METHODS AND RESULTS

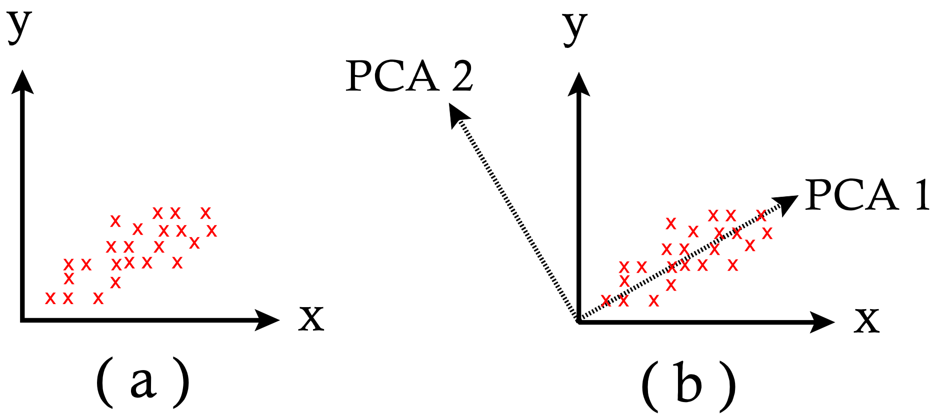
The "How" of Synoptic Weather Typing (in this study)

Cheng et al., (2005) provides an 8-page literature review of synoptic weather typing methods, in the development of a rationale for the process used in this study. As one follows the logic through this development, a consistent theme emerges once the structure of the process has been settled: as much as possible (in terms of data management and analysis) "the process should make the decisions".

There are three steps in the process: principal component analysis (PCA); an hierarchical (average linking) clustering procedure (ALCP); and a non-hierarchical classification procedure, discriminant function analysis (DFA).

Principal Component Analysis

Figure 4. A simple two-dimensional representation of PCA.



In panel (a) of Figure 4 above, it appears that there is a relationship between the data plotted on the x- and y- axes, such that y is correlated with x. However, by rotation of the axes to a new position as shown in panel (b), it can be seen that on the new axes the correlation disappears. The first component is defined as that along which there is the greatest variation in the transformed data, and the second component is that with the lesser variation. In a two or three dimensional system it is easy to visualize the process: in practice with complex data sets there may be many dimensions and many components. The process of resolution into components is usually limited by an arbitrary definition of the maximum allowable remaining variance in the data. The purpose is twofold: to reduce the number of new transformed variables (components), and to eliminate correlation among variables.

The hallmarks of the process are as follows:[6]

- Calculation of new transformed variables (components) by a coordinate rotation
- Components are uncorrelated
- First component axis aligned in the direction of the highest percentage of the total variance in the data
- Component axes are mutually orthogonal
- Maximum "signal to noise ratio" and largest percentage of total variance in the first component

In the Cheng et al., (2005) study the PCA was performed to reduce the 24 inter-correlated weather variables into a smaller number of linearly independent component variables, which explain much of the variance within the original dataset. Component loadings (coefficients) were calculated to express the relationships between the original weather variables and the newly formed components. The principal components which explained 2% of the total variance or more were retained to calculate component scores. Days with similar meteorological situations will tend to exhibit similar component scores.

The procedure was run separately for the warm season (April–September) and cold season (October–March) at each of the selected four cities. The PCA produced eight to ten component solutions that explain 88–92% of the total variance within the original dataset for both seasons and all cities. The remainder of the components, each of which can explain less than 2% of the total variance, were discarded.

Average Linking Clustering Procedure

The purpose of cluster analysis[7] is to place objects into groups or clusters suggested by the data, not defined a priori, such that objects in a given cluster tend to be similar to each other in some sense, and objects in different clusters tend to be dissimilar. Any generalization about cluster analysis must be vague because a vast number of clustering methods have been developed in several different fields, with different definitions of clusters and similarity among objects.

Several types of clusters are possible:

Disjoint clusters place each object in one and only one cluster.
Hierarchical clusters are organized so that one cluster may be entirely contained within another cluster, but no other kind of overlap between clusters is allowed.
Overlapping clusters can be constrained to limit the number of objects that belong

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[6] http://doppler.unl.edu/~bcorner/pca.html

[7] SAS Institute Inc., Cary, NC, USA:1999.

> simultaneously to two clusters, or they can be unconstrained, allowing any degree of overlap in cluster membership.
>
> *Fuzzy* clusters are defined by a probability or grade of membership of each object in each cluster. Fuzzy clusters can be disjoint, hierarchical, or overlapping.

In "agglomerative hierarchical clustering" (used here), each observation begins in a cluster by itself. The two closest clusters are merged to form a new cluster that replaces the two old clusters. Merging of the two closest clusters is repeated until only one cluster is left. The various clustering methods differ in how the distance between two clusters is computed.

In Cheng et al., (2005), the average linkage clustering procedure was employed to derive clusters possessing similar large-scale synoptic characteristics in terms of the daily 8- to 10-component scores for the four selected cities. The number of clusters for retention was determined using a variety of statistical tests, and optimizing a number of statistical parameters.

Using the above procedures, for both seasons together, about 30 major synoptic weather types with sizes above 1% of the total days were identified for each of the selected cities, although the number of weather types varied slightly from one city to another. All weather types were based primarily on differences in their meteorological characteristics for all days in the developmental dataset.

Discriminant Function Analysis

A nonhierarchical method—discriminant function analysis—was used to reclassify all days within the dataset using the centroids of the hierarchical weather types as "seeds".

> The term "discriminant analysis" refers to a wide range of statistical procedures which are designed to measure the differences between two or more groups of objects with respect to one or more variables simultaneously. The principal objective is the assignment of new objects to predetermined groups using developed classification rules. These rules, called discriminant functions, are calculated and used to identify the group to which an object belongs. The discriminant analysis is based upon the development of a set of linear equations. A separate discriminant function is derived for each group and evaluated for each day. Using the covariance matrix and mean values of the variables selected, discriminant analysis develops classification functions, which in turn are used to identify which group best fits the characteristics of an individual day. The day is then classified into the group with the highest score.
>
> Thus, where groups (air masses) are predetermined and represented by seed days, linear discriminant analysis is a robust procedure which produces a daily categorization with spatially continuous results.[8]

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[8] Kalkstein LS, Nichols MC, Barthel CD, and Greene JS, 1996: A new spatial synoptic classification: Application to air-mass analysis. International Journal of Climatology, 16: 983–1004.

Approximately 30–35% of the total days were reclassified for each of the selected cities. Generally, differences between cluster sizes resulting from the nonhierarchical reclassification were smaller than the originals classified by the hierarchical clustering procedure alone. The number of new weather types with a size above 1% of the total days was increased; for example, in Toronto such weather types increased to 36, which captured about 84% of the total days. However, the smaller synoptic weather types, which comprised the remaining 16% of the total days, were still included in the analysis. These smaller types were largely made up of days with no or low elevated mortality.

To quantify any improvement in the cluster structure resulting from the nonhierarchical reclassification, a variety of statistical tests on both classification results were analyzed, including within- and between-cluster standard deviations and the number of days with extreme weather conditions or temperature above certain critical thresholds. Results from the tests showed that the cluster structure resulting from nonhierarchical reclassification was better than that using the hierarchical procedure alone.

Weather-type verification

To validate the identified weather types, discriminant function analysis was used to assign each day of the *validation* dataset (1977, 1983–86, 1992, 1994, 1996, and 1998) into one of the weather types predetermined from the *developmental* dataset. The results were found to be similar for both developmental and validation datasets, suggesting that the discriminant function analysis performed well in verifying or predicting the weather types. The weather types from both developmental and validation datasets were pooled for further trends analysis, below, unless separation was used for validation purposes.

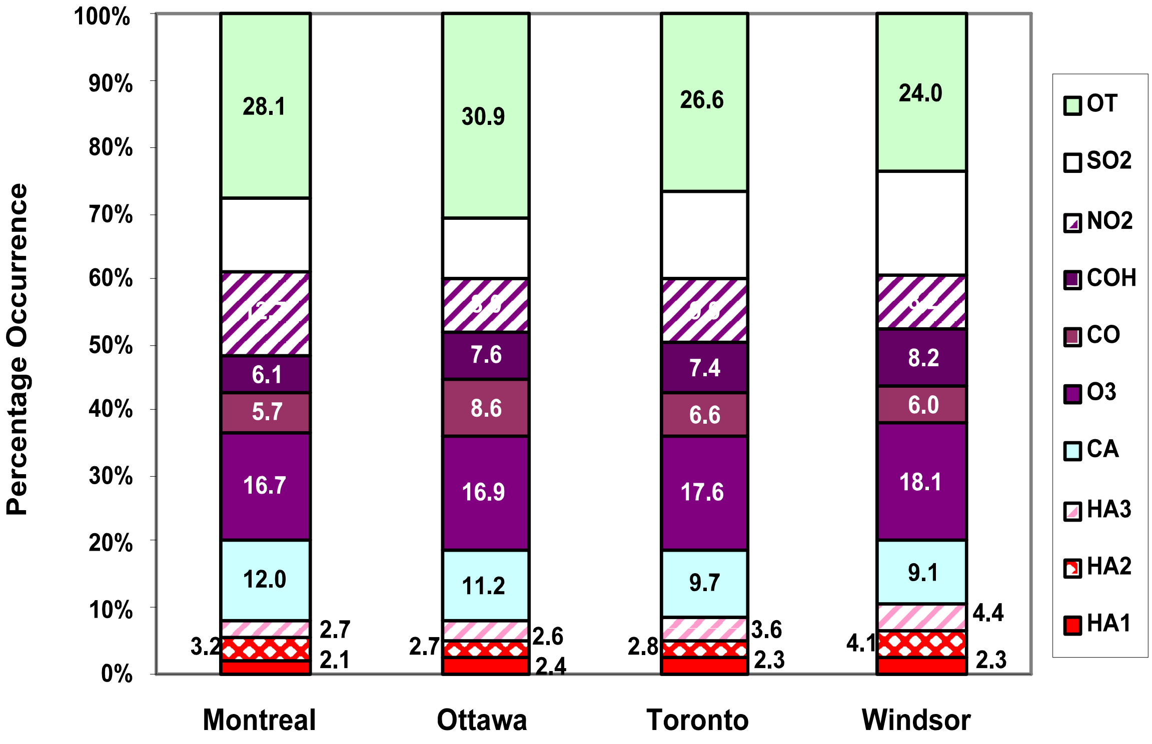
The Link between Weather Types and Air Pollution

Hot and cold weather types were determined before identifying the weather types most associated with high air pollution levels. For each of the four selected cities, three hot weather types were identified; the rest of the weather types usually having lower mean afternoon temperatures. The criterion for determining the cold weather type depended on the difference of January mean afternoon temperature among the cities. Identified cold weather types were combined as a cold weather group.

Since each of the weather types represented a distinctive air mass and synoptic signature, a specific regime of air pollution was related to each type. Two measurements, within-weather-type mean air pollution concentrations and frequency of high air pollution episodes, were used to identify weather types associated with high air pollution concentrations. Results indicated that mean pollution concentrations varied considerably among the synoptic weather types. For example, some weather types have a mean O3 concentration that is much greater than the overall mean; others are associated with concentrations much lower than the overall mean.

Similar methods were also applied to the remainder of the pollutants for each of the selected cities. Some weather types were significantly associated with high air pollution concentrations for many pollutants (up to five); other types possessed good air quality and were not significantly related to any pollutant. Weather types were divided into ten groups, as shown in Figure 5: three hot weather-related (including air pollution) groups (HA1, HA2, HA3), one cold weather-related (including air pollution) group (CA), five air pollutant-related groups (O_3, CO, COH, SO_2, NO_2), and one "other" group that usually possesses relatively good air quality and comfortable weather conditions. In the study area, all three hot weather types were associated with high O_3 concentrations; however, there were some individual cold weather types not significantly associated with high air pollution levels. In this study, such cold weather types were combined with other cold/air pollution-related weather types because of the small size of the weather types.

Figure 5. Percentage occurrence of the ten weather groups in the four cities



Notes: HA1, HA2, and HA3 represent three hot weather types (including air pollution; CA is cold weather groups (including air pollution); O3, NO2, SO2, CO, and COH are different pollutant-related weather groups; and OT is "other" or comfortable weather groups. The sequence of the legend is the same as the sequence of the bars.

Outcome of this step

The analysis so far has defined an air mass classification process; applied to each of four cities; that allows information on daily weather, air pollution and mortality to be assigned to one of the ten categories for every day in the 25 year period for which data were available.

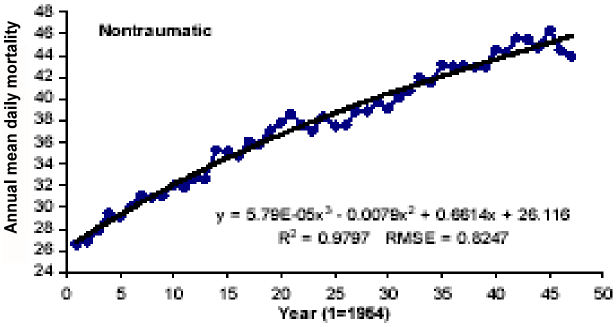
Trends in the data.

As was mentioned previously, given that the data of interest covered a period of many years, it is evident that data associated with human activity would show trends over this period. As a result of government regulations and technological change, except for ozone, air pollution levels on the whole have reduced over time. Population in the area of study has increased, and to some extent aged, so that the overall number of deaths in the population has increased. The study needed to remove these other influences on mortality to uncover the effects of weather and air pollution.

Mortality

Figure 6 shows mortality data, and a plot of the polynomial regression function used to correct for non-environmental factors. The difference between each day's actual mortality count and the "baseline" annual mean daily mortality as defined by a regression model (with some additional adjustment; see below) is the "elevated" mortality used in the analysis.

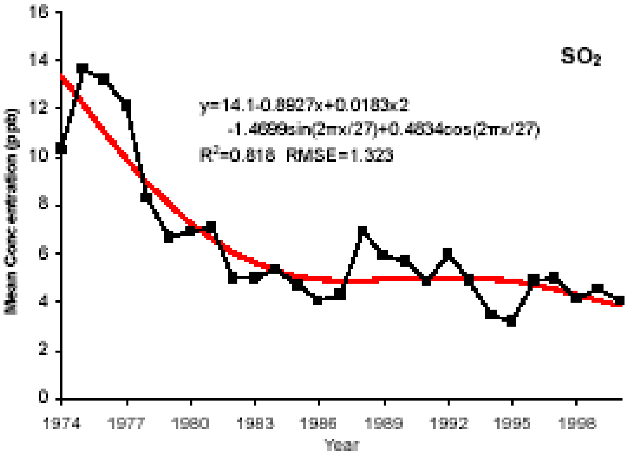
Figure 6. Toronto mortality data



Air Pollution

In order to examine the relationship between weather and air pollution using air mass classification, the air pollution trends were removed in a similar way (Figure 7). However, once the weather/ air mass relationships were defined, for the air pollution data used to establish the relationships between air masses and mortality, the "raw" data were used, without removing the trends.

Figure 7. Toronto SO_2 data

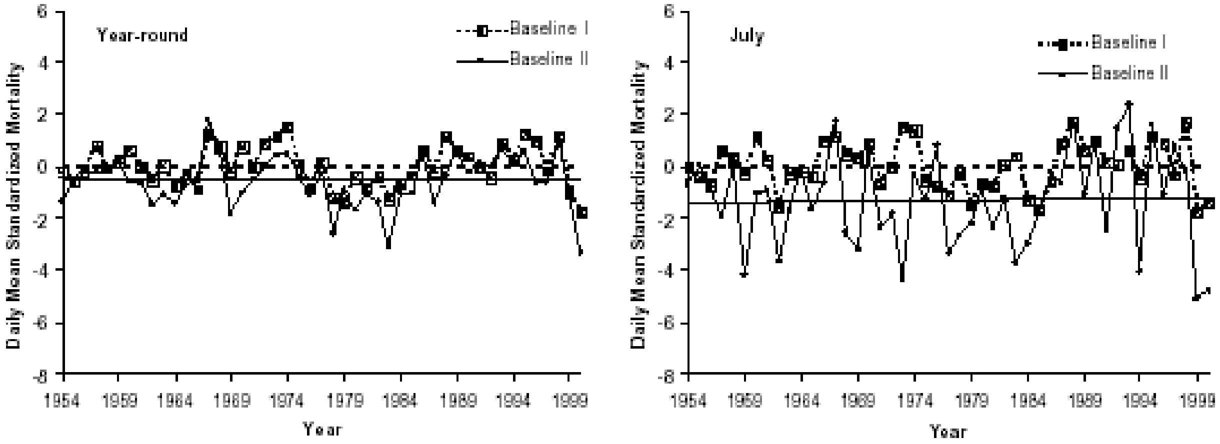


Additional adjustments for mortality baseline

Following determination of the ten weather groups, the weather group “other,” which usually possesses good air quality (low pollution concentration) and comfortable weather conditions, represents non-weather- and non-air pollution-related weather types. By using these “other” weather types, the annual mean daily mortality baselines were constructed by calculating the within-“other”-weather-group mean mortality from anomaly data against the year-to-year trends, as shown in Figure 8, for Toronto. A positive mortality residual (above the baseline) should represent the elevated daily mortality associated with extreme temperatures (hot/cold) and air pollution. In other words, the baseline should represent normal or natural deaths without the effects of extreme temperatures and air pollution.

The mortality baseline in the Cheng *et al.* study differs from previous studies. For example, a recent study [9] used the 3-year running mean of daily mortality (centred on the year in which the particular day lies) to represent the mortality baseline for development of the Heat-Watch Warning System currently piloted in many cities over the world, including Toronto, Canada. Their baseline was developed using all days including hot and polluted days; consequently, some heat/air pollution-related mortality was removed, which should be included in analysis. In addition, a 3-year running mean would also remove some inter-annual heat impacts on mortality.

Figure 8. Samples of baseline mortality I and II in Toronto.



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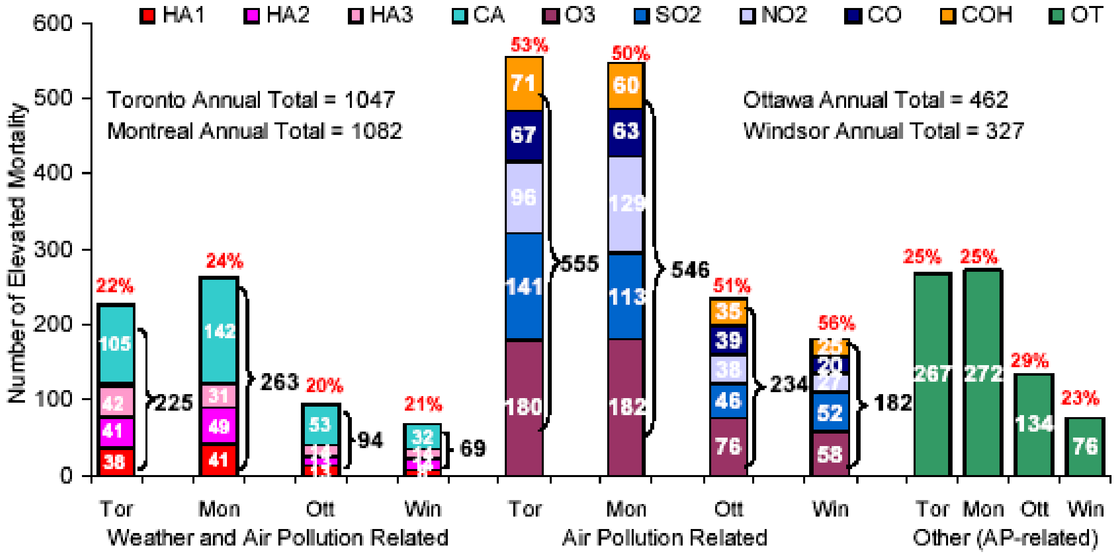
[9] Sheridan SC and Kalkstein LS, 2004: Progress in heat watch-warning system technology. Bulletin of the American Meteorological Society, 85: 1931–1941.

Figure 9. Mean annual total elevated non-traumatic mortality caused by heat/cold and air pollutants in four cities (1954–2000).



Notes: HA1, HA2, and HA3 represent three hot/air pollution-related weather types; CA is cold/air pollution-related weather types; O3, NO2, SO2, CO, and COH are each pollutant-related weather types; and OT is "other" weather types. Tor, Mon, Ott, and Win indicated the four cities: Toronto, Montreal, Ottawa, and Windsor. Legend "left-to-right" is equivalent to bars "bottom-to-top"

Air mass classification: an important new dimension

Elevated mortality associated with weather and air pollution

Figure 9 shows the results of the impacts of extreme temperatures (heat/cold) and air pollution on elevated non-traumatic mortality for the selected four cities. A mean annual total elevated mortality was calculated for all days within each of the ten weather groups (three hot weather types, five air pollution-related groups, cold, and other) divided by the total number of years. Generally, the proportion of elevated mortality associated with extreme temperatures and air pollution was consistent across the study area. Extreme temperature-related weather events were usually associated with over 20% of mean annual total elevated mortality; air pollution was related to the remaining 80% of elevated mortality. In air pollution-related weather types, three pollutants (O_3, SO_2, and NO_2) were associated with about 75% of the total air pollution-related elevated mortality across the study area. The remaining 25% of the total air pollution-related mortality were almost evenly associated with other two pollutants (COH and CO) used in the study. Of the five pollutants, O_3 was the most highly associated with elevated mortality in each of the cities, responsible for one-third of the total air pollution-related mortality. Although "other" weather types are usually associated with better air quality and comfortable weather conditions, elevated mortality within the "other" weather types was still found to be associated with air pollution. In summary, air pollution will be present in all weather types: in the really hot weather types, most elevated mortality is due to heat; in those weather types where air pollution is the dominant problem, most elevated mortality is due to air pollution; and in the "nice weather, low pollution" weather type, most of the remaining (but likely numerically small) elevated mortality is due to air pollution.

City-to-city comparisons

Elevated mortality related to extreme hot weather (HA1), on average, was much higher in the two bigger cities (as expected: 38 and 41 deaths for Toronto and Montreal) than in the two smaller cities (13 and 8 deaths for Ottawa and Windsor). When expressed in terms of average population over the period, the numbers are 21.5, 26.1, 26.5 and 46.7 deaths per million population for Toronto, Montreal, Ottawa and Windsor respectively. In addition, the percentage of total elevated mortality associated with air pollution-related weather types in Windsor was slightly higher than for the rest of the cities; the corresponding value for the "other" weather types in Ottawa was the highest of the four cities.

Air pollution results specific to Toronto

The annual total air pollution-related mortality for Toronto as determined by this study is consistent with the findings of another recent study (Toronto Public Health 2004). Toronto Public Health (2004) estimated about 1,700 premature deaths related to air pollution in Toronto (based on 1999 data) including both acute and chronic exposures to pollutants (PM, SO_2, CO, NO_2, SO_2, O_3), and of these there were 695 deaths attributable to acute effects. From the Full Technical Study for the period 1954-2000, the yearly average number of elevated mortality events associated with extreme temperatures and air pollution for Toronto was 1047. When the value specific to 1999 was estimated, it was 964; and elevated mortality events due only to air pollution was 705. This was to be expected, for two reasons: first, the present study only considered acute effects of extreme temperatures and air pollution on human mortality; and second, the general trend for air pollution over the 45 years has been a reduction of levels of air pollution. It is noteworthy that, although the methodology used in both studies was different, the air pollution-related mortality findings were similar.

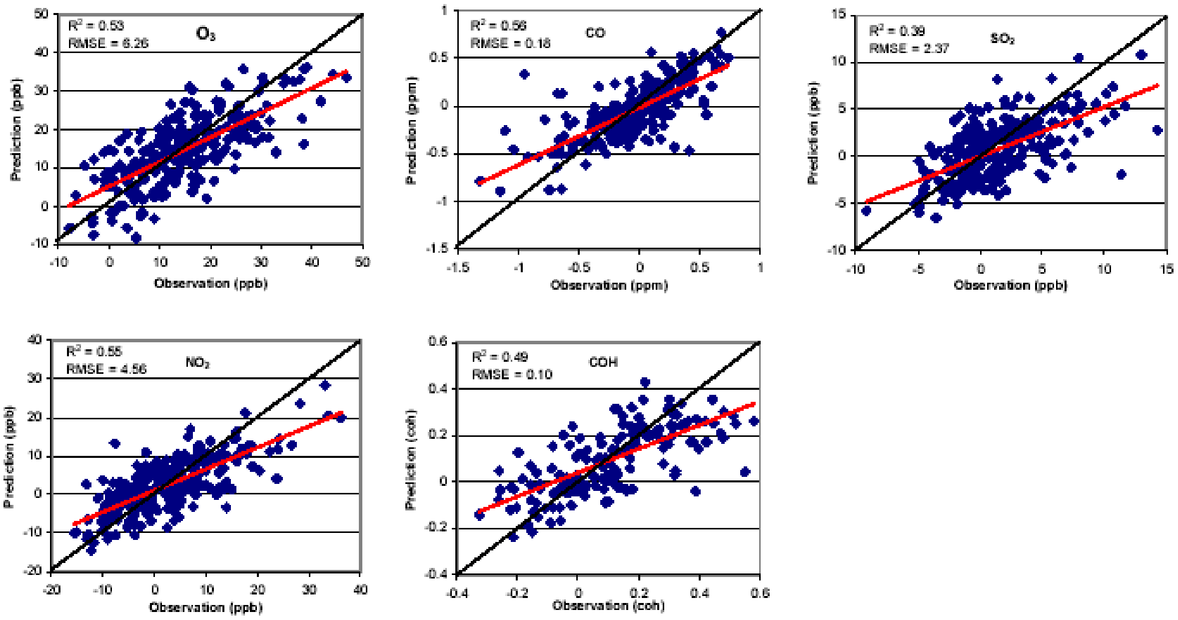
Day-by-day assessment and modelling of mortality by air-mass

The analysis so far has been able to assign the *annual mean* burden of illness (in terms of elevated mortality) associated with extreme weather and air pollution as defined by air masses in the four cities. The investigators set themselves two more important tasks, however: (a) the development of a model system that can be used (for each air-mass) to assess the changing meteorological and air pollution factors that contribute to the *day-to-day variability* in mortality, and to use the coefficients from this assessment to forecast mortality based on current or forecast daily weather and air pollution information; and (b), the application of the daily model, in conjunction with existing Global Climate Models (GCMs), suitably adapted, to assess the *impact of climate change* on public health associated with extreme weather and air pollution, in terms of elevated mortality and frequency of severe temperature-related weather events and high air pollution episodes.

Development of Air Pollution "day-to-day" Prediction Models

Synoptic weather typing approaches facilitate analyses of climatic impact on air quality because they characterize *similarities* in atmospheric circulation patterns and active meteorological elements within a holistic framework. However, the *differences* remaining within the four major weather groups (hot, cold, air pollution-related, other) were used to develop within-weather-type air pollution prediction models. Since there is variability from one day to the next in both weather conditions and air quality, a regression procedure was performed on all days within each weather group to determine which environmental factors were contributing the most to high air pollution concentrations for each of five selected pollutants. To avoid the problems associated with collinearity among the explanatory variables, an orthogonal regression procedure was used as before (in the development of elevated mortality prediction models). PCA was employed for all normally distributed variables to transfer linearly intercorrelated variables into a number of linearly independent component variables; and component scores were then used with other non-normally distributed dummy variables for development of regression models. The "dummy variables" included the "previous day air pollution anomaly" and seasonal and day-of-week functions. The dependent (output) variables are the daily mean and one-hour maximum concentrations of O_3, CO, COH, SO_2, and NO_2 (refer to the Full technical report, Section 5.6 for details).

Figure 10. Validation dataset: relationships between observed air pollution concentrations and predicted values for the hot weather types in Toronto (red line represents a regression line and black line is a perfect line)



The "validation" data-set was used to compare daily values predicted by the model to observed actual values: as an example, the results for the "hot weather types" of air mass in Toronto are shown in Figure 10. In general there is good agreement, although there seems to be a trend to overestimate at low pollutant levels, and underestimate at high levels. The same observations with respect to agreement between observed and predicted values were found in the developmental data-set.

Regression analyses on elevated mortality

As a first step, the same general method (as that described for air pollution above) was used to predict within weather-type daily elevated mortality on the basis of daily weather and air pollution values.

Predictors used in the regression procedure were derived from air pollution measurements, as well as hourly surface weather observations and six-hourly upper-air interpolated data. PCA was employed for all normally distributed variables in order to transfer linearly intercorrelated variables into a number of linearly independent component variables; component scores were then used with other non-normally distributed dummy variables to develop regression models. The dummy variables were defined to consider health impacts of extreme temperatures and high air pollution concentrations as well as event episodes.

Logistic regression was used in the study to develop heat/air pollution-health prediction models, because the results from logistic regression were better than those from other regression methods tested in the study. A logistic regression methodology was used that followed the method of maximum likelihood, which is a popular and widely used method for estimating a variety of statistical models. The dependent variable was set to one when daily elevated mortality existed (i.e., daily mortality anomaly against baseline was greater than zero); otherwise, it was set to zero. The output from the logistic regression procedure is easy to interpret in practice, as it is in the form of probability of elevated mortality occurrence. The stepwise logistic regression was employed for all days within each of three hot weather types.

Note that this methodology was designed to predict daily elevated mortality events, and not the magnitude of the elevated mortality. There could be several premature deaths occurring during a single elevated mortality event. Also, there could be several daily elevated mortality events in an adverse weather episode lasting for a number of days.

Table 1. Annual mean occurrence of elevated mortality events identified in the three hot-weather-type prediction models and the associated level of post agreement, classified by logistic regression probability

Logistic Probability	Montreal		Ottawa		Toronto		Windsor	
	AMO*	PA**	AMO	PA	AMO	PA	AMO	PA
$0.9	5	96%	1	92%	2.54	85%	1.77	91%
0.8 - 0.9	5.39	77%	2	85%	2	85%	1.69	86%
0.6 - 0.8	11.33	70%	6.31	72%	17.46	66%	9.08	61%

* Annual mean occurrence (AMO) of elevated mortality events
** Post Agreement (PA) represents the number of correct predictions divided by the total number of predictions for elevated mortality events, with a perfect PA equal to one (or 100%).

Annual mean occurrence of elevated mortality events identified by the three hot-weather-type prediction models (HA1, HA2, HA3) and their post agreements were calculated for the whole period with combination of model development and validation data sets (Table 1). The number of elevated mortality events identified by the models varied from city to city, with 5.0, 2.5, 1.8, and 1.0 days per year for Montreal, Toronto, Windsor, and Ottawa, respectively, when a logistic probability of 0.9 was used as a cut-off. The corresponding post agreement for those identified elevated mortality events was very high, ranging from 85% to 100%. The number of identified days with elevated mortality deaths depends on the strength of the prediction models. The stronger the model, the greater the number of days with elevated mortality that are identified correctly. For 80 and 90% probability there was 85% agreement with observations, but with 60% probability only 66% agreement. For the purposes of development of alert systems for other cities, it is recommended that various cut-off probability thresholds be evaluated to balance the number of “advisories” or “warnings” given (and reduce the number of “false alarms”).

Outcome of this step

As a result of the work to this point, it is possible to design a combined heat/ air pollution advisory / warning system for each of the four cities studied, based on data in real time, or forecast in the near (24-48 hr) future. In order to have the statistical power to achieve this, however, it was necessary to combine data for all three hot-weather-type classes. To deal with the other air mass classes, it was necessary to employ a different approach, as described briefly in the next section. The Cheng *et al.* model for a heat-health warning system is a different design from that currently being evaluated for Toronto, since it also includes air quality, and for this reason the number of “alerts” forecast by the two systems may be different.[10]

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[10] The current Toronto HHAS determines an “Extreme Heat Alert” when the probability of increased mortality is greater than 90%; a “Heat Alert” from 65-89%.

Elevated Mortality Prediction Models from Multiple Regression Analysis

The daily mortality regression results showed that there was a strong relationship between elevated mortality and the model predictions in the hot weather types, but it was necessary to use a different regression procedure for the rest of the weather types in order to obtain suitable regression models. Within each of the eight weather groups (hot, cold, comfortable, and five air pollutant-related weather types), the data were regrouped using a ranking procedure. The advantage of the ranking procedure is to enhance relationships between elevated mortality and the ranking factor within a certain weather or air pollution type as well as to eliminate other factors' impacts. For the weather types (hot and cold) the 3 pm temperature was used for ranking; and for the air pollution types, the strongest air pollution component was used. The independent variables, including weather and air pollution predictors, were the same as previously used, with the exclusion of the "dummy variables". Mean PCA scores of the predictors within each of the ranking groups were used to develop elevated mortality prediction models. For comfortable ("other") weather types, five air pollutants were tested for ranking the data; the strongest model was used for the analysis. As a result of testing, O_3 was used to rank data for development of elevated mortality prediction models in comfortable weather types for Montreal and SO_2 was selected for the rest of the cities.

Different lag times (0–4 lag days) were also tested to develop prediction models; the strongest one was selected for the analysis. Across the study area, the no-lag-time prediction model in hot weather types was usually more significant than other lag-time models. For the rest of the weather types (e.g., pollution-related or cold), most of the prediction models were more significant with one day lag or no lag time between the deaths and environmental factors.

Many weather variables (such as surface and upper-air temperatures, humidex, wind chill) and all selected pollutants (O_3, CO, COH, NO_2, SO_2) were statistically significantly associated with elevated mortality in the different weather types. The relationships between elevated mortality and weather and air pollution predictors are outlined as follows:

1. Thermal and moisture weather variables, but not air pollutants, were significantly associated with elevated mortality in the hot weather types for Montreal; however, in the other cities, both temperature and O_3 were statistically significantly found to contribute to elevated mortality.
2. In cold weather types, low temperatures, low windchill equivalent temperatures, and high air pollution concentrations contributed to elevated mortality across the study area.
3. In five pollutant-related weather types, both weather and air pollution conditions were significantly important to elevated mortality in all the selected cities.
4. In comfortable weather types, air pollution levels, but not weather variables, were significantly associated with elevated mortality across the study area.

Although these models resulted from ranking group data rather than using daily values, the models can provide useful information on overall impacts of combined weather and air pollution on human mortality. These models have the potential for short-term prediction of elevated mortality associated with current climate and air pollution conditions and long-term estimation under future climate and air pollution scenarios. However, unlike the logistic regression models within the hot weather types, these prediction models are not suitable to develop a daily-based weather and air pollution-related elevated mortality forecast system since they were not built using daily information. In order to develop daily based cold weather or air pollution/- health prediction models, more research is warranted on relationships between weather/air pollution and human health using health outcome data with a much larger number of daily events (e.g., hospital admissions and/or emergency visits).

Results from Snowfall and Freezing Rain Impacts on Elevated Mortality

Mortality from ischaemic heart diseases for three winter months (December–February, 1954–1999) was analyzed in relation to snowfall, assessed two ways. The first, examination of mean daily mortality from ischaemic heart disease for snowy days and snow-free days, and also with snowfall amount one standard deviation above the overall mean. The relationships between snowfall and mortality was evaluated on the day of the snowfall (zero lag), as well as one, two, and up to a few days after the snowfall event.

From Table 2, it is seen that mortality from ischaemic heart disease significantly increased with snow occurring on the same day and the previous day of the deaths across the study area. For example, in Montreal and Toronto respectively, the difference in mortality between days with a snowfall amount one standard deviation above the overall mean and snow-free days was 0.94 and 0.84 (an increase of 55% and 56% in comparison with daily mean deaths of snow-free days).

Table 2. Difference in daily mean mortality from ischaemic heart disease between snowy days and snow-free days in winter season (December–February), 1954–1999

City	Montreal		Ottawa		Toronto		Windsor	
Lag time	All snowy days	Snow (1 std + m)	All snowy days	Snow (1 std + m)	All snowy days	Snow (1 std + m)	All snowy days	Snow (1 std + m)
Lag 0 days	0.23**	0.51**	0.05	0.17**	0.08	0.39*	0.05*	0.04
Lag 1 day	0.19	0.94**	0.06	0.22**	0.23**	0.84**	0.08**	0.18**
Lag 2 days	0.11	0.32	0.05	0.09	0.18*	0.58**	0.09**	0.12
Lag 3 days	0.02	-0.11	0	0.02	0.08	0.43*	0.05	0.11*
Lag 4 days	-0.17	0.3	-0.12	-0.18	0.25	0.17	0.07	0.07

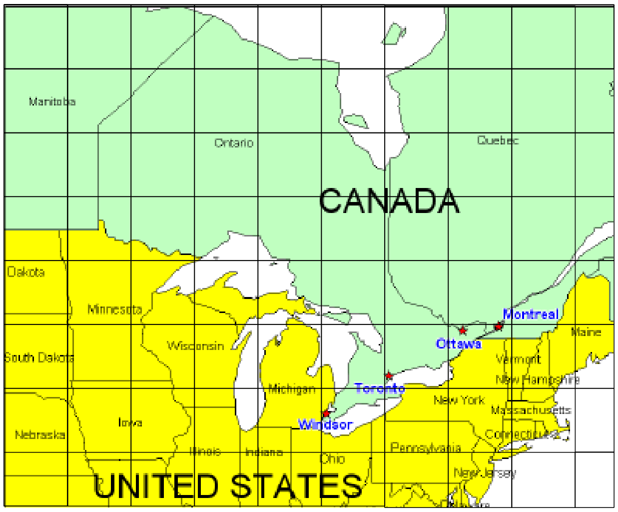
Notes: (1sd+m) means snowfall 1 standard deviation above the mean.
* t-test $p < 0.05$; ** t-test $p < 0.01$

Results from analysis of freezing rain events showed a trend for increased traffic accidental mortality (a separate category from non-traumatic mortality), especially for Toronto, but the difference was not statistically significant. Studies of the effects of pollen on respiratory mortality did not show significant results.

Potential Impacts of Climate Change on Elevated Mortality

To estimate trends and changes in elevated acute mortality from adverse weather events and air pollution that might occur with projected global climatic warming, it is necessary to assess changes in the number of days within weather types classified by historical data. It is expected that all weather variables used in weather typing will be modified as a result of climate change. Daily climate change scenarios for the 2050s and 2080s, when CO_2 is expected to double and triple relative to the 1975–1995 level, were used to estimate changes in the number of days within weather types. To achieve these goals, statistical downscaling methods were used.

Figure 11. Map of domain for downscaling GCM scenarios. Grid lines at approximately 300km intervals are shown for illustration only.



Statistical Downscaling Methods

Projections from Global Climate Models (GCMs) are currently used as scenarios of future climate in the 21st century. However, due to their coarse spatial resolution (typically 300 km x 300 km in the tropics), GCMs are restricted in their usefulness for projecting weather phenomena at a city level. As an illustration, we can see in Figure 11 that it might be possible that Ottawa and Montreal could fall within the same grid space, and the "coarse" GCM would project identical weather scenarios for both. As a result, GCM outputs must be converted or downscaled to specific weather stations of interest, using historical observed weather data to assess local impacts.

One accepted technique for doing this is statistical (empirical) downscaling. Since station-scale weather information was required for this study, the statistical downscaling method was used to downscale daily GCM outputs to the locations of weather observation stations in the four selected cities. The future hourly scenarios were derived from the historical relationships between the hourly observation and its daily mean as well as other weather predictors.

Since synoptic weather patterns are markedly different in summer and winter seasons, the year was divided into a summer season (April–September) and a winter season (October–March). Downscaling was applied to these two seasons separately.

Steps in downscaling

The statistical downscaling methods used in the study consist of five steps:

1. Selection of the GCM domain (as shown in Figure 11), and regridding interpolated weather data to the GCM model grids.
2. Principal component analysis (PCA)
3. Regression model development
4. Downscaling daily GCM scenarios
5. Deriving future 6- hourly data at the four cities according to various GCM scenarios

The details of the methodology are provided in the full technical report, Section 4.4.1; the results are given in 5.10.1.

In a manner similar to the methods used to validate the other models developed in this study, the projected weather values from Canadian Coupled GCM historical runs (1961-2000) were compared with weather observations at the study sites. These results suggest that the downscaling methods developed for this study performed well in downscaling hourly weather variables, and thus may be relied upon to give reliable projections of future weather using different GCM scenarios. An example of this type of comparison for Toronto is given in Figure 39, the full technical report .

The results of the downscaling process provide predicted future daily and hourly weather values according to different climate change scenarios. These are then applied to the same models which have been developed in this study; to estimate the impact of CO2-driven climate change on air pollution and elevated mortality, as well as the occurrence of episodes of extreme temperature-related weather events and /or high air pollution episodes which are projected to occur. This is shown as the “third objective” in Figure 1.

Impact of climate change on air pollution

To clearly show changes in the number of days with high/low air pollution categories in response to climate change scenarios, results from the five GCM scenarios were averaged for each city and each pollutant emission policy scenario. According to the results, across the study area the number of low O_3 days would decrease and the number of high O_3 days would increase under the three emission scenarios. Under the pollution emission scenario III for all pollutants, the number of low pollution days would generally decrease, and the number of high pollution days would increase, in response to climate change.

Results for Toronto are shown in Table 3. For Scenario II, representing pollutant emissions maintaining current levels, in general climate change will lead to increased high air pollution days, and decreased low air pollution days, especially for ozone. For Scenario III, representing increased emissions, this coupled with climate change leads to many fewer “low” days and increased moderate or high days for all pollutants.

Table 3. Projected changes for Toronto in mean annual number of days within high/low air pollution categories, depending on 3 air pollution control scenarios, and associated with climate change as determined by an average of the five GCM scenarios.

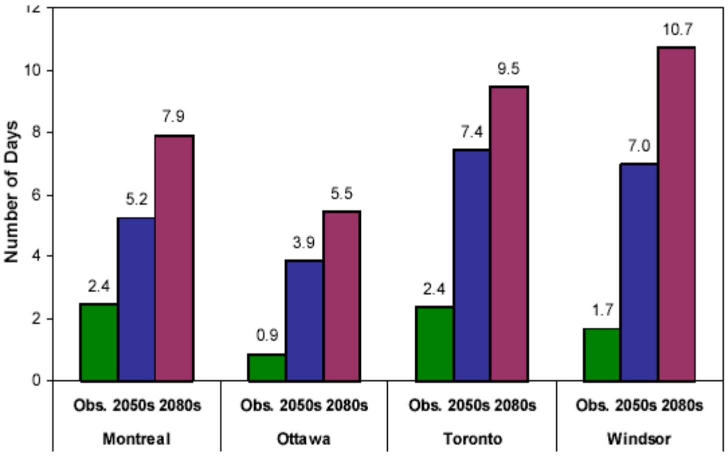
Pollutant	Pollut Categ	Days (obs)	Air Pollution Scenario I		Air Pollution Scenario II		Air Pollution Scenario III	
			2050	2080	2050	2080	2050	2080
O3	High	8.0	1.8	2.7	4.2	7.7	8.9	15.3
	Mod	48.2	14.6	10.6	22.2	23.8	30.8	36.3
	Low	308.8	-16.4	-13.3	-26.4	-31.5	-39.7	-51.6
CO	High	68.1	9.0	-9.6	45.0	46.2	88.2	118.0
	Mod	183.8	-77.6	-84.4	-68.6	-64.7	-71.5	-75.0
	Low	113.1	68.6	94.0	23.6	18.5	-16.7	-43.0
COH	High	73.8	-14.2	-26.8	19.8	23.3	62.2	94.0
	Mod	121.1	-11.0	-23.9	7.4	3.5	13.7	4.2
	Low	170.1	25.2	50.7	-27.2	-26.8	-75.9	-98.2.
NO2	High	61.1	-24.1	-37.2	17.6	20.0	81.7	121.7
	Mod	147.5	-42.2	-67.9	-10.0	-15.2	-4.3	-17.8
	Low	156.4	66.3	105.1	-7.6	-4.8	-77.4	-103.9
SO2	High	29.7	-2.7	-5.8	4.3	5.0	12.8	18.5
	Mod	86.5	-2.5	-8.9	7.4	6.5	17.1	22.9
	Low	248.8	5.2	14.7	-11.7	-11.5	-29.9	-41.4

Notes: Pollution Categories: “High” for O3 $81 ppb; rest of pollutants, one standard deviation above the mean; “Low” for O3 # 50 ppb; rest of pollutants, below the mean; “Moderate”, between “high” and “low”. Scenarios **I**, **II**, and **III** represent three air pollution policy emission scenarios: (**I**) a decrease of 20% and 32% by 2050 and 2080, (**II**) maintenance of the same level as at the end of the 20th century, and (**III**) an increase of 20% and 32% by 2050 and 2080.

Heat-Health Warnings

Results from mortality prediction models in the full technical report for the hottest weather type (HA1) can be associated with a potential set of rules that might be used to give public health warnings (or “alerts”). The number of alerts using these rules was applied to current (observed) data, as well as future weather estimates, as shown in Figure 12. The number of heat-health warning alerts

Figure 12. Projected number of “Extreme Heat Alert” Days from the hottest weather type (HA1)

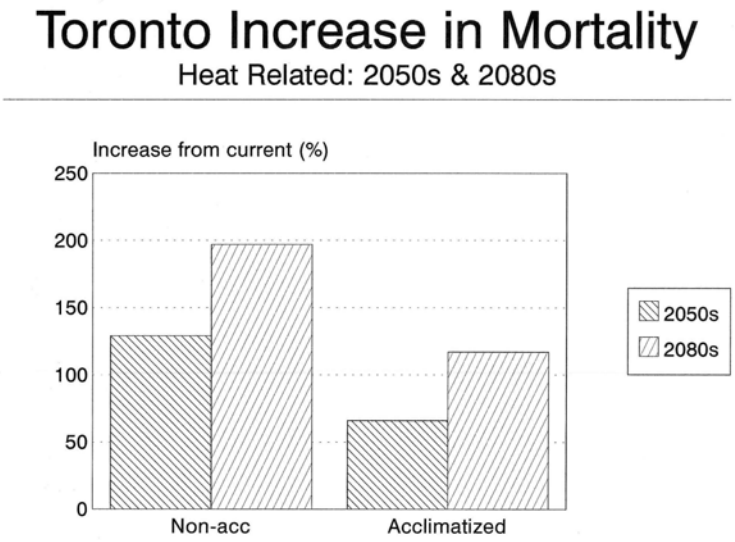


are projected to increase dramatically toward the end of this century.

Heat-related elevated mortality

This study has estimated that currently there are 120 premature deaths annually, associated with three hot weather types for Toronto (Full technical report Table 28). Global Climate Models all project increases in global warming, but there is evidence that populations tend to acclimatize to increased heat: the extent to which this happens is unclear. The full technical report has made an estimate of acclimatization, and for the sake of comparison, both non-acclimatized and acclimatized estimates have been developed, as shown in Figure 13. Elevated heat-related mortality is projected to double or triple by the end of the century. Estimates also showed an approximate 70% decreased premature mortality associated with cold weather events in the same period.

Figure 13. Projected percent increase in annual Toronto heat-related mortality, using average of 5 GCM models.



Air pollution related elevated mortality

With no increase in emissions (Scenario II), air pollution related mortality could increase by from 25 to 45% in the four cities by the end of the century: for Toronto the figure could be approximately 25% (Figure 14). The increase in the study area would be largely driven by increases in ozone-associated elevated mortality.

Figure 14. Projected percent increase in annual air-pollution-related mortality in the 4 cities, using average of 5 GCM models, and according to the three air pollution scenarios.