3B.3 AN AUTOMATED SYNOPTIC TYPING PROCEDURE TO PREDICT FREEZING RAIN: AN APPLICATION TO OTTAWA, ONTARIO

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1. INTRODUCTION

Freezing rain is a major hazard which affects many parts of Canada; however, it is especially common in a corridor from Ontario to Newfoundland (Regan 1998; Stuart and Isaac 1999). In Ontario, freezing rain is most common in the Ottawa River Valley when "warm" precipitation falls into a shallow sub-freezing layer trapped within the valley basin. On average (for the period 1953/54 - 2000/01), Ottawa International Airport reported freezing rain 10 days a year, for a total of 38 h yr^{-1}. Of course, there are years when freezing rain is much more common; for example, during the winter of 1997/98, Ottawa received a total of 95 h of freezing rain. Sixty-five of these hours were recorded during the Ice Storm of January 5-9 1998. During this extreme ice storm, freezing rain accumulations of close to 70 mm water equivalent were recorded in Ottawa (Milton and Bourque 1999). Regan (1998) reported that the ice storm was responsible for 25 fatalities, left some 1 million householders without power, caused nearly US$3 billion in damages, and resulted in another US$3 billion in short-term lost economic output and insurance claims across Quebec and Ontario.

Ice Storm '98 was a reminder of just how vulnerable our society has become to severe freezing rain storms. As populations continue to increase and societies become even more urbanized, both the size and number of targets impacted by these severe winter storms will increase. Added to this vulnerability will be a continued dependence on electronics and an uninterrupted supply of electricity along with the dependence of businesses and industries on "just-in-time" delivery. As a result of these shifts, society has collectively become extremely vulnerable to the power of severe ice storms to interrupt supplies and distribution of electricity, water supplies, and communications and to delay ground and air-based transportation. In order to be better prepared for future severe ice storms, communities need to know current and future risks from severe ice storms of magnitudes approaching those of Ice Storm '98. Improved severe ice storm risk information and predictions will allow better emergency planning in regions or communities identified as more at risk from this hazard. This study will describe a synoptic map typing procedure that has potential to provide a tool to distinguish the more severe ice storms from less destructive freezing rain events, to serve as a prediction tool for operational meteorologists, to be used to diagnose and attribute synoptic contributions to severe ice storms and for study of trends in the synoptic components of these storms.

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Over the past decade, automated synoptic typing approaches have become popular for an evaluation of the impact of climate on environmental issues, particularly since these methodologies characterize similarities in active meteorological elements within a holistic framework (Kalkstein et al. 1987). Environmental issues treated using these methodologies include air quality (Kalkstein and Corrigan 1986; Eder et al. 1994; McGregor and Bamzelis 1995; Lam and Cheng 1998; Cheng and Lam 2000), human health (Kalkstein 1991; Cheng 1991; Kalkstein et al. 1997; McGregor et al. 1999) and climate research (Kalkstein et al. 1990; Cheng and Kalkstein 1993, 1997). To date, the automated synoptic typing approach has shown considerable world-wide success for the prediction of air pollution concentrations and heat-related mortalities. However, it appears that this strictly automatic approach has not been applied to the assessment and prediction of freezing rain events. The objective of this study, therefore, was to develop a new method - a quantitative, automated synoptic typing - to assess and predict air masses or weather types most highly associated with historical freezing rain events. Within-synoptic-type logistic regression analysis was applied to predict the likelihood of freezing rain occurrence for the study area.

2. DATA SOURCES AND TREATMENT

Hourly surface meteorological data for Ottawa International Airport were retrieved from Environment Canada's Digital Archive of Canadian Climatological Data for the winter months (Nov.-Apr.) of 1958/59-2000/01. The meteorological data used in this study included hourly weather station observations of air temperature (°C), dew point temperature (°C), sea-level air pressure (hPa), total cloud cover (tenths of sky cover), wind speed (m s^{-1}), wind direction (degrees), and occurrence of freezing rain (1 for yes or 0 for no). A sine-cosine transformation was used to convert wind speed and direction into southerly and westerly scalar velocities. With the exception of freezing rain occurrence, missing data were interpolated using a temporal linear method when the data were missing for 3 consecutive hours or less; otherwise, days with data missing for 4 or more consecutive hours were excluded from the analysis. For Ottawa, only 0.04% of the total hours required missing data interpolation; after interpolation, the dataset was 100% complete.

The 6-hourly upper-air reanalysis weather data were retrieved from the National Centers for Environmental Prediction (NCEP) website. The reanalysis data (Kalnay et al. 1996; Kistler et al. 2001) were available daily for 0600, 1200, 1800, and next day 0000 UTC for the period 1958-2001 and included a variety of meteorological variables on a 2.5^{o} x 2.5^{o} latitude-longitude grid at 17 standard upper-air pressure levels, including air temperature (^{o}C), relative humidity (%), geopotential height (m), vertical velocity (Ω, Pa s^{-1}), west-east and south-north wind velocities (m s^{-1}). Data from only 6 pressure levels: 1000, 925, 850, 700, 600 and 500 hPa were used in this study since the atmospheric parameters needed to determine both production and type of precipitation are primarily confined to levels below 500 hPa. Although the reanalysis data were available for the entire 54 year period 1948-2001, only the data for the period 1958-2001 were used in this study. Prior to 1958, the reanalysis data were based on observations taken 3 h later than the current synoptic time (e.g., 0300, 0900, 1500, and 2100 UTC) (Kistler et al. 2001). This is not consistent with the reanalysis data after 1958 which are valid for the same hours that observations were taken (e.g. 0000, 0600, 1200 and 1800 UTC).

For this study, the NCEP-NCAR reanalysis relative humidity data field was converted into dew point temperature based on Tetens' equation (Berry et al. 1945). Dew point temperature was preferred over relative humidity since it is highly conservative on a diurnal level and moderately conservative among various micro-environments (Kalkstein and Corrigan 1986). In order to combine the gridded reanalysis data with the surface weather data, the reanalysis data were interpolated for the Ottawa International Airport site using the inverse-distance method.

In order to create two independent datasets, the surface and upper-air reanalysis weather data were divided into two parts: a developmental dataset (1958/59-1990/91) used for construction of the model and a validation dataset (1991/92-2000/01) used to test the model.

3. ANALYSIS TECHNIQUES

3.1 *Automated Synoptic Typing*

An automated synoptic typing procedure, based primarily on air mass differentiation, was used to assign every day of the developmental dataset to a distinctive weather type. The surface weather data used in the study included the following variables: hourly surface weather observations of air temperature, dew point temperature, sea-level air pressure, total cloud cover, south-north and west-east scalar wind velocities. The 24 different times and 6 different weather elements produced 144 surface weather variables. The upper-air reanalysis data used in the study included the weather variables of air temperature, dew point temperature and south-north and west-east scalar wind velocities at 6-hour intervals and 6 atmospheric levels, which produced 96 upper-air weather variables. The entire suite of 240 surface and upper-air weather variables was used in the synoptic typing procedure.

This synoptic typing procedure produces a temporal synoptic index using principal components analysis (PCA) (Jolliffe 1986) and a hierarchical agglomerative clustering procedure. Since the number of weather types is not predetermined, a hierarchical agglomerative clustering procedure is suitable for this study (Kalkstein et al. 1996a, 1996b; Cheng and Kalkstein 1997; Cheng and Lam 2000).

3.2 *Identification of the Weather Types Most Highly Associated with Freezing Rain Events*

The occurrence of freezing rain was used in the identification of the synoptic types which are most highly associated with those events. The occurrence frequency of freezing rain for each type was then determined to ascertain whether the frequency of freezing rain within a particular type was distinctively high or low. In addition, a ratio of the type's association with freezing rain events (actual frequency) to the occurrence of the type in the entire record (expected frequency) was utilized to determine whether any of the categories were over-represented for freezing rain events. Types with ratios significantly greater than 1.0 had a greater proportion of days with freezing rain events than would be expected based on the frequency of the weather type. The statistical χ^2-test was employed to determine whether or not the theoretical frequency among the freezing rain events was significantly higher than the expected frequency. This method was then applied to specific hourly categories, such as $\geq$1, $\geq$4 and $\geq$6 h, representing the number of hours when freezing rain was observed during a day (0:00 – 23:00 LST).

3.3 *Development of Freezing Rain Prediction Model*

Although the weather conditions for each day within a weather type are most similar to each other, there still exists some degree of within-category variance. Furthermore, not all days within an identified freezing rain type possess freezing rain events. Therefore, the day-to-day variation of weather conditions within an identified category could be important to the occurrence or non-occurrence of freezing rain. A stepwise logistic regression procedure was performed on all days within the identified weather types most highly associated with freezing rain to determine which meteorological factors were the most significant in contributing to freezing rain events. The logistic regression procedure was the preferred prediction model for this study since the measurement data represented a dichotomous variable (taking the value of either 1 or 0 for occurrence or non-occurrence of freezing rain) (Chap 1998; Allison 1999). As well, the output from this regression procedure, in the form of probability of freezing rain occurrence, was easy to interpret.

Predictors used in the regression procedure were derived from hourly surface observations and 6-hourly upper-air reanalysis data. In order to avoid multicollinearity, the hourly surface temperatures alone were not used as predictors since they were used to derive other variables. The predictors were straightforward, with the exception of some of the derived predictors that are described in the following sections. A wind direction index (WDI) was used in the regression analysis since the wind direction angle is discontinuous at 360°. The WDI is defined differently for the surface and upper-air winds since predominant wind directions tend to be different between the surface and upper level under freezing rain conditions. The surface WDI was defined as follows:

$$WDI = 1 + \sin(\theta) ,$$

where θ is the wind direction expressed in radians. This index ensured that the WDI attains its maximum value of 2 when the surface wind is from the east and its minimum value of 0 when the surface wind is from the west. These values corresponded to the maximum and minimum occurrence frequency of freezing rain events in Ottawa, respectively. For upper-air winds, the WDI was modified as follows:

$$WDI = 1 - \sin(\theta + \frac{\pi}{4}) \cdot$$

In this case, the WDI reached its maximum value when the upper winds were from the southwest and its minimum value when the upper winds were from the northeast, coinciding with the maximum and minimum occurrence frequency of freezing rain events in Ottawa.

Warm- and cold-layer variables were also used in the stepwise logistic regression and measured in temperature-height coordinates over the depth of the layer. A variable termed the warm area was defined as the area between the 0°C axis and the portion of the temperature profile that is greater than 0°C aloft and measured in m °C. Similarly the cold area was defined as the area between the 0°C axis and the temperature profile that is less than 0°C near the surface. The heights of the warm and cold layer tops are measured in m above ground level. When required, a linear interpolation with respect to height was used to determine the warm and cold layer variables. The dew point temperature areas and heights were derived using a similar method. Another set of the variables represented the difference between the maximum temperature at the 6 upper levels and the surface temperature in °C. All of these warm- and cold-layer variables were only calculated when the warm and cold layers were present (i.e., the temperature profile must possess a value >0°C aloft and ≤0°C near the surface); otherwise, they were set to zero.

The logistic regression methodology used a model that followed the method of maximum likelihood, which is a popular and widely used method of estimation for a variety of statistical models (Allison 1999). Accordingly, the dependent variable was set to 1 when freezing rain occurred on at least 1 hourly observation during a day; otherwise, it was set to 0. The stepwise logistic regression was then employed for all days within the identified weather types most highly associated with freezing rain events. For *k* explanatory variables and *i* = 1, …, n individual cases, the logistic equation for predicting the likelihood of freezing rain events was given by

$$p_i = \frac{e^{\alpha+\beta_1 x_{i1}+\beta_2 x_{i2}+\ldots+\beta_k x_{ik}}}{1+e^{\alpha+\beta_1 x_{i1}+\beta_2 x_{i2}+\ldots+\beta_k x_{ik}}},$$

where p_i is the probability of freezing rain occurrence; x is a predictor; a and β are parameters of the model.

3.4 *Validation of the Model*

The developed model was verified for the independent or validation dataset during the winter seasons (Nov.-Apr.) from 1991/92 to 2000/01. The evaluation was divided into two steps: (1) weather type verification and (2) logistic regression model verification. For weather type verification, component scores for each day of the validation dataset were determined by multiplying the post-eigenvector matrix (using data from 1958-1991) by validation data matrix. The new component scores were used to compare with the original scores since both used the same eigenvector matrix. Based on the new component scores, discriminant function analysis was used to assign each of all days within the validation dataset into one of the predetermined weather types using the centroids of the weather types as seeds. Since the weather types and their respective characteristics have already been predetermined, discriminant analysis is an appropriate tool to assign each day of the validation dataset into one of the predetermined weather types (Klecka 1980, Lam and Cheng 1998).

Following determination of the weather type for each day of the validation dataset, a within-category logistic regression algorithm from the developed model was used to predict the probability of freezing rain occurrence within the weather types that were most highly associated with freezing rain. These results were then compared with actual freezing rain observations within the validation dataset to assess the validity of the prediction model.

4. RESULTS AND DISCUSSIONS

4.1 *Developmental Dataset: Identification of Synoptic Types Associated with Freezing Rain*

The PCA was applied to the 240 weather variables for all days within the winter season from 1958/59 to 1990/91, producing an 18-component solution that explained 92% of the total variance within the developmental dataset. The remainder of the components with resulting eigenvalues less than one were discarded. The thermodynamic variables (air temperature and dewpoint) were found to be the main contributors to component 1, explaining over 36% of the total variance. Sea-level pressure, total cloud cover, and south-north wind velocity aloft also contributed to component 1. The loadings for component 2, explaining an additional 17% of the total variance, were dominated by west-east wind velocity and sea-level pressure. Component 3, explaining over 10% of the variance, was largely dominated by south-north surface wind velocity and winds aloft. Component 4, explaining nearly 10% of the variance, was largely determined by sea-level pressure and total cloud cover. The remaining components 5-18 explained nearly 20% of the total variance and were largely comprised of terms that describe the diurnal changes of the variables.

The average linkage clustering procedure was employed to derive clusters possessing similar large-scale synoptic characteristics in terms of the daily 18-component scores. Determination of the cluster number to retain was achieved through a variety of statistical tests which included: the semipartial R^2, pseudo-F, pseudo-t^2, and explained variance R^2. The semipartial R^2 is the ratio of the increased within-cluster variance after joining two clusters to the variance for the entire dataset. The pseudo-F is the ratio of between-cluster to within-cluster variances. The pseudo-t^2 is the ratio of the increased within-category variance after joining two clusters to the variance within each of two clusters (SAS Institute Inc. 1999; Eder et al. 1994). The number of weather types for retention in the model is determined by observing the largest decrease in R^2, the largest increase in both the semipartial R^2 and pseudo-t^2, after joining two clusters, and a local maximum in the pseudo-F.

Using the above procedures, 13 major synoptic weather types were identified for Ottawa for all days within the winter season of 1958/59-90/91 based on differences in their meteorological characteristics. These 13 major synoptic weather types represented 85% of the total number of days during the period. The smaller synoptic weather types, which comprised the remaining 15% of the days, were removed from the analysis. These smaller types were largely made up of days which either had no freezing rain occurrence or freezing rain events involving 1 h during a day.

To identify the synoptic types most highly associated with freezing rain events, a category frequency ratio was calculated. This ratio compares the percentage frequency of days with freezing rain events (actual frequency) to the percentage frequency of the weather type within the entire record (expected frequency). If a weather type possessed a reasonable number of freezing rain cases (i.e. greater than the number of the cases within each of the remaining non-freezing rain weather types) and the frequency ratio was >1.0, it was selected as a freezing rain-related weather type. Based on these two criteria, four synoptic types were identified over the 33 year period as the primary freezing rain weather types. These weather types accounted for 81%, 90% and 97% of the freezing rain events lasting greater than or equal to 1, 4 and 6 h during a day, respectively, at Ottawa International Airport.

4.2. *Developmental Dataset: Results from Stepwise Logistic Regression*

A stepwise logistic regression procedure was performed on all days within the 4 freezing rain weather types. The data sample used in the regression consisted of 1280 days, of which 266 days experienced freezing rain events occurring 1 h or more during a day. The freezing rain predictors which were identified in the stepwise logistic regression model with an entry and retention significance level of 0.05. The regression results are summarized as follows:

1. There is a significant correlation between the occurrence of freezing rain events and the model predictions, with a concordance of 91.5%. Concordance is a measure of the model performance and is commonly used for logistic regression (The model R^2, judging the overall fit of a multiple regression model, is not suitable for binary data analysis (Chap 1998; Chatterjee et al. 2000)).
2. The logistic regression model identified freezing rain predictors at Ottawa that included wind direction indices, temperature differences between the upper air and surface, 6 h temperature changes, and warm air advection. These predictors are consistent with the physical processes typically associated with freezing rain events. Based on the logistic regression model results, we can define the weather conditions associated with a high probability of freezing rain occurrence at Ottawa International Airport. These include: easterly-northeasterly surface winds and southwesterly winds at mid-atmospheric levels, the presence of a temperature inversion in the low-mid atmospheric levels with an associated air temperature >0^{o}C aloft and ≤0^{o}C at the surface, falling sea-level air pressure, high total cloud cover, increasing air temperatures aloft (i.e. warm air advection at mid-atmospheric levels), surface temperatures decreasing in the past 6 h, and dew point depression decreasing in the past 6 h (i.e. increasing moisture), both at the surface and mid-atmospheric levels. These results are corroborated in previous studies (Bocchieri 1980; Huffman and Norman 1988; Rauber et al. 2000).

When attempting to use multiple regression to develop a model, it is important to consider multicollinearity among the explanatory variables. Variance inflation factors (VIFs) can be used to identify multicollinearity. High VIFs indicate that two or more collinear independent variables are included in the model (Draper and Smith 1998). Chatterjee et al. (2000) suggested that a VIF in excess of 10 is an indication that multicollinearity may be causing problems in estimation. No strong collinear relationships existed within the explanatory predictors in this model since the VIF value of each predictor was less than 2 (Draper and Smith 1998; Lawrence and Arthur 1990; SAS Institute Inc. 1999). The largest VIF value of any of the predictors used in the model was 1.72, indicating that the largest multiple coefficient of determination (R^2) was 0.42 among the model explanatory predictors (VIF = $(1 – R^2)^{-1}$).

Using the probability of 0.6 as a threshold, the model was able to correctly identify 154 freezing rain cases lasting ≥1 h during a day, while yielding only 28 false alarms, resulting in a post agreement of 85% and a false alarm rate (FAR) of 15% for freezing rain events. The corresponding post agreement and FAR associated with a cut-off probability of 0.8 were 96% and 4%, respectively. Post agreement represents the number of correct predictions divided by the total number of predictions for freezing rain events, with a perfect post agreement equal to 1 (or 100%). The FAR is defined as (1 - post agreement) (Stanski et al. 1989). Of the 28 false alarms, snowfall/rainfall and freezing drizzle were observed on 19 and 6 days, respectively. Of the 369 days with no observed precipitation used in logistic regression analysis, only 3 days were incorrectly identified as freezing rain events with logistic probability ≥0.6.

It is noteworthy that this model may be particularly well suited for prediction of the occurrence of freezing rain events lasting several hours in duration. For example, the probability of detection (POD) resulting from the model was 58% for freezing rain events lasting ≥1 h during a day, but 89% for freezing rain events lasting ≥8 h during a day. POD is defined as the number of correct forecasts divided by the total number of observed in that category, with a perfect POD equal to1 (or 100%) (Stanski et al. 1989).

There are three factors which may have contributed to the shortfall in identifying some shorter duration freezing rain events. One factor is based on the limited temporal resolution of the NCEP-NCAR reanalysis data (every 6 h), which may contribute to difficulties in predicting events shorter than the temporal resolution of the data. The other two factors are related to limitations in the spatial and vertical resolution of the NCEP-NCAR reanalysis data. These resolution limitations likely contributed to short duration freezing rain events sometimes being observed when reanalysis data identified a minimal warm layer aloft. A warm layer aloft is defined in this study as a layer warmer than 0^oC extending above a surface-based layer of air colder than 0^oC. In most of the short duration events, a mix of precipitation types was reported (i.e. snow, ice pellets, freezing drizzle), indicating the presence of a vertical temperature profile with either a minimal or non-existent warm layer aloft. For example, there were a total of 53 days with a 1-hour occurrence of freezing rain for the period 1958/59-1990/91; 31 of these events were essentially missed by the model where the predicted probability was <0.6. Examining the NCEP-NCAR daily vertical pressure level temperature profiles for 4 times daily on each of these 31 days, it was determined that 17 days or 55% had no warm layer aloft during any of the 4 re-analysis hours. Of the remaining 22 days with a 1 h occurrence of freezing rain specified with a high probability (≥0.6), only 4 days or 18% were identified without a warm layer on any of the 4 hours. In fact, about 31% of freezing rain days in the developmental dataset had no warm layer, as determined from the NCEP-NCAR profiles, and only about 13% of these events can be identified by the model with the probability ≥0.6.

4.3 *Validation of the Model*

In order to validate the model, discriminant function analysis was used to assign each day of the validation dataset (1991/92-2000/01) into one of the weather types predetermined from the developmental dataset (1958/59-1990/91). This validation dataset yielded similar meteorological characteristics within synoptic types to those constructed from the developmental dataset. The within-category frequency of freezing rain events for the validation dataset was also used to validate the weather typing procedure. The results showed that within-type percentage frequencies of freezing rain events for both the developmental and validation datasets were similar. These results implied that the discriminant function analysis performed well in identifying or predicting the weather types most highly associated with freezing rain events.

Following the determination of the weather type for each day within the validation dataset, the logistic regression algorithm was used to calculate the probability of freezing rain occurrence for each of the days within weather types 1-4 for the period 1991/92-2000/01. As was the case for the developmental dataset, a probability of 0.6 was selected as the cut-off threshold for prediction of freezing rain. Of the 46 days in the validation dataset forecast to have a probability ≥0.6, freezing rain was observed on 35 days, or a post agreement of 76% with the remaining 11 days or 24% representing false alarms. Of the 35 freezing rain days correctly forecast by the model, 16 days received freezing rain events lasting between 2 to 5 hours, while 17 of the days experienced events of duration ≥6 hours. For the 11 false alarm events, freezing drizzle or snow/rain were observed for 5 and 2 days, respectively. Of the total 85 days in which precipitation was not observed, only 4 days were incorrectly identified as freezing rain events by the model when using a prediction probability ≥0.6). For freezing rain events lasting 8 h or more during a day, the model predicted 91% (POD) of the total freezing rain cases from the validation dataset. In general, these percentages were better than the results from the developmental dataset for longer duration freezing rain events.

Although major freezing rain events are relatively rare, we used the opportunity to test the model on data observed during a particularly severe ice storm that affected the northeastern U.S. and eastern Canada, including the Ottawa area, during the period January 5-9, 1998. Within this 5-day period, the model correctly predicted the occurrence of freezing rain on all 5 days, with a very high probability >0.995 for the first 4 days, dropping to 0.68 for the final day. Interestingly enough, the weather types differed for the 5 days with the first 4 days classified as type 2, and the final day classified as type 3. This change in classification and lowering in probability on the final day likely can be related to a transition in weather patterns during the day. By 0000 UTC on January 10, the 500 hPa wind flow over Ottawa began to shift from a southwesterly to a more westerly direction (Environment Canada, 1998), a less favorable direction for a flow of warm moist air and the occurrence of freezing rain.

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