extreme for a particular site, the relative sensitivity to changes in σ, as compared to μ, becomes more important.

Scenarios from the Canadian Climate Centre GCMII model point to an average increase of daily maximum

TABLE 8. GCM Output from 20-yr simulation (Jul and Aug series) for daily maximum temperature (°C).

Parameter	Victoria Gonz., BC	Lacombe, AB	Indian Head, SK	Morden, MB	Welland/ Toronto	Ottawa/ Montreal	Charlotte-town, PEI
			1 × CO_2 GCM output for nearest grid point				
Minimum	7.61	0.57	6.19	7.85	8.63	7.13	8.56
Maximum	24.61	23.45	35.56	33.01	33.65	29.67	29.99
Mean	15.46	16.72	22.79	22.78	22.45	20.41	20.55
Standard deviation	3.11	3.30	3.81	3.80	3.36	3.42	3.44
Autocorrelation	0.807	0.799	0.763	0.738	0.716	0.707	0.692
			2 × CO_2 GCM output for nearest grid point				
Minimum	10.26	7.75	12.36	12.69	16.07	11.91	13.23
Maximum	27.12	26.19	41.73	43.52	39.26	32.51	33.06
Mean	18.92	20.18	28.24	27.53	26.99	24.28	24.62
Standard deviation	2.74	2.46	4.36	4.17	3.63	3.19	3.24
Autocorrelation	0.821	0.772	0.808	0.801	0.740	0.678	0.655

TABLE 9. Effects of changes in the mean and standard deviation of the daily maximum temperature (°C) time series on the mean and standard deviation of the daily peak power demand (MW) series at Toronto.

Change in standard deviation (°C)	Peak power (MW)	Change in mean daily maximum temperature (°C) 0	+1	+2	+3
−3	μ	16 896	17 256	17 674	18 124
	σ	411	439	472	512
−2	μ	16 941	17 306	17 722	18 176
	σ	739	799	861	928
−1	μ	17 042	17 404	17 801	18 259
	σ	1095	1157	1251	1383
0	μ	17 158	17 499	17 936	18 369
	σ	1462	1551	1689	1785
+1	μ	17 271	17 611	18 103	18 542
	σ	1823	1996	2122	2282
+2	μ	17 386	17 776	18 189	18 809
	σ	2270	2396	2558	2842
+3	μ	17 665	18 090	18 460	18 812
	σ	2742	2959	3108	3245

temperature of 4.5°C for the sites in this study for a 2 $\times$ CO_2 equilibrium climate. There is no clear trend for changes in the standard deviation or autocorrelation, for which the magnitude of changes are modest.

Plotting of the mean and variance for decade spans of the historical record of each site was used in order to gain insight into feedback relationships. Lacombe, Morden, and, to a lesser extent, Victoria Gonzales displayed positive correlation between the mean and the variance. A regression of the variance on the mean at Charlottetown points to a possible negative correlation. Relationships between the autocorrelation and variance and autocorrelation and mean were more difficult to determine, and there may not be any discernable relationship among model parameters. While the historical relationships are interesting in their own right, their extrapolation to future climatic conditions is not certain. The study of feedback mechanisms and their physically based model formulation will be necessary in order to better understand extreme events in a changing climate.

In Ontario, summer daily peak power demands are positively correlated with daily maximum temperature, with an R^2 of 0.72. Daily peak power demand series were simulated using the resulting regression relationship. Increases in the mean daily maximum temperature led to predictable increases in the mean daily peak power demand, but the magnitudes of such changes were modest with only a 7% increase in mean peak power demand from 17 160 MW to 18 370 MW corresponding to a 3°C increase in mean daily maximum temperature. Changes in the standard deviation of the peak power series were more pronounced with a 22% increase in standard deviation for the same 3°C increase in the mean of the temperature series. Increases in the standard deviation of the peak power series were, as expected, more pronounced with increases in the standard deviation of the daily maximum temperature series. Changes in the autocorrelation of the temperature series produced only marginal changes in the moments of the peak power series, with differences generally less than 0.5% for the mean and 2.5% for the standard deviation.

As more extreme temperature events occur, power demand will tend to increase. The sensitivity of the standard deviation of the power series to both the mean and spread of the temperature series underscores the risk of a greater frequency of high power demand days despite only modest changes in the average summer daily peak power demand. Other factors such as humidity and wind play a significant role in air conditioner use and, thus, affect power consumption as well. Better correlations between peak power demand and daily maximum temperature would be obtained if the influence of those factors were removed, although correlations between extreme temperature and humidity events and peak power demand may be more instructive than just temperature events alone.

The results of the sensitivity analysis only have predictive meaning in a warmer climate if the fundamental model assumptions hold under changed conditions. The AR(1) model used by Mearns et al. (1984), Hennessy and Pittock (1995), and in this study is a stochastic model that can reproduce observed historical series well. Although the model is not physically based there is a physical basis behind the autoregressive behavior of daily maximum temperature time series. The fact that its assumptions are valid in different parts of the world and for different climates such as in Southeastern Australia, the U.S. Midwest, and Canada for describing historical daily maximum temperature time series suggests that they will be valid under future conditions.

In short, the simulations in this study serve a descriptive purpose in that they demonstrate that design considerations for power supply infrastructure and other engineered systems will need to include climate change concerns due to the significant potential impact on consumption.

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