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ORIGINAL PAPER

Modeling climate effects on hip fracture rate by the multivariate GARCH model in Montreal region, Canada

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Abstract Changes in extreme meteorological variables and the demographic shift towards an older population have made it important to investigate the association of climate variables and hip fracture by advanced methods in order to determine the climate variables that most affect hip fracture incidence. The nonlinear autoregressive moving average with exogenous variable-generalized autoregressive conditional heteroscedasticity (ARMA*X*-GARCH) and multivariate GARCH (MGARCH) time series approaches were applied to investigate the nonlinear association between hip fracture rate in female and male patients aged 40–74 and 75+ years and climate variables in the period of 1993–2004, in Montreal, Canada. The models describe 50–56 % of daily variation in hip fracture rate and identify snow depth, air temperature, day length and air pressure as the influencing variables on the time-varying mean and variance of the hip fracture rate. The conditional covariance between climate variables and hip fracture rate is increasing exponentially, showing that the effect of climate variables on hip fracture rate is most acute when rates are high and climate conditions are at their worst. In Montreal, climate variables, particularly snow depth and air temperature, appear to be important predictors of hip fracture incidence. The association of climate variables and hip fracture does not seem to change linearly with time, but increases exponentially under harsh climate conditions. The results of this study can be used to provide an adaptive climate-related public health program and ti guide allocation of services for avoiding hip fracture risk.

Keywords Hip fracture · ARMA*X*-GARCH · Multivariate GARCH · Conditional covariance · Climate

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Introduction

Hip fracture (HF) is already a cause of mortality and morbidity and is a growing problem in western countries associated with overall aging of societies. Hip fracture constitutes a significant economic burden in developed countries, reducing quality of life and leading to a 20 % reduction in expected survival (Benetos et al. 2007). It has also been reported that mortality rates after HF continue to rise over subsequent months and peak at 1 year, with a rate of 36 % for men and 21 % for women (Harvey and Dennison 2010). The importance of preventing at least some of the clinical and economic consequences of HF has led researchers to try to identify factors affecting HF incidence and risk.

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Various factors affect HF risk and incidence, including genetics, demography (increasing age and gender), chronic diseases such as osteoporosis and diabetes, medication (hormone replacement therapy and drugs altering the central nervous system), medical and gynaecological history (past fractures), anthropometric variables (increased or decreased body weight), life style factors such as physical inactivity or activity and exposure to sunlight as well as nutrition factors (calcium and vitamin D intake) (Benetos et al. 2007). Nursing home design and care procedures (Quigley et al. 2012) as well as urban design (Cummings and Melton 2002) are also important. Lan et al. (2010) suggested multiple risk factors for HF incidence such as low consumption of milk, grip strength and bone-mineral density. However, these are more clinical-level risk factors and seem to ignore climate factors, with the exception of the effect of sunlight (Bulajic-Kopjar 2000; Edvardsen et al. 2009) and its indirect effect on physical exercise.

Many studies have indicated an association between climate and HF, some of which are presented here. For example, a recent study in Valencia (Spain) showed a significant impact of meteorological variables on HF, especially in cold seasons (Tenias et al. 2009). The climate and its seasonal variation influence the risk of HF incidence in Scandinavian countries (Gullberg et al. 1993; Gronskag et al. 2010; Lofthus et al. 2001). An effect of day length, sunshine duration and temperature on daily activity of elderly people and high HF risk was indicated by Mirchandani et al. (2005) and Sumukadas et al. (2009) using Pearson product correlation coefficient. After adjustment for season, trend, day-of-week and autocorrelation, Turner et al. (2011) indicated the effect of low temperature on fall-related HF hospitalization in New South Wales, Australia, using a Poisson regression model.

Time series methods are a particularly promising statistical approach for modeling the variation of different variables and their influence on each other through time. However, these (linear) models are rarely applied to address epidemiologic time-varying variables such as HF, and very few studies can be found in literature (e.g., Lin and Xiraxagar 2006). The linear assumptions of these models are sometimes not enough to model the nonlinearity embedding the HF association with climate variables.

The main objective of this study was to introduce a nonlinear time series modeling approach—generalized autoregressive conditional heteroscedasticity (GARCH)—for modeling the nonlinear relationship between HF and climate variables. Our hypothesis was that the change in HF association to climate variation is partially nonlinear and could be modeled by a nonlinear approach. Moreover, this study aimed to model and predict daily variation of HF and its association with weather conditions.

Methods

Hip fracture data collection

The data set used in this study includes the daily HF incidences over the Montreal region, Quebéc province, Canada, which are population-standardized for 100,000 person-days from 1993 to 2004. The data set includes hospital discharge data of patients from the Montreal region aged ≥40 years (total population ≥40 in mid-period census of 2001 was about 900,000) where the main diagnosis of the admission was a HF (ICD-9 codes 820); patients with injury causes other than "accidental fall" (ICD-9 codes E880 to E888) were excluded. Daily hospitalization events extracted from Québec's hospital database (MED-ÉCHO) were supplied by the Institut national de la santé publique du Québec (INSPQ) and the Ministère de la Santé et des Services Sociaux du Quebec (MSSS) (Lambert et al. 2010). The reliability of the assessment of patient morbidities using Quebec's medico-administrative data has been rated as very high for various diagnoses (Levy et al. 1999).

Hip fracture rates were calculated for two age groups (40–74 years and 75 years and older), and for female and male patients separately. This decision was made in order to maintain sufficient numbers of fractures in gender groups allowing for a meaningful analysis. These female and male groups are called F1, F2, M1 and M2 hereafter in this study.

A total number of 22,850 HF incidences were observed during 1993–2004 in the Montreal region, among which 75.8 % were female and 24.20 % were male patients. The age-standardized HF incidences during 1993–2004 are 66, 284, 193 and 626 per 100,000-person-year for groups M1, F1, M2 and F2, respectively. The female to male ratio of HF rate is 1.52 and 2.3 for age groups 40–74 and 75+, respectively. A seasonal variation in HF rate for the groups was observed, with the HF rate increasing from November to January, then decreasing towards summer time (Modarres et al. 2012).

Meteorological variables

To model the relationship between climate variables and HF rate in this study, data of 12 climate variables from ten stations within the Montreal region in daily time scale were gathered. These climate data are measured and recorded using standard measuring methods of the World Meteorological Organization (WMO) by the Environment Canada, National Climate Data and information Archive (http://www.climate.weatheroffice.gc.ca).

The daily time series were then averaged over the region to obtain one single time series for each climate variable. These climate variables include maximum, minimum and average temperature, rainfall depth, snow depth, precipitation depth, maximum snow depth, mean wind speed, day length, and maximum, minimum and average air pressure. Figure 1 shows the geographic location of Montreal region and the location of the meteorological stations.

Statistical analysis

The statistical methods used in this study include two univariate and multivariate nonlinear time series models. The univariate approach includes modeling the conditional mean by the autoregressive moving average model with exogenous variables (ARMA*X*) and modeling the conditional variance of its residuals (errors) by a GARCH model. This type of model is called an ARMA*X*-GARCH error model (Hamilton 1994).

Using independent climate variables as exogenous variables, many models can be developed with different climate variables. We followed a stepwise procedure to select the final model. The stepwise procedure considered the climate variables with the highest correlation coefficients to include in the model. Another single climate variable was subsequently added in order to increase the R^2 of the model. This procedure was repeated for different climate variables until the highest R^2 is obtained and the parameters of the models were significant at the 5 % level.

The relationship between conditional variance of two or more variables was modelled by a multivariate GARCH (MGARCH) model (Engle and Kroner 1995)—a popular model in finance and econometrics. In a univariate GARCH model, the past values of the residuals, ε, makes a sigma field, $\mathcal{I}_{t-1}$ with measurable variance (σ_t^2). In other words, the current conditional variance, σ_t, depends on the previous variances and the residuals. In this study, we propose a class of MGARCH model called the constant conditional correlation (CCC) model (Bollerslev 1990).

Here, the dynamic variances and covariances of HF and climate variables based on the CCC-GARCH model can be estimated to show how the predictive value of climate variables for HF rate changes across the full range of HF rate values.

The first step for a CCC model is to estimate the conditional variance for each time series based on a GARCH model. The conditional variance allows us to test how the variance itself changes over time by comparing the variability of different HF rate time series. The conditional covariance is

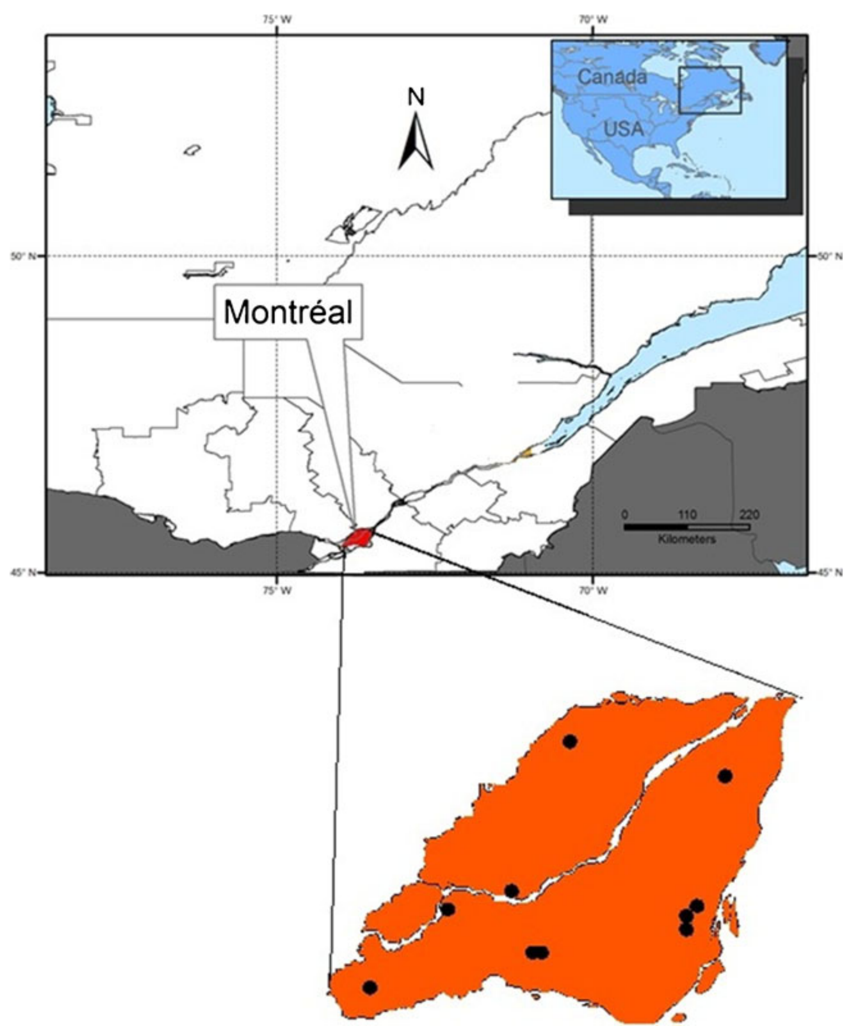


Fig. 1 Geographical location of study area and meteorological stations

then estimated by multiplying the conditional variances and conditional correlation coefficients. The details of these models are given in the supplement.

Results

Preliminary data analysis

The relationship between HF rate and climate variables was first investigated through a simple Pearson product correlation coefficient (see Supplemental Material, Table S1). One can see that these correlations are weak and show that the fluctuation of climate variables may not influence HF incidences in a daily time scale. Looking at the autocorrelation functions (ACF) of the HF rate time series (Supplemental Material, Fig. S1) reveals that the coefficients are statistically insignificant (fall within the 95 % confidence level). Thus, the daily information data set is insufficient to establish MGARCH models.

Therefore, we transformed the daily time series into two new time series in order to increase the autocorrelation structure. Then, in the following step, daily HF rate time series were extracted from the output of the models fitted to new time series, to show the effect of climate variables on HF rate on a daily time scale.

The new time series were created by adding up the daily HF rate in 3- and 5-day periods. The 3- and 5-day aggregations were selected to have a short time scale for our analysis. Climate variables were also transformed to 3- and 5-day variables to maintain the uniformity of HF rate-climate time series. This transformation increases 12 climate variables to 16 variables. These new four climate variables include the number of snowy days, the number of days with rainfall, the number of days with precipitation and the maximum snow depth. The descriptive statistics, average and standard deviation, of the meteorological variables for the study period (1993–2004) are given in Table 1.

The Pearson product correlation coefficients between aggregated HF rate and climate variables are given in Tables 2 and 3. These tables show a significant association between climate and HF rate time series. They also indicates stronger correlation coefficients than the coefficients between climate variables and HF rate in the daily time scale.

From the ACF of the aggregated time series (see Supplemental Material, Figs. S2 and S3), it is clear that the autocorrelation coefficients of aggregated 3- and 5-day time series are higher than those for daily time series and remain significant to the higher lags. Therefore, we used the 3-day and 5-day data set instead of the daily time series for modeling the relationship between climate variation and HF rate in the Montreal region using the proposed approaches.

ARMA*X*-GARCH models

Using the aggregated HF rate time series and 16 independent climate variables for HF rate time series, it was observed that the GARCH(1,1) model is enough to reveal the conditional variance remaining in the residuals of the linear ARMA*X* models in both time series. The final selected ARMA*X*-GARCH models and the climate variables

Table 1 Average and standard deviation of 3-day and 5-day meteorological variables time series

Climate variable	3-day		5-day	
	Average	Standard deviation	Average	Standard deviation
Maximum temperature (°C)	14.27	11.77	15.66	6.18
Minimum temperature (°C)	−0.37	12.21	−1.68	11.08
Mean temperature (°C)	6.83	11.73	6.84	9.52
Rainfall depth (mm)	6.50	10.76	10.83	29.35
Snow depth (mm)	16.10	41.26	26.84	5.18
Precipitation depth (mm)	8.31	11.06	13.84	29.79
Number of snowy days	0.60	0.97	1.00	1.41
Number of rainy days	1.54	1.16	2.56	0.31
Number of days with precipitation	2.12	0.94	3.53	0.33
Maximum snow depth (mm)	7.61	13.86	8.16	4.49
Maximum wind speed (km/s)	36.42	16.31	42.69	0.22
Mean Wind speed (km/s)	22.28	12.89	22.28	1.07
Day length (h)	17.24	10.00	28.73	12.33
Maximum pressure (hp)	101.90	0.72	102.11	0.99
Minimum pressure (hp)	100.20	0.77	99.93	0.34
Mean pressure (hp)	101.11	0.63	101.11	0.45

Table 2 Correlation coefficients between 3-day hip fracture (HF) rate and climate variables

Climate variable	F1r	F2r	M1r	M2r
Maximum temperature (°C)	−0.107*	−0.128*	−0.172*	−0.137*
Minimum temperature (°C)	−0.122*	−0.131*	−0.200*	−0.143*
Mean temperature (°C)	−0.114*	−0.128*	−0.188*	−0.141*
Rainfall depth (mm)	−0.029	−0.046*	−0.027	−0.072*
Snow depth (mm)	0.125*	0.064*	0.097*	0.072*
Precipitation depth (mm)	0.013	−0.017	0.018	−0.045*
Number of snowy days	0.121*	0.105*	0.163*	0.097*
Number of rainy days	−0.092*	−0.079*	−0.118*	−0.096*
Number of days with precipitation	−0.028	−0.031	−0.020	−0.040*
Maximum snow depth (mm)	0.130*	0.079*	0.198*	0.082*
Maximum wind speed (km/s)	0.017	0.020	0.060*	−0.021
Mean wind speed (km/s)	0.010	0.015	0.047*	−0.033
Day length (h)	−0.022	−0.077*	−0.069*	−0.069*
Maximum pressure (hp)	0.061*	0.064*	0.107*	0.069*
Minimum pressure (hp)	−0.004	−0.015	−0.033	−0.023
Mean pressure (hp)	0.035	0.024	0.056*	0.048*

* $P<0.01$

included in each model as the exogenous variables are given in Tables 4 and 5 for the 3-day and 5-day HF rate time series, respectively.

For the younger groups (F1 and M1), it can be seen that the snow depth and temperature are the most important climate variables, describing 59 % and 62 % of the temporal variation of 3-day HF rate, respectively. For the older groups (F2 and M2) of 3-day time series, maximum pressure and day length play the most important roles. These variables describe 57 % and 56 % of the variation in HF incidence. It is also clear that day length is the climate variable most frequently governing HF incidence in Montreal.

For the 5-day HF rate time series, the models (Table 5) indicate that the temperature and snow depth are also the most important climate variables for the younger groups (F1 and M1 groups). Wind speed and maximum pressure also appear in the models. The ARMA*X*-GARCH models capture 76 % and 78 % of the temporal variation of the 5-day HF incidence for the younger groups. On the other hand, for groups F2 and M2 the maximum pressure seems to be the most important factor while rainfall depth and day length also appear in the models. These climate variables define 73 % variation of 5-day HF incidences for older groups in the Montreal region.

Table 3 Correlation coefficients between 5-day HF rate and climate variables

Climate variable	F1r	F2r	M1r	M2r
Maximum temperature (°C)	−0.150*	−0.162*	−0.239*	−0.177*
Minimum temperature (°C)	−0.170*	−0.164*	−0.277*	−0.186*
Mean temperature (°C)	−0.159*	−0.162*	−0.261*	−0.181*
Rainfall depth (mm)	−0.057*	−0.048*	−0.072*	−0.095*
Snow depth (mm)	0.187*	0.099*	0.159*	0.100*
Precipitation depth (mm)	0.017	−0.001	0.003	−0.057*
Number of snowy days	0.168*	0.151*	0.245*	0.137*
Number of rainy days	−0.137*	−0.103*	−0.190*	−0.119*
Number of days with precipitation	−0.040*	−0.027	−0.040*	−0.039
Maximum snow depth (mm)	0.182*	0.101*	0.265*	0.109*
Maximum wind speed (km/s)	0.064*	0.029	0.039*	−0.017
Mean wind speed (km/s)	0.046*	0.018*	0.027	−0.015
Day length (h)	−0.055*	−0.130*	−0.114*	−0.105*
Maximum pressure (hp)	0.081*	0.086*	0.157*	0.094*
Minimum pressure (hp)	−0.026	−0.044*	−0.059*	−0.048*
Mean pressure (hp)	0.038	0.042*	0.070*	0.054*

* $P<0.01$

Table 4 Time series models for 3-day HF rate time series

Group	Model	Climate variables included	R^2
M1	ARMAX(4,1,1)- GARCH(1,1)	Snow depth, minimum temperature, day length	0.624
M2	ARMAX(4,1,1)- GARCH(1,1)	Maximum pressure, day length	0.562
F1	ARMAX(4,1,1)- GARCH(1,1)	Snow depth, minimum temperature	0.596
F2	ARMAX(4,1,1)- GARCH(1,1)	Day length, maximum pressure	0.578

Daily hip fracture estimation

The daily HF rate time series were extracted from the model-predicted 3- and 5- day aggregated time series to demonstrate the model performance for modeling daily HF rate. The predicted daily time series are plotted against the observed daily HF rate in Figs. 2 and 3. The figures indicate that the model can describe (on average) 50 % of daily variation in HF rate in the Montreal region in relation to climate variables. Figures 2 and 3 also appear to show that the error of the model decreases while the number of hip fractures increases. In other words, the performance of the model is better for high values of HF rate than for low values.

Conditional variance and covariance

The conditional variances of the 3- and 5-day hip fracture rate [see Supplemental Material, Figures 4 and 5] show that peak variances for the F1 group were observed in 1994, 1997, 1998 and 1999. All peak variances were observed in January except for a high value in April 1997. The highest variances for the F2 group were observed in March 1993 and January 1998. For the M1 group, the peaks were observed in January 1998, 1999 and 2002, while for the M2 group, the highest variance is observed in January 1994. The variance of the older groups (F2 and M2) seems to have more variability and fluctuation than that of the younger groups (F1 and M1). This suggests that the HF rate for the F2 and M2 groups changes over a larger range than that of the F1 and M1 groups.

The monthly average and standard deviation of the conditional variance of the 3-day HF rate is illustrated as an example in Figs. 4a,b. The highest average conditional variance is observed in the fall–winter season for the younger group (Fig. 4a), while no sharp seasonal variation is evident for groups F2 and M2. On the other hand, the monthly change of the standard deviation of the conditional variance (Fig. 4b) for the younger groups (F1 and M1) is consistent with the monthly change in the average (Fig. 4a) while the standard deviation for the elder group (M2 and F2) shows high monthly variation for both winter and summer months. Seasonality of the mean is also observed. Therefore, one can see that both linear and nonlinear characteristics of the HF rate time series show seasonality.

The standard deviation of the conditional variance of winter season is higher than that in the summer time for all groups. The higher dispersal of the variance can also be observed in the boxplot of monthly conditional variance given for group F1 as an example in Fig. 4c. The boxplots also reveals the higher variability and range of variance in winter time, especially in December and January when temperature and day length are decreasing and snow depth is increasing

The time varying covariance between HF incidence and climate conditions was also estimated by applying Eq. 3 (see appendix). For the CCC models, we use the climate variables determined by the ARMA*X*-GARCH model for each HF rate time series.

The conditional covariance between different HF groups and climate variables are plotted against the HF rate (Figs. 5, 6) for the 3-day HF time series. Other figures related to 3-day HF are presented in supplementary Figs. S6 and S7. All these figures indicate a strong and nonlinear relationship between the time varying HF variances and the variances of the climate variables. It can be observed that the association between HF incidence and climate variables is very weak or linear for small numbers of HF incidences while this association (climate effect on HF rate) increases rapidly and in a nonlinear fashion for the higher HF rate values. For example, the conditional covariance between F1 and snow depth is almost constant or zero for HF rate <1

Table 5 Time series models for 5-day HF time series

Group	Model	Climate variables included	R^2
M1	ARMAX(6,1,1)- GARCH(1,1)	Minimum temperature, maximum snow depth, maximum pressure	0.782
M2	ARMAX(6,1,1)- GARCH(1,1)	Maximum pressure, rainfall depth	0.736
F1	ARMAX(6,1,1)- GARCH(1,1)	Snow depth, minimum temperature, maximum wind speed	0.767
F2	ARMAX(6,1,1)- GARCH(1,1)	Maximum pressure, day length	0.733

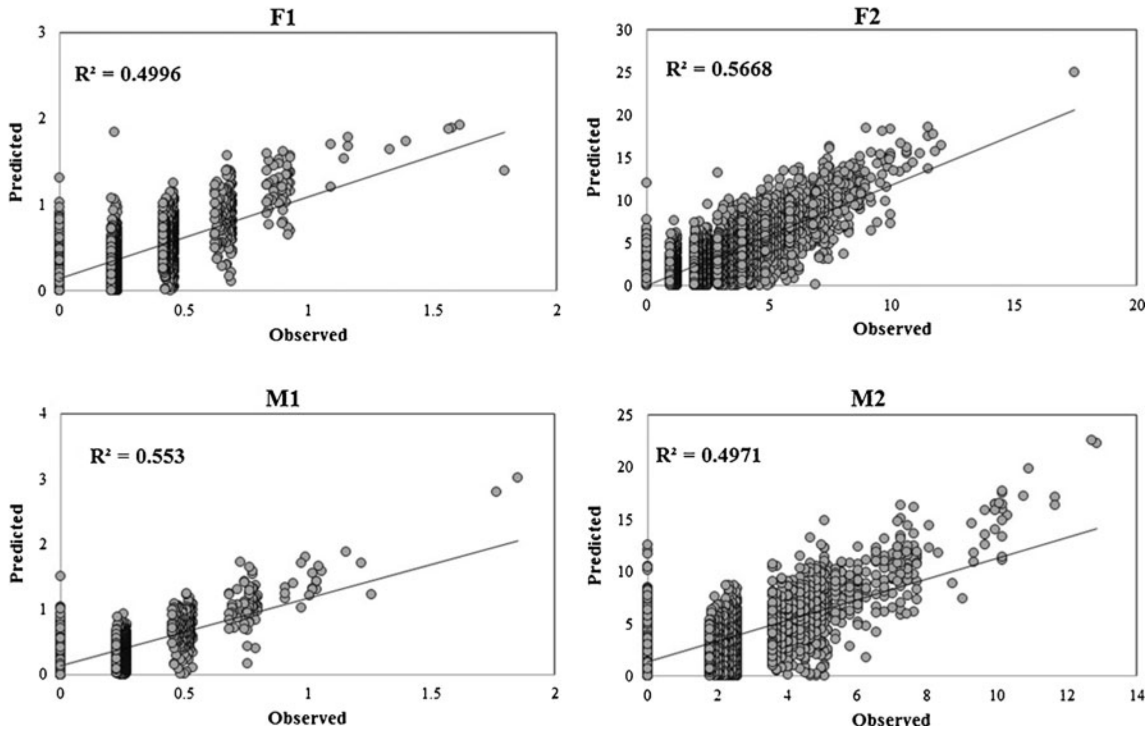


Fig. 2 Observed against estimated daily hip fracture (HF) rate time series extracted from 3-day HF rate time series

and begins increasing exponentially afterward. Similar results are observed for the 5-day HF rate data and for other groups and climate variables (see Supplemental Material, Figs. S8 to S11).

Discussion

These results of this study demonstrate strong nonlinear associations between the variances of climate variables and

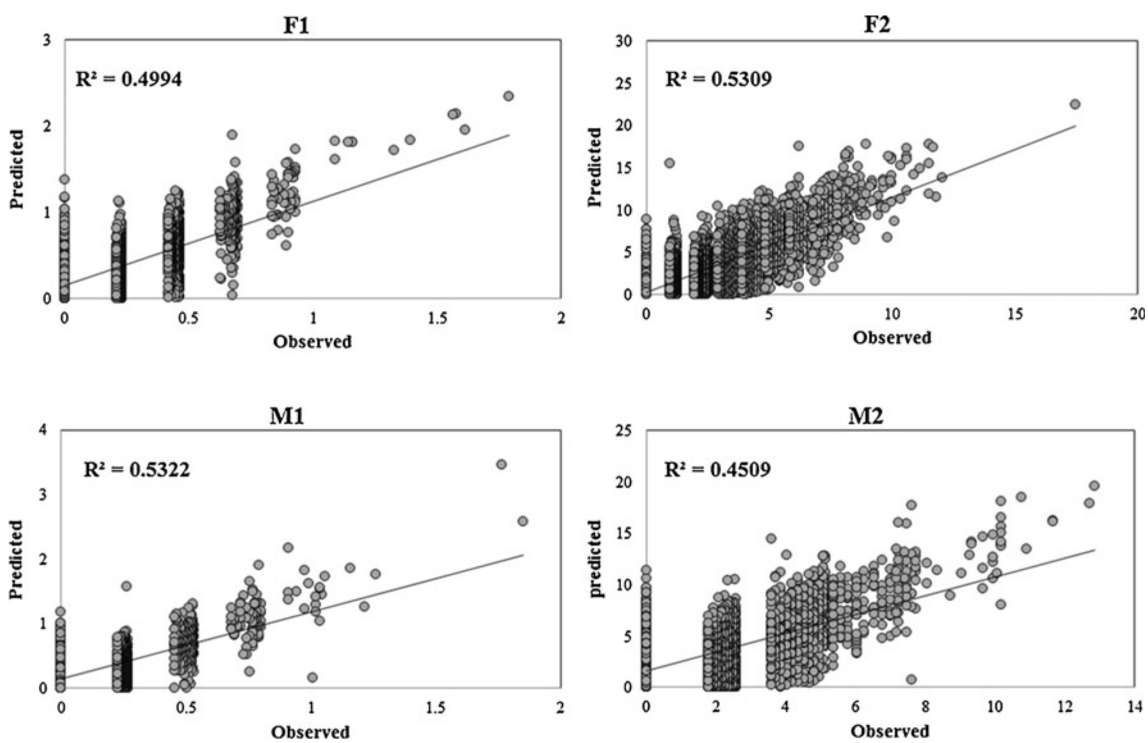
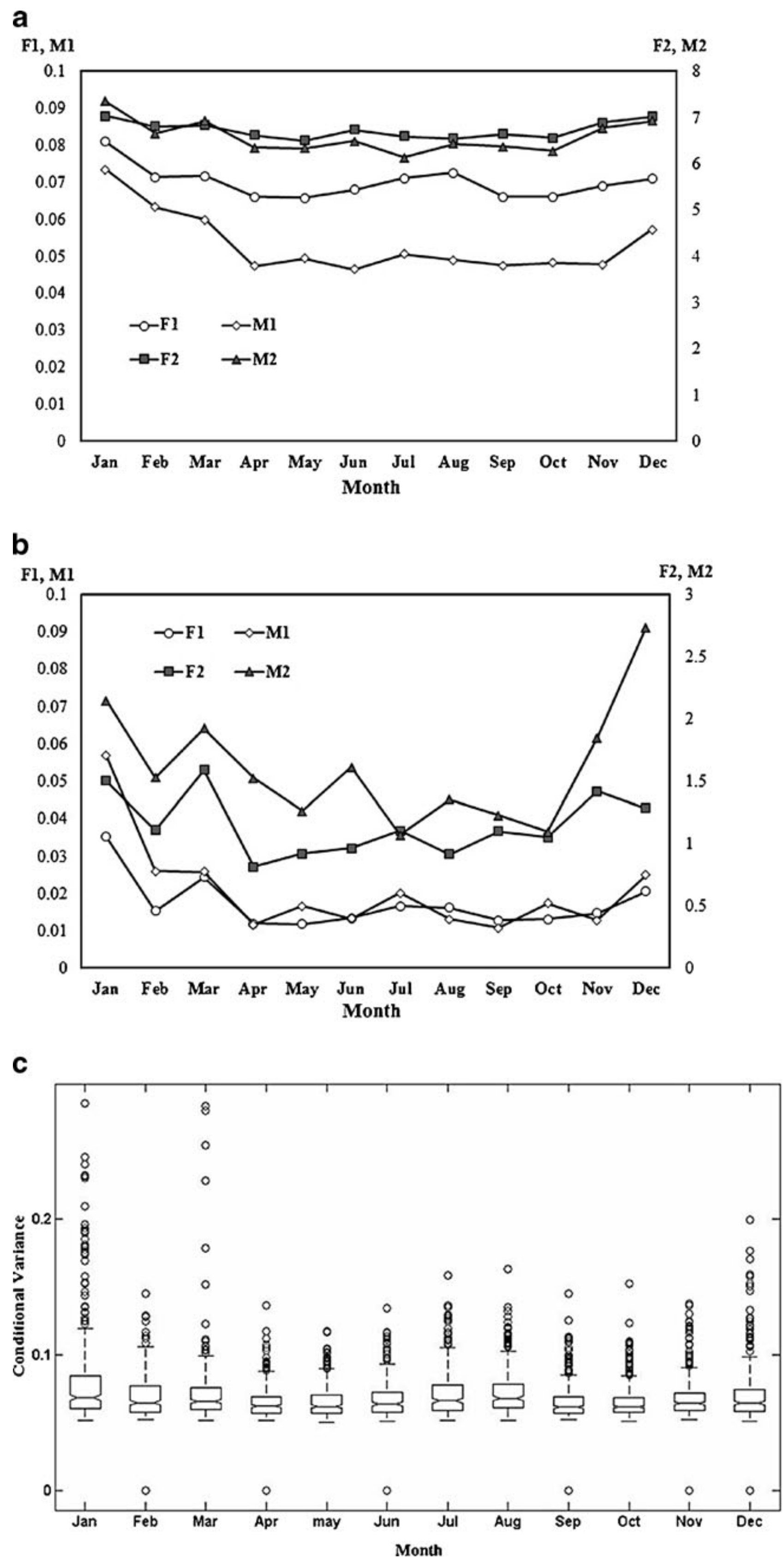


Fig. 3 Observed against estimated daily HF rate time series extracted from 5-day HF rate time series

Fig. 4 **a**, **b** Seasonality of the average and **c** variance of the conditional variance of 3-day time series



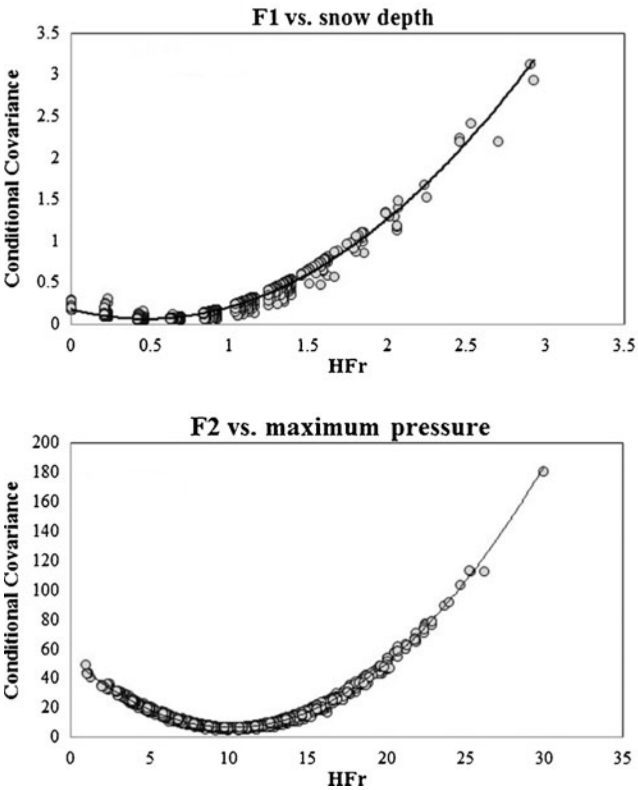


Fig. 5 Conditional covariance against 3-day HF rate. Example for groups F1 and F2

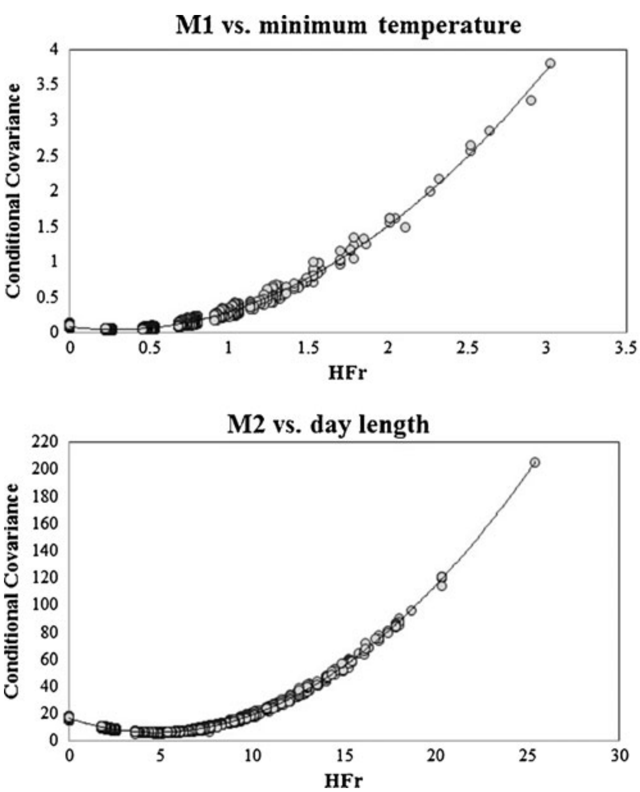


Fig. 6 Conditional covariance against 3-day HF rate. Example for groups M1 and M2

HF rates, implying that high HF risk depends more strongly on severe weather conditions than on average conditions. Accordingly, the risk of HF incidences appears to increase when specific climate conditions, such as heavy snowfall or low temperature, remain for a time period (e.g., a couple of days). The nonlinear model applied in this study clearly supports this statement.

Nonlinear models such as ARMA*X*-GARCH not only identify the most important climate variables affecting HF incidence but also show the time-varying second order moment or the variance in HF rate. Previous studies by Lin and Xiraxagar (2006) and Modarres et al. (2012) or the Poisson regression model (Turner et al. 2011; Bischoff-Ferrari et al. 2007) considered only the conditional mean (first order moment) of HF and its temporal variation.

The multivariate CCC model shows a nonlinear relationship between HF rate and climate variables for both gender and age groups. The covariances between HF rate and climate variables are strongly significant and increase exponentially. The insignificant covariance between low HF rate and climate variables probably suggests that the variation in the background of low HF rate may not depend on weather conditions and we should seek other explanations such as indoor falls or drug consumption.

Though this study shows a nonlinear relationship between weather and HF, some disadvantages of the lack of information should be noted.

As the available HF data in this study does not separate indoor and outdoor falls, and given that the majority of HF incidences are caused by a fall (Masud and Morris 2001), future studies should separate indoor and outdoor incidences in order to establish a more precise climate-HF association. Although simultaneously examining in which weather variables the elderly may prefer to stay at home, the MGARCH approach shows that the risk of HF incidences may increase if adverse climate conditions remain for several days. This suggests future investigation of the dynamic and social behavior of people through another study, for example a questionnaire-based study, to understand the preferences of the elderly for staying at home or going outside during and after harsh climate conditions.

This could lead to free automated alert systems like those already found in the field of air quality in countries such as Canada (Sante et service sociaux Quebec, http://www.msss.gouv.qc.ca/sujets/santepub/environnement/index.php?cote-air-sante-abonnement-aux-alertes-en), the United States (Airalert service for Herts and beds, https://www.airalert.info/hertsbeds/registration.aspx), the United Kingdom and France [north-east London and city (NHS), http://www.onel.nhs.uk/for-health-professionals/severe-weather-warnings.htm].

It should also be noted that the climate variables were averaged over the study region. Future studies should consider more dense meteorological data to achieve a better understanding of the association between climate variation and HF on a daily time scale. In addition, other possible confounders such as people's behavior, weekends and holiday vocations should be considered in future studies.

Many extreme weather conditions have shown an increase in frequency, intensity or duration in Quebec Province (Lemmen et al. 2008) and will most likely follow a similar trend in the future. It then becomes important to plan future medical services based on the most robust models that include climate determinants for the best approximation of the expected incidence of such severe and debilitating injuries as hip fractures, especially for a short-period time scale. The approach proposed here will support informed decisions for a better allocation of scarce resources and provide a climate-related preventive message to people at risk for HF. Some climate change adaptation programs are already starting to use weather data for service planning (Oven et al. 2012).

Conclusions

This study implemented a novel multivariate nonlinear GARCH model to show how climate variables affect HF rates in Montreal, Canada. We estimated the time varying second order moment or the conditional variance of the HF rate and its relationship to the conditional variance of climate variables. The proposed approaches for modeling HF rate-climate association indicate that the effect of the climate condition on HF incidence in the Montreal region appears to be a nonlinear process, increasing exponentially and becoming more significant with adverse weather conditions.

Furthermore, the proposed model building procedure based on estimation of daily HF rate from short-period aggregated time series suggests a good method for future studies on daily HF time series modeling in the absence of significant autocorrelation.

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