Variations of disinfection by-product levels in small drinking water utilities according to climate change scenarios: a first assessment
I. Delpla, A. Scheili, S. Guilherme, G. Cool and M. J. Rodriguez

ABSTRACT
In Québec, Canada, shifts in climate patterns (i.e., rainfall increase) could have consequences on source water quality due to the intensification of surface/groundwater runoff contamination events, leading to a decline in drinking water treatment efficiency and ultimately disinfection by-products (DBPs) formation following treatment. To assess the impacts of climate change (CC) scenarios on DBP formation, a suite of models linking climate to DBPs was used. This study applies three emissions scenarios (B1, A1B and A2) for three 30-year horizons (2020, 2050 and 2080) in order to produce inputs to test several DBP models (total trihalomethanes (TTHMs), haloacetic acids and haloacetonitriles). An annual increase is estimated for all DBPs for each CC scenario and horizon. The highest seasonal increases were estimated for winter for all DBP groups or species. In the worst-case scenario (A2-2080), TTHMs could be affected more particularly during winter (+34.0%), followed by spring (+16.1%) and fall (+4.4%), whereas summer concentrations would remain stable (−0.3 to +0.4%). Potentially, small water utilities applying only a disinfection step could be more affected by rising TTHMs concentrations associated with CC than those having implemented a complete water treatment process (coagulation–flocculation, filtration and disinfection) with +13.6% and +8.2% increases respectively (A2-2080).

key words | disinfection by-products, drinking water quality, emissions scenarios, empirical models, small water supplies, water resources

INTRODUCTION
Surface waters can be highly vulnerable to climatic conditions. It has been shown that between one-third and one-half of organic carbon export occurs during heavy rainfall events (Frank et al. 2000; Clark et al. 2007). As climate-related runoff events exert control over organic carbon export in rivers (Hope et al. 1994), it is expected that
increases in precipitation volume and intensity could have impacts on raw water quality. Indeed, Clair et al. (1999) suggest that a doubled CO₂ concentration in the atmosphere will increase dissolved organic carbon (DOC) exports by approximately 14% in Canadian ecosystems due to higher runoff volumes.

The drinking water of most inhabitants of the Province of Québec (Canada) is supplied by surface waters (MDDEP 2012). Increases in annual maximum precipitation, mean and maximum air temperatures and a reduction in the number of frozen days and duration of ice cover have been observed in southern Québec (Yagouti et al. 2008). Climate change (CC) projections indicate increases in mean temperatures (DesJarlais et al. 2010), annual precipitation maxima (Mailhot et al. 2013), annual precipitation mean (DesJarlais et al. 2010), and a reduction in the number of frozen days and the duration of ice cover in Québec (DesJarlais et al. 2010) that could ultimately affect the quality of drinking water sources. The possibility of increased frequency of water quality degradation events could be of particular concern for small water systems (SWS). Indeed, SWS are more vulnerable to contamination episodes than larger utilities due to their limited technical, human and financial resources, and because they are often located in isolated rural areas (WHO 2011). In Québec, SWS providing water to less than 8,000 people account for the majority of municipal utilities and supply water to almost 50% of the population (MDDEP 2012).

Disinfection is usually used as a final step in water treatment to reduce microbiological risks linked with exposure to micro-organisms such as bacteria, viruses or protozoa. However, it has been shown that commonly used disinfectants (chlorine, chlorine dioxide, ozonation, etc.) react with organic matter to form potentially harmful disinfection by-products (DBPs) such as trihalomethanes (THMs), haloacetic acids (HAAs), nitrosamines, haloacetonitriles (HANs) and oxyhalides (Richardson et al. 2007). Epidemiological studies have suggested positive associations between DBP exposure and adverse effects such as cancers (bladder and colon) and reproductive outcomes (stillbirth and growth retardation) (Villanueva et al. 2003; Toledano et al. 2005; Richardson et al. 2007; Levallois et al. 2012).

Some recent studies have also shown that rainfall events could constitute a risk for microbial contamination of surface water resources (Beaudeau et al. 2010) and are correlated with waterborne disease outbreaks (Curriero et al. 2001). Increases in precipitation predicted with CC could intensify surface and groundwater contamination events by increasing runoff leading to a decline in water treatment efficiency (Charron et al. 2004; Delpla et al. 2009).

Research about the impacts of CC on chemical drinking water quality modifications related to DBPs is very recent (Gough et al. 2014; Ritson et al. 2014a, 2014b). However, no studies have tried to predict variations in DBPs using CC scenarios. In order for SWS to adapt to this future challenge, it is essential to understand the impacts of various environmental conditions on drinking water quality and to assess the capacity of SWS to provide safe water under these new conditions.

In this paper, we aim to define an approach providing a first assessment of the impacts of CC scenarios on annual and seasonal DBP variation levels in finished waters of SWS in Québec. The approach is based on an estimation of the impact of climate variables on source water quality and the use of empirical models for DBPs prediction in drinking water based on different CC scenarios.

**MATERIALS AND METHODS**

In this study, we first generated climatic change outputs (air temperature and rainfall) for the area under study (southeast Québec, Canada) on the basis of Intergovernmental Panel on Climate Change (IPCC) emissions scenarios. Then, DBP models were reviewed and tested on a southeast Québec SWS water quality database. This step allowed us to select the DBP models best fitting the observed data in order to test the impacts of the outputs of CC scenarios on DBP variations for these SWS.

**Emissions scenarios**

Emissions scenarios described in the Special Report on Emissions Scenarios (SRES) were developed to explore alternative development pathways, including demographic, economic and technological driving forces, and resulting greenhouse gases emissions (IPCC 2007). The impacts of changes in temperature and precipitation on drinking water quality were assessed in this study by testing three
SRES scenarios (B1, A1B and A2). Each scenario assumed a distinctly different direction for future development pathways. The scenarios were selected to simulate a wide range of potential climate variations. Outputs of the Third Generation Coupled Global Climate Model (CGCM3) developed by the Canadian Centre for Climate Modelling and Analysis (CCCma) were used with these scenarios. The T47 version of CGCM3 was applied to one climatic grid cell (centre: 46.389N 71.25W, spatial resolution: 3.75°×3.75°) corresponding to the southeast Québec area where the SWS considered in this study are located. All data were provided by the CCCma website (http://www.cccma.ec.gc.ca/data/cgcm3/cgcm3.shtml). It should be noted that only one global climate model (GCM) was used to generate the climate outputs, since the primary objective of this study was to test the response variability of various DBP models to SRES scenarios, rather than to assess climate intermodel uncertainty. The projected seasonal and yearly climate series were produced for the reference period (1971–2000) and three 30-year horizons (2011–2040, 2041–2070 and 2071–2100) noted here as 2020, 2050 and 2080, respectively.

Seasons were defined as winter (December–February), spring (March–May), summer (June–August) and fall (September–November). A summary of CC inputs under the various scenarios and horizons chosen for the southeast Québec region is provided in Table 1.

A general annual increase in mean (+1.1 to +4.9 °C) and maximum (+1.1 to +4.6 °C) air temperatures is anticipated for the area, with the climate becoming warmer and warmer over time. Among seasonal variations in mean and maximum temperatures, the most significant variations are predicted for winter (+1.4 °C to +6.1 °C and +1.2 °C to +5.4 °C, respectively).

Total precipitation are also expected to increase in annual mean (+38.0 to +146.8 mm/y) even if a different temporal variation may be noted with a predicted decrease after 2050 (B1 and A2 scenarios). A significant increase in total precipitation is anticipated for winter (+75.7 to +369.7 mm/y) and spring (+63.1 to +314.8 mm/y), whereas summer will experience substantial decreases (−23.1 to −164.6 mm/y). Finally, slight increases are noted for the fall (+17.6 to +104.4 mm/y).

**Water quality database**

For this study, the database chosen to test and validate the different existing DBP models and apply the emissions scenario outputs consisted of 169 water samples from 13 SWS. The samples were collected monthly by our team for an entire year (October 2010–October 2011). These SWS are located in southeast Québec where the climate is classified as humid continental with a mean precipitation (1981–2010) of 1,160 mm/y and a mean air temperature of 4.7 °C. Climatic means for 2010–2011 were close to the 1981–2010 climate normals for mean precipitation (1,170 mm/y) and warmer for mean air temperature (6.4 °C) (MDDELCC 2014a).

### Table 1 | Summary of the scenarios tested (Global Climate Model CGCM3T47, grid centre: 46.389N 71.25W, spatial resolution: 3.75°×3.75°; data available at http://www.cccma.ec.gc.ca/data/cgcm3/cgcm3.shtml)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>ΔTmean (°C)</th>
<th>ΔTmax (°C)</th>
<th>ΔR (mm/y)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1 2020</td>
<td>1.4</td>
<td>1.1</td>
<td>0.9</td>
</tr>
<tr>
<td>2050</td>
<td>2.7</td>
<td>2.0</td>
<td>1.8</td>
</tr>
<tr>
<td>2080</td>
<td>3.4</td>
<td>2.4</td>
<td>2.1</td>
</tr>
<tr>
<td>A1B 2020</td>
<td>1.8</td>
<td>1.3</td>
<td>1.1</td>
</tr>
<tr>
<td>2050</td>
<td>3.7</td>
<td>2.5</td>
<td>2.3</td>
</tr>
<tr>
<td>2080</td>
<td>4.9</td>
<td>3.7</td>
<td>3.2</td>
</tr>
<tr>
<td>A2 2020</td>
<td>1.8</td>
<td>1.3</td>
<td>1.2</td>
</tr>
<tr>
<td>2050</td>
<td>4.0</td>
<td>2.8</td>
<td>2.5</td>
</tr>
<tr>
<td>2080</td>
<td>6.1</td>
<td>4.8</td>
<td>4.2</td>
</tr>
</tbody>
</table>

ΔTmean: variation of mean air temperature; ΔTmax: variation of maximum air temperature; ΔR: variation of total annual precipitation; W: winter; Sp: spring; Su: summer; Fa: fall.
The SWS provide drinking water from surface waters to a population of between 1,200 and 6,200 inhabitants. For the most part, the SWS have implemented a complete water treatment process (coagulation–floculation, sedimentation, sand filtration and disinfection). Twelve of the 13 water treatment plants use chlorination as their disinfection process (mainly for final disinfection); the remaining SWS uses chloramination for final disinfection. DBP analyses targeted the four THMs (chloroform, bromoform, bromodichloromethane and dibromochloromethane), nine HAAs (monochloroacetic acid, monobromoacetic acid (MBAA), dichloroacetic acid (DCAA), trichloroacetic acid (TCAA), bromochloroacetic acid (BCAA), bromodichloroacetic acid, dibromoacetic acid, chlorodibromoacetic acid and tribromoacetic acid), and four HANs (trichloroacetonitrile, dichloroacetonitrile, bromochloroacetanitride and dibromoacetanitride). Complementary information about raw water, water treatment type and the analytical methods used is provided elsewhere (Guilherme & Rodriguez 2014; Scheili et al. 2015). The mean raw water temperature was 9.0 °C and mean DOC concentrations were 5.9 mg/L and 2.4 mg/L for raw and treated waters, respectively. THM4 and HAA5 values at the beginning of the distribution system across the 13 SWS were generally under the regulatory limit (mean THM4: 39.6 ± 26.2 µg/L; mean HAA5: 40.9 ± 38.6 µg/L). Mean values for HANs were 2.0 ± 1.3 µg/L. Water quality parameters data were averaged on the entire year and by season (winter, spring, summer and fall).

**DBP models reviews and selection**

DBP prediction models could be useful to monitor operational parameters in treatment plants, assess impacts of treatment process modifications, or produce retrospective data for epidemiological studies and future data for assessing upgrade process requirements (Rodriguez et al. 2000). In the present paper, models were used to evaluate the impacts of CC scenarios on DBP variations. First, a bibliographic study on existing empirical models for predicting DBPs in drinking water was conducted by updating the recent review of Sadiq & Rodriguez (2011).

A wide range of parameters affecting the formation levels of DBPs are commonly included in DBP predictive models. They include chlorine dose, contact time, organic matter content (expressed with indicators such as dissolved and total organic carbon (TOC), UV254 and specific ultraviolet absorbance (SUVA)), water temperature, bromide ion and pH. Natural organic matter is the main precursor of DBPs (Singer 1994). Past research has also determined that levels of THMs are strongly influenced by raw water temperatures (Singer 1994). Moreover, water temperature and DOC could be particularly influenced by climatic conditions as reported in previous studies (Clair et al. 1999; van Vliet et al. 2011; Couture et al. 2012). In our study, these parameters were considered as the main factors that might be influenced by CC. Consequently, only the models including one or both of these two parameters were considered. A total of 63 DBP models were identified in the literature, mainly for total THMs (TTHMs). These models establish empirical relationships between water quality and operational parameters with observed concentrations of DBPs. They are based on laboratory- and field-scale data.

Validation of the models was achieved by using the data of the 13 SWS to select the most suitable models for the application of the CC scenarios. Hypotheses were developed for residence times and chlorine doses applied, since the information on these two parameters was not available in the SWS database. Residence time was defined on the basis of interviews with water treatment technicians and set at 8 h, representing an estimation of the mean residence time at the beginning of the distribution network. Chlorine dose was estimated as equivalent to the total chlorine concentration at the beginning of the distribution network if the sampling point was located in the station. In other cases, the mean chlorine dose values reported in a large-scale study conducted by Coulibaly & Rodriguez (2005) on 51 SWS in Québéc were applied (1.56 mg/L for samples collected between April and September, n = 32; 1.11 mg/L for samples collected between October and March, n = 33). Raw water quality data were used as inputs into DBP models if they had been developed specifically for raw waters.

DBP model selections were made on the basis of the adjusted coefficient of determination ($R^2$), p-value, Spearman correlation coefficient ($\rho$), F-test and percentage of underestimation between observed and predicted values. As none of the different DBP models tested was developed...
and validated for the database used in this study, low thresholds of selection were chosen intentionally. First, models with $R^2$ lower than 0.25 and $r$ lower than 0.5 were excluded. It should be noted that the highest coefficient of determination between predicted and observed values was obtained for the DCAA model (0.67) and that $R^2$ for TTHM models was comprised globally between 0.00 and 0.51. Then, as variances were similar with observations for one model only, we chose to set a high F ratio threshold (110) for model selection. Finally, models leading to an underestimation of observed data higher than 75% were excluded.

Finally, 17 DBP models that presented relatively acceptable adequacy with observed values were selected to test the different CC scenarios. Ten TTHM models and four HAA models were selected. In addition, HAN, TCAA and DCAA models were selected. A description of these models is provided in Table 2. It should be noted that these models were calibrated and validated for various water quality and treatment types. However, most of them (13 of 17) were developed using data originating from studies conducted in Eastern Canada and the United States.

### Water quality parameters modelling

A suite of empirical models was developed to link climate (rainfall and air temperature) and the water quality parameters under consideration (water temperature and DOC). These models were calibrated using the Québec SWS database described previously.

Water temperature at the source collection point was modelled on the basis of air temperature data for the studied areas. Although it has been shown that flowrates could constitute a good proxy of water temperature (van Vliet et al. 2014), this parameter could not be included in the model due to the lack of monitoring stations at source watersheds of the SWS under study. The final parameters included in the water temperature model were: (i) 3-month mean air temperature; (ii) 30-day mean air temperature; and (iii) 30-day maximum air temperature. Shorter-term metrics such as 3, 7 and 14 days prior to sampling were also tested but were found to be less significant.

It was then assumed that water temperature was not subject to important variations during treatment and, consequently, that raw and treated water temperatures were equal.

### Table 2 | Description of selected DBPs models ($n = 17$). Units for DBPs are in $\mu g/L$

<table>
<thead>
<tr>
<th>Compound</th>
<th>Data source</th>
<th>Author</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TTHMs</strong></td>
<td>Laboratory</td>
<td>Chang et al. (1996)</td>
<td>$12.7^*(TOC)^{0.291}(T)^{0.271}(D)^{0.072}$</td>
</tr>
<tr>
<td>Field</td>
<td>Rodríguez et al. (2000)</td>
<td>$1.392^*(DOC)^{1.092}(pH)^{0.551}(T)^{0.255}$</td>
<td></td>
</tr>
<tr>
<td>Laboratory</td>
<td>Rodríguez et al. (2000)</td>
<td>$0.044^*(DOC)^{1.050}(pH)^{0.262}(TOC)^{1.149}(D)^{0.277}(T)^{0.968}$</td>
<td></td>
</tr>
<tr>
<td>Laboratory</td>
<td>Sohn et al. (2004)</td>
<td>$10^{-1.385^<em>(DOC)^{0.482}(Br)^{0.339}(T)^{0.023}(pH)^{0.617}1.609^</em>(T)^{0.261}}$</td>
<td></td>
</tr>
<tr>
<td>Field</td>
<td></td>
<td>$0.42^<em>(UV254)^{0.421^</em>(D)^{0.145^<em>(Br)^{0.014^</em>(pH)^{0.616}}(T)^{0.261}}$</td>
<td></td>
</tr>
<tr>
<td>Laboratory</td>
<td></td>
<td>$3.29^<em>(DOC)^{0.801}(Br)^{0.223^</em>(T)^{0.264}}$</td>
<td></td>
</tr>
<tr>
<td>Field</td>
<td></td>
<td>$23.9^<em>(DOC)^{0.103^</em>(Br)^{0.225^*(T)^{0.141}}$</td>
<td></td>
</tr>
<tr>
<td>Laboratory</td>
<td>Al-Omari et al. (2004)</td>
<td>$4.53^<em>(DOC)^{0.127}(T)^{0.596}(TOC)^{0.996}(Br)^{0.103^</em>(pH)^{0.66}}$</td>
<td></td>
</tr>
<tr>
<td>Field</td>
<td>Chowdhury et al. (2010)</td>
<td>$-51.408 + 8.44^*DO + 15.529^*D + 2.997^*pH + 0.805^<em>T + 0.504^<em>t + 0.141^</em>(D-4.47)^</em>(T-15.03)$</td>
<td></td>
</tr>
<tr>
<td><strong>HAA9</strong></td>
<td>Field</td>
<td>Zhang et al. (2011)</td>
<td>$-2.6 + (0.6^*T) + (0.6^*TOC)(100.4^*Br) + (0.5^*TTHMs)$</td>
</tr>
<tr>
<td><strong>HAA4</strong></td>
<td>Laboratory</td>
<td>Sérides et al. (2003)</td>
<td>$2.72^*(T)^{0.295^<em>DO^0.458^</em>(TOC)^0.633}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$1.33^*(T)^{0.102^<em>DO^0.458^</em>(TOC)^2.612}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$-8.202 + 0.364^*t + 1.053^*D + 4.869^*TOC$</td>
<td></td>
</tr>
<tr>
<td><strong>DCAA</strong></td>
<td>Field and laboratory</td>
<td>Chen &amp; Westerhoff (2010)</td>
<td>$189^<em>(DOC)^{0.57^</em>(UV254)^0.73^*(Br + 1)^{2.42}}$</td>
</tr>
<tr>
<td><strong>TCAA</strong></td>
<td>Field</td>
<td>Zhang et al. (2011)</td>
<td>$-5.2 + (0.5^*T) + (0.4^*TOC) + (0.2^*TTHMs)$</td>
</tr>
<tr>
<td><strong>HAN4</strong></td>
<td>Field and laboratory</td>
<td>Chen &amp; Westerhoff (2010)</td>
<td>$1.65^<em>(DOC)^{0.87^</em>(Br + 1)^{2.22}}$</td>
</tr>
</tbody>
</table>

TOC: total organic carbon (mg/L); DOC: dissolved organic carbon (mg/L); UV254: UV absorbance at 254 nm (cm$^2$/L); T: water temperature (°C); Br: bromide (mg/L); D: chlorine dose (mg/L); t: contact time (h); TTHMs: total trihalomethanes (μg/L); HAA4: haloacetic acids (TCAA, DCAA, BCAA and MBAA) (μg/L).
This assumption is consistent with the data collected in the SWS database.

For DOC, two simple models linking: (i) climate and DOC in raw waters (DOCRW model) and (ii) DOC in raw waters and DOC in treated waters (DOCTW model) were calibrated on SWS data. The first model included five input parameters linked with catchment (percentage of wetland area, slope and river basin area) and climate characteristics (60-day sum of precipitations and 15-day mean air temperatures). It was constructed with data from May to October only which correspond to the season when rainfall–runoff events occur and could lead to degradation of surface water sources. In fact, the transport of organic matter from watersheds to surface waters is generally limited by ice cover during the frozen season (Rodriguez et al. 2005). The second model included one variable describing the treatment characteristics (number of treatment steps and presence of a coagulation–floculation step) and three others describing raw water quality (DOC, pH and temperature). Finally, the accuracy of the different models with the observed data was tested using coefficient of determination ($R^2$), F-test, t-test and standard error. Results of the statistical comparisons between observed and fitted data show that DOC and water temperature models have an adequate accuracy (Table 3). We performed a sensitivity analysis on climatic variables for the water temperature and the DOCRW models. The results show that precipitation and maximum air temperatures are the most sensitive parameters for the DOCRW and water temperature model respectively.

Figure 1 describes the information and data flows between the different models and parameters.

**Potential effects of climate scenarios**

To assess the effects of CC on DBP concentrations, we used a delta approach to generate temperature and precipitation time series. The observed data were modified using the annual or seasonal differences between the GCM simulations for each respective scenario and the control run (Equations (1) and (2)).

$$T_{year} = T_{year \ (actual)} + (T_{year \ future \ (Model)} - T_{year \ actual \ (Model)}) \quad (1)$$

$$Prec_{60d} = Prec_{\sum_{60d\ -\ actual}^{\sum_{60d\ -\ actual}}} + 60 \times (Rain_{year \ future \ (Daily\ -\ model)} - Rain_{year \ actual \ (Daily\ -\ model)}) \quad (2)$$

**Table 3** | Results of the statistical comparisons between observed and fitted data for the different models

<table>
<thead>
<tr>
<th>Model</th>
<th>$N$</th>
<th>$R^2$</th>
<th>F Test</th>
<th>T-Test</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water temperature</td>
<td>153</td>
<td>0.83</td>
<td>1.17</td>
<td>0.08</td>
<td>2.77</td>
</tr>
<tr>
<td>DOCRW</td>
<td>58</td>
<td>0.83</td>
<td>1.67</td>
<td>0.41</td>
<td>1.96</td>
</tr>
<tr>
<td>DOCTW</td>
<td>149</td>
<td>0.80</td>
<td>1.13</td>
<td>0.33</td>
<td>0.62</td>
</tr>
</tbody>
</table>

DOCRW: DOC raw waters; DOCTW: DOC treated waters.

**Figure 1** | Description of data integration between climatic and water quality parameters (RW: raw waters, TW: treated waters).
For temperature (mean and maximum) and precipitation, we elected to distribute the daily change evenly over the entire period of observations. Values of seasonal or annual change (as shown in Table 1) were then applied. For precipitation however, only the changes in rainfall were considered, as changes in snowfall were not considered to have the potential of degrading surface water quality and snow cover limits the transfer of pollutants into surface waters (Rodriguez et al. 2003).

The reduction of the duration of ice cover with CC was also considered for the DOC modelling step for each scenario and horizon. Changes in rainfall were attributed only for periods where mean positive temperatures were measured during the 2 weeks preceding the sampling.

The influence of the different climate scenarios on the accuracy of the DBP models was tested. Results show that there was no significant change in the goodness of fit of these models.

Given the difficulty of modelling the variations of other DBP precursors such as bromide and UV254 with CC, it was assumed that their levels would remain constant in the future. Moreover, although treatment operations will undoubtedly differ in future decades to adapt to changes in raw water quality (i.e., modifications in coagulant and chlorine doses), water treatment was also considered as unchanged for this study. This assumption is relevant, since the assessment of changes in raw water quality is a crucial step in allowing an evaluation of the needs for drinking water treatment adaptation. Finally, water residence times were also considered as constant for the different scenarios and horizons.

Changes in DBP levels were estimated using a delta approach and expressed as a percentage of variation for treated waters at the beginning of the treatment network (i.e., for a residence time of 8 h). The results obtained for each scenario and horizon were compared to the current DBP concentrations measured on SWS. These concentrations were also modelled to allow the calculation of DBP variation percentages. The results obtained with HAA4 (TCAA, DCAA, BCAA and MBAA) and HAA9 models were combined because the differences between the observations of these two parameters were not significant. Moreover, HAA4 was used for purposes of comparison with regulations (HAA5) for identical reasons.

**RESULTS AND DISCUSSION**

**Input parameters**

Levels of natural organic matter indicators in Eastern Canada surface waters are generally highest during summer and especially fall (Rodriguez et al. 2003; Eimers et al. 2008). Compared to the reference period, a small increase in DOC concentration was modelled during winter and spring, reaching a maximum of 0.45 mg/L and 0.60 mg/L in raw waters and 0.14 mg/L and 0.15 mg/L in treated waters respectively. This increase is related to the substantial rise in total precipitation predicted in winter and spring, comprising between 76 mm/year and 370 mm/year and 63 mm/year and 315 mm/year respectively, according to the different scenarios and horizons. This finding is consistent with that of Clair et al. (1999), who found that winter and spring were the seasons that could experience the highest increases in DOC export under a doubling CO2 scenario. In summer, a small DOC decrease of 0.50 mg/L and 0.11 mg/L was calculated for raw and treated waters respectively, and is related to the predicted decrease in precipitation during this season, comprising between −23 and −165 mm/year.

Water temperatures are also generally the highest during summer and fall in Québec (Rodriguez et al. 2007). The model results show an increase in annual temperatures and for all different seasons. Seasonal water temperature increases matched those modelled for air temperature. The highest increases were obtained for the summer and fall seasons for all the different scenarios and horizons, with the highest values being observed for the A2 scenario for the horizon 2071–2100 (+2.3°C and +2.2°C, respectively).

**Total trihalomethanes**

A total of 10 models were tested to assess the range of average variations in total trihalomethanes (TTHMs). Average annual and seasonal estimated variations in TTHMs are provided in Figure 2. A general annual increase in TTHMs was observed for all scenarios and horizons compared to the current scenario (+2.7 to +9.5%). As expected, the highest annual increase (9.5 ± 6.8%) was calculated for the A2
scenario for the horizon 2080 (2071–2100). In fact, this result is related to an average highest air temperature and total precipitation increase predicted in this scenario for this horizon.

Important differences were observed between seasons, with the highest increase observed during winter and spring (+7.7% to +34.0% and +6.5% to +16.1%, respectively). This could be explained by a reduction in the number of frozen days and a sharp increase in temperature and precipitation predicted for both seasons. In southern Québec, the transport of natural organic matter from water-sheds to surface waters is limited by ice cover during the frozen season, i.e., from December to March (Rodriguez et al. 2003). In southern Québec, since the duration of the frozen season is predicted to decrease with CC (DesJarlais et al. 2010), this will ultimately increase mean organic matter content in receiving waters during winter and spring.

Furthermore, TTHM levels in utilities are known to be highest during summer and fall in Québec (Rodriguez et al. 2007). However, concentrations are predicted to remain stable during summer and range between −0.3 and +0.4%. In the fall, a slight increase was modelled for all scenarios and horizons, the highest being for the A2 scenario and 2080 horizon (+4.4%).

It should be noted that the standard deviation is high for the TTHM variations modelled. The different models show

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**Figure 2** Mean percentage of estimated variations in TTHMs concentrations by SRES scenario (B1: low; A1B: medium; A2: high) and horizons compared with current situation for small water utilities (10 models tested, bars represent standard deviations): (a) annual and (b) seasonal.
important differences between each other in terms of their variation levels, even if all the models predict an increase in annual TTHM concentrations. Discrepancies between the results obtained are also linked to the fact that some models require raw water quality data as input parameters (i.e., DOC), whereas others use treated water quality data.

To compare model responses, a comparison between average annual results obtained with models requiring raw waters data and models using treated waters data is provided in Figure 3. Globally, it was observed that models using raw water DOC values had a higher TTHM increase range (+3.7 to +13.6%) than models using treated waters DOC values (+2.5 to +8.2%). The highest increase was also found for the A2 scenario for the 2080 horizon (+13.6% and 8.2% for raw and treated waters, respectively). Moreover, winter constituted the period where the greatest differences were observed (+49.6% and +28.2% for models using raw and treated waters data, respectively (A2-2080), data not shown). This result shows that utilities supplied by surface waters and having already implemented a complete water treatment process will probably be more resilient to increases in organic matter content, water temperature and increases in TTHMs than utilities using only a simple chlorination step. The latter situation is often encountered in small utilities in Canada (Holmes 2002; Peterson & Torchia 2008).

We compared the relative percentage of increase with mean seasonal current TTHM concentrations measured in the SWS study. The highest average increase in TTHM concentrations following the A2 scenario for the 2080 horizon would be encountered in winter (+10.4 μg/L corresponding to a mean concentration of 41.0 μg/L), followed by spring (+4.2 μg/L corresponding to a mean concentration of 30.5 μg/L) and fall (+2.1 μg/L corresponding to a mean concentration of 50.2 μg/L). In the summer, the average TTHM concentration would remain stable (−0.1 to +0.6 μg/L corresponding to a maximum of 50.7 μg/L).

Although the TTHM standard of 80 μg/L established in the Province of Québec (Gouvernement du Québec 2012) is not exceeded regardless of whether the scenario and the horizon are tested annually or seasonally, two TTHM models using raw water quality data showed that this limit could be exceeded in the fall.

**Haloacetic acids (HAA4)**

Four different models were tested to assess the range of average variations in HAA4. Average annual and seasonal variations in HAA4 are presented in Figure 4. An annual increase in HAA4 levels was found for all scenarios and all horizons. The most important increase was noted for the A2 scenario for the 2080 horizon (+7.6 ± 4.9%). The increase ranging between 2.3 and 7.6% is less than the increase observed for TTHMs. However, the influence of the different scenarios on HAA4 is linked directly to the levels of variation predicted for air temperature and total precipitation.

Important differences between seasons were noted, as was the case with TTHMs. Winter and spring showed the highest increases (+4.1% to +18.7% and +8.3% to +13.8%, respectively). During the fall, there were slight increases (+0.3 to +2.2%), whereas decreases were noted for the summer season (−0.5 to −4.5%). Model response variability was less significant than that observed for
TTHMs and could be due to the limited number of models tested and source data used. Here, three in four models were tested with treated waters data.

When calculating the relative increase in concentration for the SWS under study, the increase was highest for winter (\(+5.5\, \mu g/L\) corresponding to a maximum of 35.4 \(\mu g/L\), A2-2080), followed by spring (\(+3.7\, \mu g/L\) corresponding to a maximum of 30.7 \(\mu g/L\), A2-2080) and fall (\(+1.5\, \mu g/L\) corresponding to a maximum of 55.0 \(\mu g/L\), A2-2050). In summer, the average HAA concentration would decrease (\(-1.8\, \mu g/L\) corresponding to a minimum of 40.7 \(\mu g/L\), A2-2080). Contrary to the TTHMs, none of the models predicted a seasonal exceedance of HAA of 60 \(\mu g/L\) in SWS finished waters, which is the regulatory standard in Québec (Gouvernement du Québec 2012).

As for TTHMs, the highest increases calculated for winter and spring were explained by highest increases in precipitation and mean and maximum temperatures predicted for these seasons. Moreover, in the HAA models tested, a higher regression coefficient was generally attributed to the DOC/TOC input parameter rather than the water temperature parameter, i.e., a higher weight was allotted to the organic matter variable. As DOC was predicted to decrease slightly in summer following the
scenarios used, this could explain the decrease observed during this season.

Recent studies have noted that haloacetic acid degradation in the distribution network is favoured by contact with pipe material or the bacteria in biofilms on internal pipe surfaces (Zhang et al. 2011), particularly during warm water conditions (Baribeau et al. 2005). This effect could also be strengthened by an increase in high temperatures. It might then be assumed that a more significant decrease than the one modelled might be expected in future decades in summer for the extremities of the distribution network.

The results obtained on TTHMs and HAA4 concentrations show that there could be a general trend towards annual increases and homogenization between seasons. Annual and seasonal increases will be higher for TTHMs than for HAA4 for all the scenarios and horizons. For both groups of DBPs, winter is the season where the highest increases might be expected for the horizons 2050 and 2080, whereas spring shows the highest increases for the horizon 2020. Currently, compliance with drinking water standards for TTHMs and HAAs in Québec is defined on the basis of an annual mean. Even if no standard exceedances were modelled annually, it should be noted that some models predicted a seasonal TTHM exceedance in fall.

**Other DBPs models (DCAA, TCAA and HANs)**

Average annual and seasonal variations of DCAA, TCAA and HAN are provided in Figure 5. Contrary to TTHMs and HAAs, only one model by compound or group of compounds could be used and was tested here. DCAA showed a different pattern of variation according to scenarios and horizons. Slight variations were modelled with an annual increase, whereas seasonal differences appeared with a decrease in summer for all scenarios and horizons, the more pronounced being for the A2 scenario in 2080 (−2.9%). The highest increase was noted for the winter season for the 2050 (+3.5 to +3.8%) and 2080 horizons (+3.8 to +4.4%), and for spring in the 2020 horizon (+2.3 to +2.5%). Annual increases in TCAA were more pronounced, with the highest being for the A2 scenario (+10.8%). Large increases were noted during winter (+24.6%, A2-2080) and spring (+23.5%, A2-2080), whereas increases modelled for the summer and fall were three times lower (respectively +7.0% and +6.5%, A2-2080). As for DCAA, the highest increases were noted for the winter season for the 2050 and 2080 horizons, and for spring for the 2020 horizon. HAN variations were close to those modelled for DCAA with a small annual increase (+4.3%, A2-2080). Seasonal variations were also close to those observed for DCAA with a slight increase in winter and fall (+10.0% and +7.4%, respectively, A2-2080) and a decrease during summer comprising between −0.6 and −4.3%. In the fall, the pattern was also different depending on the scenario and horizon (−0.6 to +0.8%).

It should be noted that the assessment of variations for DCAA, TCAA and HAN was limited due to a lack of useable existing models. Complementary assessments aimed at assessing intermodel variability for these compounds should be conducted once a larger range of models becomes available.

**Results implications and limitations**

This study presents an original and useful approach that provides some insight into the impacts of CC through the use of various emissions scenarios on DBP levels in drinking waters. The approach chosen offers major advantages over simple assumptions based on historical rates of rising DOC levels (Freeman et al. 2001). However, the results obtained have some practical implications and limitations.

It should be highlighted that SWS with simple treatment consisting only of chlorination could face higher increases in TTHMs. In Québec, this situation currently concerns approximately one-third of the municipal drinking water stations supplied by surface water (MDDELCC 2014b).

In Québec, compliance with standards for chlorination by-products is based on annual mean concentrations. However, drinking water quality shows considerable seasonal variations. Previous studies in Québec and elsewhere have shown that annual averages are not representative of the seasonal variations in DBPs that could be particularly high (Rodriguez et al. 2007; Gough et al. 2014). In Québec, it has been shown that TTHM concentrations are highest in the summer and fall (Rodriguez et al. 2003, 2007) and could be 2.5–5 times more elevated than during winter (Rodriguez et al. 2005). HAA concentrations are also generally higher during the summer and fall than in winter (Rodriguez et al. 2007). The present study shows that average changes in DBP
concentrations could be considerably different between each season and between seasons and annual averages. In addition, some models predicted a possible exceedance of TTHM standards in Québec during the fall and associated with CC.

Seasonal variations in DBP levels will result in variations of population exposure to these substances. For example, epidemiological studies that associate DBP exposure in drinking water with reproductive outcomes must consider the variability of seasonal exposure to DBPs. Recently, a slight excess risk of delivering small-for-gestational-age neonates was found for high exposures to TCAA (>17.8 μg/L), HAA5 (>39.6 μg/L) and HAA9 (>48.5 μg/L) during the last trimester of pregnancy (Levallois et al. 2012). Consequently, the results of this study suggest the importance of taking into account seasonal DBP variations in future regulations, in particular if CC could potentially influence seasonal DBPs, as suggested in this study.

Some limitations and strategies for improving this study should be mentioned. The results obtained in this study are highly dependent on the manner in which the DBP models used were developed previously. The types of parameters and coefficients selected were decisive in model responses.
to CC scenarios. It is also necessary to better consider the effect of contact time (or location in the distribution network) on DBP variations, for example, to assess the effect of rising temperatures on HAA levels in treated waters, since lower HAA concentrations could be found at the distribution network extremities. In this study, it was not possible to accurately estimate this effect as the information was not available. Moreover, residence times in the distribution network were increasingly difficult to evaluate as the network became increasingly complex at points located at its extremities.

It was also assumed for this study that levels of other factors related to DBP formation, such as UV254, chlorine dose, pH or residence time would remain constant under climate modifications. It is obvious that these parameters will certainly be influenced by a change in organic matter concentration (DOC/TOC) or temperature. Accordingly, the organic matter flux increases that could be expected with precipitation will probably lead to higher SUVA values owing to a higher proportion of aromatic compounds resulting from soil leaching (Vidon et al. 2008), but could also lead to lower pH values. It is also likely that increasing rainfall could modify concentrations of a key DBP precursor such as bromide ion in waters. However, not enough information was available on the 13 catchments studied to allow an accurate understanding of organic matter behaviour throughout the year. Similarly, the difficulty in assessing the competing effects of inputs from roads, agricultural soil leaching, weathering rocks and dilution (Flury & Papritz 1995) makes it hard to determine a future trend in bromide concentration at our sites. The ensemble of environmental mechanisms leading to a variation of DBP precursors with CC are complex and have yet to be explored in order to be included in a complete evaluation.

There is also the need to develop predictive models for emerging DBPs such as nitrogenous DBPs (N-DBPs), halonitromethanes, halocarbonates and halonitromethanes that have been proven to be far more cytotoxic and genotoxic than TTHMs and HAAs (Bond et al. 2011). Since appropriate N-DBP precursors may yet be discovered (Chen & Westerhoff 2010), very few models have been published in the literature. To our knowledge, only the study of Chen & Westerhoff (2010) focuses on the development of predictive models for N-DBPs (NDMA and HAN).

The issue of the impacts of CC on treatment methods and costs is of paramount importance, but beyond the scope of this paper. Improving treatment for small utilities will certainly be associated with a rise in treatment costs that should be included and quantified in further studies.

Finally, one should not overlook the fact that the assessment of DBP model responses to CC scenarios does not necessarily provide a projection of the likely consequences of CC. However, our study offers valuable insight into the sensitivity and vulnerability of drinking water systems in the area of CC studies. Further studies could combine our approach with the development of decision support systems to help drinking water managers anticipate the potential consequences of CCs on their drinking waters (Delpla et al. 2014).

CONCLUSIONS

This paper provides estimates of the possible impacts of CC scenarios on DBPs in the drinking water of small utilities. A general annual increase was estimated for all DBPs studied (TTHM, HAA4, DCAA, TCAA and HAN), for each SRES scenario (B1, A1B and A2) and for the three 30-year horizons considered (2020, 2050 and 2080). The findings highlight the fact that impacts will be different according to the season, with the highest increases estimated in winter for all DBPs considered. According to the worst-case SRES scenario (A2-2080), the impact on total THMs could be considerable during this season (+34.0%), followed by spring (+16.1%) and fall (+4.4%), whereas no clear trend could be noted for summer (−0.3 to +0.4%). Results suggest that water systems without treatment before chlorination could be faced with relatively more impacts through TTHM variations associated with possible CCs.

To our knowledge, this study is the first to assess the impacts of various CC scenarios on DBP variations for different horizons in several SWS. This study also served to define a methodology to address the complex issues of the impacts of CC on the quality of treated waters. This methodology should be improved in the future and could be applied in others regions that may also experience high DOC increases with CC. Regulations in Québec set a standard for TTHMs of 80 μg/L that could be exceeded seasonally under CC conditions, particularly during the
fall. Consequently, it might be relevant to consider these seasonal variations in future regulations.

The results of this study provide valuable inputs that can be used further to adapt the treatment operations of these systems, in order to allow them to be more resilient to future CC.

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