Mechanisms of spring freshet generation in southern Quebec, Canada

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Abstract

Seasonal forecasting of spring floods in snow-covered basins is challenging due to the ambiguity in the driving processes, uncertain estimations of antecedent catchment conditions and the choice of predictor variables. In this study we attempt to improve the prediction of spring flow peaks in southern Quebec, Canada, by studying the preconditioning mechanisms of runoff generation and their impact on inter-annual variations in the timing and magnitude of spring peak flow. Historical observations and simulated data from a hydrological and snowmelt model were used to study the antecedent conditions that control flood characteristics in twelve snow-dominated catchments. Maximum snow accumulation (peak SWE), snowmelt and rainfall volume, snowmelt and rainfall intensity, and soil moisture were estimated during the pre-flood period. Stepwise multivariate linear regression analysis was used to identify the most relevant predictors and assess their relative contribution to the interannual variability of flood characteristics. Results show that interannual variations in spring peak flow are controlled differently between basins. Overall, interannual variations in peak flow were mainly governed, in order of importance, by snowmelt intensity, rainfall intensity, snowmelt volume, rainfall volume, peak SWE, and soil moisture. Variations in the timing of peak flow were controlled in most basins by rainfall volume and rainfall and snowmelt intensity. In the northernmost, snow-dominated basins, pre-flood rainfall amount and intensity mostly controlled peak flow variability, whereas in the southern, rainier basins snowpack conditions and melt dynamics controlled this variability. Snowpack interannual variations were found to be less important than variations in rainfall in forested basins, where snowmelt is more gradual. Conversely, peak flow was more sensitive to snowpack conditions in agricultural basins where snowmelt occurs faster. These results highlight the impact of land cover and use on spring flood generation mechanism, and the limited predictability potential of spring floods using simple methods and antecedent hydrological factors.

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Short running title

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Introduction

The hydrology of cold regions is characterized by long winters dominated by snowfall and rapid spring melting, which is the main cause of the high spring streamflow (Pomeroy et al., 2016). In the province of Quebec, Canada, the amount of accumulated snow is very important, with a mean annual maximum of 200 to 300 mm of snow water equivalent (SWE) (Brown, 2010). As a result, the streamflow regime is nival to nivo-pluvial and strongly influenced by the snowmelt contribution, which occurs between April and June depending on the basin geographic location and the year. In the southern part of the province, snow begins to accumulate in November and melting occurs between March and May. Peak flow typically occurs in the spring following snowmelt while a second flood peak typically occurs in summer in response to convective rainstorms, or in the fall caused by the advection of moist air masses with above-freezing temperatures. In northern Quebec, snow accumulation begins earlier in October and melting occurs later, in June and July, with a single streamflow peak mainly driven by snowmelt (Assani et al., 2010a; Buttle et al., 2016; Saint-Laurent et al., 2009).

Knowledge of the SWE stored in the winter snowpack and of ablation dynamics in the spring is key for accurate streamflow predictions and operational management of reservoirs in Quebec. As such, a reliable seasonal forecast of spring freshet based on winter and early spring conditions is essential for reservoir operators to optimize two conflicting objectives, namely flood protection and hydropower production (Turcotte et al., 2010), as well as for governmental agencies to prepare flood mitigation and disaster relief measures. Nevertheless, the relation between snowpack conditions and the inter-annual variations in the magnitude and timing of the spring peak flow is not straightforward, due to the complexity of spring runoff generation mechanisms (Merz and Blöschl, 2003; Tarasova et al., 2019). In fact, the same annual snow accumulation can induce more or less severe floods because of the multiplicity of antecedent hydrological conditions that can control runoff in addition to snowpacks, such as meteorological conditions during the melt period, the occurrence of rain-on-snow events, soil moisture and soil freezing. Therefore, a good understanding of the flood generation mechanisms and of the relative contribution of the key driving factors involved is essential to explain the interannual variability of the spring peak flow characteristics and guide future forecasting efforts.

The variability in flood characteristics in North America has been linked with large-scale climatic indices, and several previous studies have studied how these indices influence extreme floods (Assani et al., 2010a; Assani et al., 2010b). Mazouz et al. (2012) studied the relationship between the interannual variations of high spring flow characteristics in southern Quebec (magnitude, duration, period of occurrence, frequency, and variability) and several global climatic indices using canonical correlation analysis. A significant correlation between the Atlantic Multi-Decadal Oscillation (AMO) and North Atlantic Oscillation (NAO) indices and four flood characteristics (duration, period of occurrence, frequency, and variability) was found, while no relationship was found between these indices and the flow magnitude. This correlation was explained by the low temperature during the negative phases of the AMO and the positive phases of the NAO, which causes a later date of occurrence, a higher frequency, a longer duration and lower variability of heavy spring floods (Mazouz et al., 2012).

Heavy rainfall events during spring can also contribute significantly to runoff while also accelerating snowmelt, causing more devastating floods (Fang and Pomeroy, 2016; Pomeroy et al., 2016; Sui and Koehler, 2001) depending on the antecedent conditions of the snowpack (Garvelmann et al., 2015). The relative contribution of melting and rainfall to runoff and floods becomes more complicated during rain-on-snow events and affects the results of forecasting studies. Rain-on-snow events in Canada have been addressed by several studies (Dyer, 2008; Mccabe et al., 2007; Pomeroy et al., 2016; Wayand et al., 2015). In Quebec, many devastating spring floods have been caused by a combination of heavy rainfall during melting and a deep accumulated snowpack, such as for the Richelieu river floods in 2011 (Saad et al., 2015). Teufel et al. (2018) studied the devastating spring floods that occurred in Montreal during May 2017, showing that heavy rainfall events during April and May combined with snowmelt were the culprit of these extreme events. Likewise, antecedent moisture conditions in catchments plays a key role in runoff generation during melt; the degree of soil saturation below the snowpack determines the infiltration and runoff of snowmelt water in snow-covered basins (Koster et al., 2010; Mahanama et al., 2012). These two studies quantified the contributions of snow accumulated on January 1st and soil moisture to the skill of seasonal forecasts of spring snowmelt in 23 basins of the eastern United States. They demonstrated that despite the important role of snow, the contribution of soil moisture to the skill of streamflow forecast was significant. Several studies showed also the importance of 'soil memory', i.e. soil moisture conditions before soil freezing (Curry and Zwiers, 2018; Mahanama et al., 2012; Webb et al., 2018; Wever et al., 2017) so that understanding the relationship between floods, soil moisture and snow cover in these basins is necessary to understand the spring streamflow generation.

The main challenges in studying how antecedent hydrological variables control spring floods are the choice of predictors, the possible interaction between them, the period over which these factors are calculated and the unavailability of observations for some variable such as soil moisture and SWE (Coles et al., 2016; Curry and Zwiers, 2018; Fang and Pomeroy, 2016; Nied et al., 2013; Nied et al., 2014). In western Canada, Curry and Zwiers (2018) investigated the influence of hydroclimatic conditions on the variability of annual maximum daily flow magnitude using multivariate linear regression models in a snow-dominated basin. Potential predictors were ranked according to their degree of control on the maximum basin peak flow. The maximum annual snowpack (SWE_{max}) ranked first, followed by the snowpack melting rate calculated between the date of SWE_{max} and that of peak flow, the Pacific Decadal Oscillation (PDO) and El Niño-Southern Oscillation (ENSO), and finally the rate of air temperature warming between April $1^{st}$and the date of peak flow. Some of the variables used were measured while others were simulated by a hydrological model, such as the snowmelt rate and soil moisture. Coles et al. (2016) studied snowmelt runoff generation in the Canadian prairies hillslopes using a decision tree learning approach to rank the processes responsible for the generation of runoff. The impact of antecedent hydroclimate conditions on flow peaks were, in order of importance, total snowfall, snow cover, fall soil surface water content, snowpack melt rate, melt season length, and fall soil profile water content. A salient result was the importance of the degree of soil saturation during the fall before the frost period, or 'soil memory', in controlling runoff. Fang and Pomeroy (2016) studied the sensitivity of the June 2013 flood in Calgary to pre-flood conditions as simulated by the physically-based Cold Region Hydrological Model (CRHM). They studied streamflow generation processes by varying the amount of precipitation, the land cover and the soil storage capacity during the pre-flood period. They showed that runoff increases rapidly in response to prior accumulation of snow and soil moisture and that antecedent soil moisture in the basin is a better indicator of flood magnitude than the antecedent snowpack in this basin. Using multiple linear regression, Maurer and Lettenmaier (2003) found that soil moisture dominates runoff predictability in the Mississipi River basin for lead times of 1.5 months, except in summer in the western part of the basin where snow dominates. In western Canada, Dibike et al. (2021) found that basin average maximum SWE, April 1stSWE and spring precipitation were the most important predictors of both annual maximum and mean springtime flow, with the proportion of explained variance averaging 51.7%, 44.0% and 33.5%, respectively.

Outside North America, Zhang et al. (2014) used path analysis to identify influential climatic factors on spring floods in an alpine catchment in Xinjiang, China. They found that winter snowfall and mean thawing degree days in spring had the most direct influence on flood peaks, while accumulated freezing degree days in winter had an indirect influence on floods.

In Quebec basins, the hydroclimatic drivers, or 'predictors' of interannual variations in the magnitude and timing of spring flow peaks are not well identified and have not been studied except in relation with global climatic indices (Assani et al., 2010a; Assani et al., 2010b; Mazouz et al., 2012). Hence, the main objective of this study is to identify and better understand the factors that control the interannual variability of spring freshet characteristics in the tributary catchments of the St. Lawrence River in view of improving seasonal flood forecasts. The limited availability of snow depth, SWE and soil moisture observations has always been an obstacle when analyzing historical hydrological datasets. In this study, we use outputs of simplified conceptual models to simulate snow accumulation and melt as well as soil moisture storage in the basins. We seek to answer the following questions: (i) is the inter-annual variability of the spring freshet magnitude mainly dependent on the antecedent snowpack, with higher flow peak occurring in years with deep snowpack? (ii) Does the quantity and intensity of rainfall during the pre-flood period have a strong influence on the characteristics of the spring freshet? (iii) How do the preconditioning factors vary between basins, according to their latitude, physiographic region and predominant land cover?

Study area and data

This study was carried out on twelve tributary catchments of the St. Lawrence River located in the province of Quebec, Canada with a natural hydrological regime (Fig. 1). Spring floods in the populated areas of the St. Lawrence valley cause frequent damages. For example, the recent major flooding events in the spring of 2017 and 2019 forced the evacuation of several thousands of people from flooded neighbourhoods in the Province and resulted in significant psychosocial and material damages (Benoit et al., 2022; Lin et al., 2019; Teufel et al., 2019) The area of the catchments varies between 367 and 4504 km^2(Table 1). They are spatially distributed between the north and south shore of the St. Lawrence River and within four homogeneous hydrological regions used by the Quebec Expertise Center for Water Expertise (CEHQ) in charge of streamflow monitoring and forecasting. The Northwest St. Lawrence region (Batiscan, Bras du Nord and Matawin basins) is characterized by a continental climate; the Saint-Laurent Southwest region (Nicolet, Acadie) is characterized by a maritime climate; the Saint-Laurent Southeast region (York, Beaurivage, Bécancour, Famine, Etchemin, Ouelle) is characterized by a mix of maritime and continental climate and the Saint-Laurent Northeast region (Godbout) by a maritime climate (Assani et al., 2010a; Assani et al., 2010b; Mazouz et al., 2012). The studied basins also encompass three different physiographic regions (i) the St Lawrence Lowlands characterized by flat Proterozoic and Paleozoic sedimentary rocks covered by glaciomarine deposits and mostly clayed soils (Acadie); (ii) the Canadian Shield on the north shore of the St. Lawrence River, with its rugged Precambrian gneissic rocks and sandy soils concentrated in incised glacial valleys (Batiscan, Matawin, Bras du Nord and Godbout); (iii) the Appalachians on the south shore of the St. Lawrence, composed of tilted and folded Paleozoic sedimentary rocks, rolling hill topography, and loamy soils (Ouelle, York, Etchemin, Bécancour, Famine, and Nicolet) (Table 1). In terms of land cover, five basins (Batiscan, Godbout, Matawin, Ouelle, York and Bras du Nord) are nearly completely (>92%) forested basins, with the remaining area covered by agriculture and lakes. The southernmost Acadie basin is dominated by agriculture (72%) with only 25% forest cover, while the remaining basins (Nicolet, Etchemin, Bécancour, Beaurivage and Famine) have mixed covers (agriculture 12-39%, forest: 61-87%) (Table 1).

Daily historical streamflow observations at the outlet of the 12 basins were obtained from the Quebec Center for Water Expertise (CEHQ). The length of the observed flow data varies between basins, from 17 to 55 years (Table 1).

Having a good estimation of pre-flood snowpack conditions is one of the challenges to understand the contribution of snowmelt to peak flow variability. The difficulty of measuring snow depth and snow water equivalent (SWE) typically results in limited data being available both over time and space. While remote sensing can be used to estimate SWE in low vegetation areas, problems remain in forested areas (Bergeron et al., 2014; Brown, 2010; Larue et al., 2017; Sena et al., 2016). In Quebec, a network of snow survey sites has been installed in forested areas to measure snow depth and SWE every two weeks in the winter and spring seasons, but the spatial distribution and density of these stations is low (Nemri and Kinnard, 2019). Consequently, using outputs of snow and hydrological models seems the only solution to derive long and continuous SWE and soil moisture records. In a previous study conducted in the same basins by Nemri and Kinnard (2019), the GR4J hydrological model (Perrin et al., 2003) coupled to the Cemaneige snow model (Valéry et al., 2014b) was calibrated and validated in order to properly simulate basin-wide SWE, soil moisture and daily streamflow. The calibration methods and validation results are well described in Nemri and Kinnard (2019). They found that a multi-objective calibration strategy gave the best simulation of both streamflow and SWE, and the simulation results using this method were used in the present study. The GR4J-Cemaneige model was forced by daily precipitation and temperature date extracted from daily grids produced by the Atmospheric Environment Information Service (SIMAT) in collaboration with the CEHQ (Bergeron 2015). Historical SWE measurements at 12 measuring points of the Quebec snow survey network located in or very close to the selected basins were used in the calibration along with the observed streamflow (see Fig. 1 for locations). The Cemaneige snow module simulates the accumulation and snowmelt in five altitude bands. The precipitation phase (rain, snow) is determined using the mean temperature of each altitude band. The snow/rain fraction is calculated according to the function used in the Hydrotel model (Fortin et al., 2001) based on the minimum (T_{min}) and maximum (T_{max}) daily temperature at each altitude band: when T_{max} [?] 0 degC, all precipitation fall as snow, while if T_{min} [?] 0 degC all precipitation fall as rain, else the snowfall fraction is estimated as 1-T_{min}/(T_{max}- T_{min}). These functions are well described by Valery (2010) and Valery et al. (2014b).

In addition, soil moisture measurements were not available for the study so that the soil moisture simulated by the GR4J model was used. In GR4J, the hydrological processes in the basin are simplified into two interconnected reservoirs. The soil reservoir has a maximum capacity (mm), which is a free parameter to be calibrated, and determines the amount of water in the basin according to the degree of soil saturation, which itself is a function of the ratio between the quantity of stored water and the maximum storage capacity. A summary of the calibrated model parameters and Nash-Sutcliffe performance criteria is given in Table 2.

Methods

Spring flood identification

Two spring streamflow characteristics, the magnitude (Q_{max}) and timing of specific peak flow (Q_{maxT}, in day of year or DOY) were selected to characterize the spring freshet, and their interannual variability calculated from the daily flow historical records. A sufficiently large spring window of four months, from March 1st to

June 30th, was selected based on the observed seasonal cycle of the streamflow records and considering the inter-annual and spatial variability of the spring freshet of all basins. The observed Q_{max} and Q_{maxT} values within this time window were identified for every year. Then, the pre-flood period was defined to extend between the flood onset point, defined here as the point that marks the beginning of the rise in streamflow, and the peak flow date (Fig. 2). The onset point was identified as the first date having a flow value above the 30% percentile of the annual flow distribution and followed by a continuous increase in flow over a minimum of three consecutive days, before the peakflow date. This automatic procedure worked well for most years and basins, but exceptions were noted upon visual inspection. Intermittent snowmelt occurred during some years due to low air temperatures associated with the advection of cold polar air masses, which interrupts snowmelt for several days and causes separate floods according to melting events (Mazouz et al., 2012). This makes it difficult in some years to precisely pinpoint a general flood onset date and this decision may subsequently influence the relation between the peak flow magnitude and the pre-event hydroclimate conditions. Hence for some years the percentile threshold was either adjusted, or the point was chosen manually when the automatic algorithm failed.

Antecedent factors and statistical analysis of spring freshet peak

In total, six antecedent factors related to snowmelt, rainfall and soil moisture were selected and calculated during the pre-flood period as defined in section 3.1., except for the maximum (peak) SWE, which was calculated between the beginnings of spring (March 1) and the peak flow date. The Cemaneige model simulates snow accumulation and melt in five equal-area altitudinal bands based on the air temperature and precipitation interpolated to the median altitude of each band. A basin-wide SWE value was derived by averaging the SWE from all bands. The contribution of snowpack conditions to the variations in spring peak flow characteristics (Q_{max} and Q_{maxT}) was assessed by three variables. The maximum SWE, SWE_{max}(mm), simulated by the model before the melt, represents the amount of snow accumulated and to be released during the spring freshet. The cumulated amount of pre-flood snowmelt, there after 'cumulative snowmelt' ($Melt_{sum}$, mm), and the snowmelt intensity, or average melting rate ($Melt_{int}$, mm/d), were also calculated over the pre-flood period to evaluate their contribution to interannual variability in peak flow characteristics.

Rainfall is used as another antecedent condition that can affect spring floods by changing snowpack characteristics or directly contributing to runoff. The sum of daily rainfall, $Rain_{sum}$ (mm), accumulated during the pre-flood period, was calculated after separating the solid and liquid fraction in the snow model. The mean rainfall intensity, $Rain_{int}$ (mm/d), was also calculated during the pre-flood period. The mean soil moisture saturation level during the pre-flood period, S_{mean} (unitless), was simulated by the model and used as another antecedent factor. The selected antecedent factors are summarized in Table 3.

The time of transfer of the basin must be considered when deriving pre-flood hydroclimatic drivers. In the GR4J, this is represented by the calibrated base time of the unit hydrograph, which varied between 2 and 4 days (see Table 2). However, this parameter (x4) was calibrated over the entire year and is likely to overestimate the faster time of transfer in spring, when rainfall events falling on snow or frozen ground cause rapid runoff. For this reason, a common value of one day was used instead for all basins, i.e., preconditioning variables were calculated from the flood onset date up to 1 day before the flood peak date.

Multivariate linear regression analysis was first used to identify the relative contribution of rainfall and snowmelt volumes to the interannual variability in flood volumes. The relative contributions were derived from the standardized coefficients of the multivariate regression model. The relationship between the antecedent hydroclimatic factors and peak streamflow characteristics was first assessed by linear univariate correlation analysis using the Pearson correlation coefficient. Then, a stepwise multivariate regression analysis was performed to identify the best predictors of peak flow (Q_{max}) (Equation 1).

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta n\mathrm{Xn} + \epsilon \quad (1)$$

where $\beta 0$ is the intercept, $\beta 1 \ldots n$ are the regression slope coefficients and ϵ is a random error term (Draper and Smith, 1998). The stepwise method consists in choosing the combination of pre-flood predictor variables

(X) which together best explain the interannual variability of flood characteristics (response variable Y) using an iterative procedure. The stepwise procedure requires two significance levels for adding and removing predictors based on a variance ratio (F) test, for the improvement of the model. Starting with the initial model, a p- value for the F-statistic is calculated at each step of adding or removing a variable in the model (Draper and Smith, 1998). An entrance tolerance p- value of < 0.05 and an exit tolerance p- value < 0.10 were used.

Results

Interannual and spatial variability of peak streamflow and its timing

The variability of the spring specific streamflow magnitude (Q_{max}) observed in the twelve basins is shown in Fig. 3a, while volumetric streamflow values are given in Table 4. The highest specific Q_{max} values are observed in the more agricultural basins (Acadie, Nicolet and Beaurivage), while the forested basins (Batiscan, Matawin, York and Godbout) have lower specific flows, except Bras-du-Nord (#9) and Ouelle (#8) (Fig. 3a). Q_{max} is also more variable in more agricultural compared to forested basins, again with the exception of the Bras-du-Nord and Ouelle basins. The seasonality of the spring peak flow is shown in Table 4. For the two northernmost basins (Godbout and York), 90% of the spring flow peaks occurred the latest, in May. For the two southernmost basins (Nicolet and Acadie), melting occurred earlier with 40% of peakflow events occurring in March and 40% in April. For the remaining basins, 65% of the peakflow events occurred during April. The peakflow timing shows pronounced interannual variability as well as spatial variability between basins (Fig. 3b). The general increasing trend from south to north in the peakflow timing also appears clearly. Also, for the three completely forested basins located on the Canadian Shield, i.e., Matawin (#7), Bras du Nord (#9) and Batiscan (#10), and melting occurs later compared to basins at the same latitude with less forested areas, such as Beaurivage (#5: 60% forest cover) and Etchemin (#6: 74% forest cover). Therefore, the spatial distribution of the Q_{max} timing appears to respond primarily to latitude and secondarily to land cover.

Contribution of snowmelt and rain to flood volumes

The contribution of pre-flood water volumes (snowmelt and rainfall) available for runoff to the total flood volume estimated from the multivariate regression method is illustrated in Fig. 4 for the twelve basins. The rainfall contribution is high for the southernmost Acadie basin (#1) compared to the other basins. While the median rainfall contribution in Acadie (0.25) is only slightly higher than that of the other basins, the interannual variability is large, with the third quartile of the distribution reaching near 0.75, and in some extreme years, rainfall was the sole contributor. For the other basins, the median rain contribution is around 0.20, but can be as high as 0.60, which shows that the rain contribution to the spring flood volume in all basins can be important.

Annual variations in water volume (snowmelt + rainfall) available for runoff explain between 67% and 93% of the interannual variability in flood volumes (Table 5). Rainfall and snowmelt volume variability had a comparable effect on flood streamflow volume for five basins (Nicolet, Acadie, Batiscan, Matawin and Bras du Nord), whereas for the other seven basins, the interannual variability in flood volume is more controlled by snowmelt volume than rainfall (Table 5), without a clear relation with latitude or land cover.

Correlation between antecedent factors and spring flow peak and timing

Correlations between Q_{max} and the six antecedent factors for the 12 basins are displayed on a correlogram (Fig. 5). Snowmelt intensity ($Melt_{int}$) is positively correlated with peak flow in all basins (r = 0.23 to 0.64); the correlation is significant ($p < 0.05$) in most basins, except for Ouelle, Batiscan and Bécancour. Peak SWE (SWE_{max}) is also positively correlated with Q_{max} in all basins; correlations are significant in all basins but Ouelle, Bras du Nord, Beaurivage and Bécancour. Thus, years with higher snow accumulation and faster melting rate (intensity) generally tended to result in higher peak flow. The pre-flood accumulated snowmelt ($Melt_{sum}$) is positively correlated with Q_{max} in all basins (r = 0.07 to 0.50) but only significant in five of them. Pre-flood accumulated rainfall and its mean intensity do not show any significant univariate correlation with Q_{max}, except for the two basins Bras du Nord and Godbout, where Q_{max} is positively correlated with rainfall intensity ($Rain_{int}$) and in Famine where Q_{max} is positively correlated with $Rain_{sum}$. Soil moisture (S_{mean}) is significantly and positively correlated with Q_{max} in only four basins (Godbout, Batiscan, Famine and Matawin) and negatively correlated in Bécancour.

The correlation coefficient for $Melt_{int}$ is stronger than for SWE_{max} in six basins, while $SWE_{max}$is a better predictor in only two basins, Matawin and Batiscan. Overall, the correlation analysis shows that the pre-flood melt rate ($Melt_{int}$) is the best overall univariate predictor of the spring peakflow, followed by the maximum SWE (SWE_{max}) and accumulated snowmelt ($Melt_{sum}$), which is logical given the strongly nival character of the hydrological regime of rivers in Quebec. On the other hand, the correlation coefficients are overall only moderate, suggesting that a combination of several factors would be required to better explain the variability in spring flow magnitude.

For the peakflow timing, the pre-flood accumulated rainfall ($Rain_{sum}$) significantly controls Q_{maxT}in all basins, except for the three basins Famine, York, and Godbout (Fig. 6). This means that spring flood peaks occur later during years with high rainfall volumes during the pre-flood period. A larger amount of accumulated snowmelt ($Melt_{sum}$) and a slower melt rate ($Melt_{int}$) also seem to favor a later occurrence of flood peaks, however with varying levels of statistical significance (Fig. 6). The correlation with soil moisture is not spatially coherent, being significantly anti-correlated with flow timing in two basins (Famine, and Beaurivage) and positively correlated in Ouelle.

Multivariate prediction of spring flow peak and timing

The stepwise multivariate regression models explain 40 to 74% of the variation in Q_{max} in all basins except in Beaurivage and Batiscan, where the models only explain 20-28% of the variation (Table 6). The snowmelt intensity ($Melt_{int}$) was the predictor most often retained in the regression models (7/12 basins). It has a positive effect on Q_{max}, i.e., more rapid melting led to higher peak flow, in all basins but York, where the effect of $Melt_{int}$ was negative. $Melt_{in}$ was notably the sole significant predictor of Q_{max} in two basins, Acadie and Beaurivage, where it explained 60% of the variability in Q_{max} for the former but only 20% for the later. Either SWE_{max} or $Melt_{sum}$ was retained in 7 basins, but never together, as these two variables are partly collinear (r = 0.45-0.69), i.e., thicker snowpacks led to larger pre-flood snowmelt volumes, with a positive effect on Q_{max} in both instances, i.e., leading to higher flood peaks.

Among the rainfall-related variables, the rainfall intensity ($Rain_{int}$) was the most frequent predictor (5/12 basins) and the one with the largest overall effect among all predictors. The accumulated rainfall amount ($Rain_{sum}$) contributed to Q_{max} variability in four basins, with an overall lesser effect than $Rain_{int}$. Pre-flood soil moisture was significant in only three basins, with a small and positive effect in Matawin and a counter-intuitive, negative effect on $Q_{max,}$ (Bécancour and York), i.e., drier pre-flood soils leading to higher peak flows in these two basins.

In order to try improving the prediction performance in basins where the initial predictor set led to a low R^2 (e.g., Nicolet, Beaurivage, Ouelle, Batiscan), the maximum rainfall ($Rain_{intmax}$) and snowmelt ($Melt_{intmax}$) intensity during the pre-flood period were added as potential predictors, to see if these or any of the other basins were sensitive to the most extreme pre-flood rainfall and snowmelt events. $Melt_{intmax}$ significantly and positively contributed to explain Q_{max} in two basins only, Nicolet and Ouelle, while $Rain_{intmax}$ also had a large positive effect in Ouelle only. The Beaurivage and Batiscan models were not improved, remaining with low R^2 values of 0.20 and 0.28, respectively.

Interannual variations in peakflow timing (Q_{maxT}) were comparatively well explained by a different combination of factors between basins, with adjusted R^2 varying between 0.27 and 0.65. (Table 7). Accumulated rainfall and its mean intensity explain most of the variation in all the basins, however with opposites effects. In southern basins, larger rainfall volumes led to earlier flood peaks, while the opposite occurred in more northern basins. Inversely, more intense rainfall events tended to delay flood peaks in southern basins while the opposite occurred in northern basins. Accumulated snowmelt ($Melt_{sum}$) had a positive effect in five basins across the latitudinal gradient, i.e., more snowmelt delayed flood peaks, except in Ouelle where the effect was opposite. The snowmelt intensity $Melt_{int}$ had a noticeable negative influence on flood timing in southern basins (5/12 basins), i.e., slower melt rates led to delayed flood peaks.

Discussion

The results found in this study using measured and simulated pre-flood hydroclimatic factors contribute to improve our understanding of interannual variations in spring flood characteristics. Overall, the ranking of preconditioning factors based on their frequency of appearance as significant predictors in the linear models of Q_{max} across the twelve basins is as follow: (i) snowmelt intensity (mean and max), (ii) rainfall intensity (mean and max), (iii) snowmelt volume, (iv) rainfall amount, (v) peak SWE and (vi) soil moisture. One note of caution to be mentioned is that the stepwise approach finds the best combination of factors explaining the most variations in Q_{max}, and as such can remove predictors that are still important on their own, but that are redundant (collinear) in a multivariate context. Still, snowmelt intensity also appears as the most important univariate predictor of Q_{max} as shown by the correlation analysis (Fig. 5), but peak SWE (SWE_{max}), which is the second-best univariate predictor of Q_{max} (Fig. 5) was often excluded from the multivariate models. A thicker snowpack is more likely to survive later into the spring season and be subjected to faster melt rates (e.g. Aygün et al., 2022; Musselman et al., 2017), which could explain the redundant predictive power of these two variables, along with $Melt_{sum}$, in the multivariate models. Still, SWE_{max} by itself could only explain 10 to 28% of the variability in Q_{max} in 8 out of 12 basins as shown by the bivariate correlation analysis (Fig. 5). This shows that the memory of the snowpack in early spring is not sufficient to accurately forecast springtime flood magnitude in southern Quebec.

The pre-flood mean melt intensity ($Melt_{int}$) emerged as a good predictor of the peakflow magnitude in seven basins (Acadie, Famine, Beaurivage, Etchemin, Matawin, Bras du Nord and York) and was the most skillful predictor for four of these basins (Acadie, Famine, Beaurivage, Etchemin). The maximum melt intensity ($Melt_{intmax}$) was also a good predictor but only in the Nicolet and Ouelle basins. So, overall, snowmelt intensity appears to be the dominant control on peakflow magnitude for 9 of the 12 basins studied. SWE_{max} on the other hand was only retained as a significant predictor of Q_{max} in four basins (Nicolet, Bécancour, Famine and Etchemin).

The sensitivity of peakflow magnitude to antecedent hydroclimatic conditions also varied according to land cover and use. Overall, the interannual variability in peakflow magnitude was primarily controlled by the snowmelt dynamics (initial snowpack SWE, snowmelt amount and intensity) in the more southerly and/or more agricultural basins, while in the northern, snowier and more forested basins rainfall conditions, especially the rainfall intensity, were more important (Fig. 7). This can at first appears counter intuitive, that spring floods in southerly basins with less snowfall and thinner snowpacks are controlled by snowmelt dynamics, while rain events are the main trigger of floods in colder, snowier northern basins. However, snowmelt in forested basins is slower due to shading by the canopy (Ellis et al., 2011; Gelfan et al., 2004), so that Q_{max} variability is less dependant on SWE_{max}. Also, the more porous forested soils and reduced soil freezing under thick snow covers have been found to favor snowmelt infiltration, which attenuates flood peaks (Aygün et al., 2022). On the other hand, SWE_{max} is more variable interannually in agricultural basins (Table 1); melting in open fields is fast, and infiltration is restricted in the often clay-rich and compacted soils (Aygün et al., 2020), which all boost the influence of snowpacks and snowmelt rates on peakflow interannual variability.

Soil moisture was considered to be a key factor in controlling runoff in snow-dominated basin in previous studies (Wever et al., 2017). In this study, no coherent correlation was found between the simulated degree of soil saturation and peakflow variations. Even within the multivariate regression analysis this factor was found to be a significant predictor of peakflow magnitude and timing only for three basins, and a counterintuitive negative effect was found for two of these basins (Bécancour and York). The negative effect of soil moisture on Q_{max} could be an indirect effect reflecting the depletion of the soil reservoir during cold winters with limited snowmelt and rainfall, which could then be associated with thicker snowpacks and higher flows in the following spring. However, the lumped GR4J model does not consider soil freezing processes, which could be important especially in agricultural basins with thinner snowpacks (Aygün et al., 2020). Therefore, further research is needed in Quebec basins using models that explicitly represents soil freezing and fall moisture 'soil memory' in order to better simulate pre-melt soil moisture and its effect on runoff partitioning. Soil freezing is often assumed to play an important role on infiltration, but deep snowpacks can also inhibit soil freezing and cancel its impact on infiltration (Aygün et al., 2021; Aygün et al., 2022).

As for the peakflow timing, a pattern emerged in which an increasing amount of low-intensity rainfall combined with increased snowmelt amounts delayed flood peaks in the more northerly basins, while in the more southerly basins, slower snowmelt and increased rainfall amounts to a lesser extent, led to later flood peaks (Table 7).

Our results are different than those reported by Curry and Zwiers (2018) in the Fraser River basin in western Canada, between the Coast Mountains and the Continental Divide, where the generation of spring runoff was found to be controlled mainly by the maximum accumulated SWE and secondly by the melt rate, with rainfall and soil moisture playing lesser roles. On the other hand, Coles et al. (2016) found that the processes responsible for the generation of runoff in the Canadian prairies hillslopes were, in order of importance, the total snowfall, snow cover amount, fall soil surface water content (0-15 cm) and melt rate. The more humid climate of southern Quebec compared to the Canadian Prairies, and the lower elevation compared to the mountainous basins of western Canada, could explain the fact that interannual variations in accumulated SWE are generally less important than the melt rate and the quantity and intensity of rainfall events during snowmelt. Our results showed that interannual variations in snowmelt volumes were either the prime driver, or as equally important as rainfall, in controlling flood volume variability (Table 5 and Fig. 4). However, our regression analysis showed that snowmelt variables were the most important drivers of peakflow interannual variability in the more agricultural southern basins, even in the southernmost Acadie basin where snowmelt contributes less water than rainfall to flood volumes. Conversely, in the more northerly, snowy and forested basins flood volumes were primarily controlled by snowmelt volumes, whereas rainfall was more important in controlling interannual variations in peakflow.

Initial basin conditions (snow storage, soil moisture) and their forecasting skill are very important for the seasonal prediction of streamflow (Foster et al., 2018; Koster et al., 2010; Li et al., 2009; Mahanama et al., 2012) but these variables are not well measured in most basins. Turcotte et al. (2010) discussed the difficulties encountered by the prediction systems developed for Quebec basins due to errors in the snow observation methods. Therefore, using satellite products of snow cover in conjunction with physically-based models might be a good way forward to improve our understanding of the spring freshet generation mechanisms and the independent role of snow cover, rain on snow events and the soil moisture status in future snow hydrology studies in Quebec. Still, this study showed that knowledge of snow storage in early spring (SWE_{max}) gives only limited forecasting capability for flood magnitude and timing in southern Quebec, and that synoptic scale weather variability plays an important role in defining rainfall and snowmelt intensity, which contribute largely to runoff processes and ensuing flood characteristics.

Conclusions

This study used observed streamflow records from 12 tributary catchments of the St. Lawrence River in southern Quebec, Canada, combined with observed and simulated antecedent hydroclimate conditions during the pre-flood period, to investigate their control on spring flood magnitude and timing. The following main conclusions can be drawn from the study:

- Interannual variations in the volume of meltwater available for runoff were usually more important, or else equally important, than rainfall volumes to explain the interannual variability of spring flood volumes.
- In contrast, the late winter snowpack (peak SWE) was not by itself a strong predictor of spring flood magnitude and timing; as such, the 'snowpack memory' offered only a limited potential for seasonal flood prediction.
- The 'soil memory' effect, represented here by the simulated soil moisture content, was poorly related to flood characteristics; however, the effect of soil freezing was not considered and should be studied further.
- The snowmelt rate during the pre-flood period was the most ubiquitous and skillful predictor of spring flood magnitude.
- SWE and snowmelt dynamics dominated the interannual variability of flood magnitude in the more southerly and agricultural basins, due to more variable snowpack conditions from year to year, faster snowmelt and restricted infiltration. In the northern, snowier forested basins, rainfall variability was instead more important in driving interannual variations in flood magnitude, which is attributed to the documented slower melt rates under forest canopies and the buffering effect of the more porous and less frozen forested soils.
- Seasonal to sub-seasonal (S2S) spring flood prediction in the humid-continental climate of southern Quebec would require an accurate knowledge of pre-melt snowpack SWE, but also S2S predictions of rainfall and temperature, a proxy for snowmelt rates, which is a more challenging requirement (White et al., 2017). Using correlations with large scale climate indices (Mazouz et al., 2012) might represent an option, while advances in the application of Machine Learning (ML) hydroclimate predictions techniques (Başağaoğlu et al., 2022; Mosavi et al., 2018) might help to unravel more complex relationships between potential hydroclimate predictors and flood conditions and help forecasting seasonal flood characteristics.

Acknowledgements

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Table 1. Characteristics of the twelve basins selected in this study ranked according to latitude, from South to North. The coefficient of variation (CV) of SWE is calculated over the flow data period. Mean precipitation and snowfall ratio are calculated over the common 1980-2015 period. Latitude and longitudes are for the basin centroids.

ID	Basin	Lat.	Lon.	Area	Forest	Agri-culture	Median Elev.	CV SWE	Mean P	Snowfall ratio
		(°)	(°)	(km^2)	(%)	(%)	(m)	(%)	(mm)	(-)
1	Acadie	45.20	-73.43	367	25.7	72.1	31	48	1011	0.20
2	Nicolet	45.99	-71.88	1551	40	60	203	31	1142	0.26
3	Bécancour	46.19	-71.56	2165	74.1	25.7	273	26	1201	0.25
4	Famine	46.26	-70.45	698	87.4	12.3	377	21	1153	0.27
5	Beaurivage	46.47	-71.29	709	61.3	38.7	152	22	1194	0.27
6	Etchemin	46.53	-70.68	1155	74.5	25.5	382	21	1190	0.28
7	Matawin	46.63	-74.14	1386	96.9	0	481	23	1037	0.29
8	Ouelle	47.19	-69.92	789	97.4	2.1	348	20	1011	0.31

ID	Basin	Lat.	Lon.	Area	Forest	Agri-culture	Median Elev.	CV SWE	Mean P	Snowfall ratio
9	Bras du Nord	47.21	-71.83	646	100	0	597	22	1077	0.31
10	Batiscan	47.25	-72.25	4505	92.6	6.7	385	23	1142	0.29
11	York	48.90	-65.24	678	100	0	482	21	1201	0.39
12	Godbout	49.69	-67.74	1602	99.5	0	368	18	1153	0.37

Table 2. Results of GR4J-Cemaneige model using the AMALGAM multi-objective algorithm (Nemri and Kinnard, 2019) for the six parameters x1: capacity of production store (mm); x2: water exchange coefficient (mm); x3: capacity of routing store (mm); x4: unit hydrograph base time (days); x5: Cemaneige snowpack thermal state (unitless); x6: Cemaneige degree-day melt coefficient (mm °C^{-1}). $\mathrm{Nash_Q}$, $\mathrm{Nash_{SWE}}$:Nash-Sutcliffe efficiency criterion for the calibration/validation period for streamflow and SWE, respectively (%).

Basin	x1 (mm)	x2 (mm)	x3 (mm)	x4 (days)	x5 ()	x6 (mm °C^{-1})	$\mathrm{Nash_Q}$ (%)	$\mathrm{Nash_{swe}}$ (%)
Acadie	200	-0.95	42	2	0.01	6.1	60/67	33/62
Nicolet	217	0.22	36	2	0.01	5.9	75/79	50/70
Bécancour	216	-0.6	87	2	0.29	5.5	74/76	84/76
Famine	25	0.27	97	2	0.3	3.2	84/82	84/76
Beaurivage	44	-0.7	66	2	0.62	4.1	72/79	72/79
Etchemin	24	-0.33	238	2	0	7.2	80/74	56/42
Matawin	117	-0.51	351	4	0.05	4.6	89/90	31/57
Ouelle	64	0.29	79	2	0.44	3.7	81/87	70/74
Bras du Nord	346	-0.59	112	2	0	4.8	84/82	65/70
Batiscan	436	0.5	134	3	0.03	4.4	89/89	49/36
York	78	-0.55	115	2	0.39	2.9	85/87	57/37
Godbout	265	5.1	305	2	0.03	7.1	82/79	49/20

Table 3. Selected antecedent hydroclimatic variables.

Predictors	Unit	Description	Source
$\mathrm{SWE_{max}}$	mm	Maximum simulated SWE between March 1st and the peak flow date ($\mathrm{Q_{maxT}}$)	Cemaneige model
$\mathrm{Rain_{int}}$	mm/d	Mean rainfall intensity during the pre-flood period	Gridded precipitatio
$\mathrm{Rain_{sum}}$	mm	Accumulated rainfall during the pre-flood period	Gridded precipitatio
$\mathrm{Melt_{int}}$	mm/d	Mean snowmelt rate during the pre-flood period	Cemaneige model
$\mathrm{Melt_{sum}}$	mm	Accumulated snowmelt during the pre-flood period	Cemaneige model
$\mathrm{S_{mean}}$	()	Mean of soil reservoir saturation level	GR4J model

Table 4. Interannual variability of spring maximum flow and its date of occurrence.

ID	Basin	Min $\mathrm{Q_{max}}$ (m^3/s)	Max $\mathrm{Q_{max}}$ (m^3/s)	Mean $\mathrm{Q_{max}}$ (m^3/s)	Std $\mathrm{Q_{max}}$ (m^3/s)	Occurrence month (
						Mar.
1	Acadie	12	219	71	42	15
2	Nicolet	161	762	390	130	15

ID	Basin	Min Q_{max} (m^3/s)	Max Q_{max} (m^3/s)	Mean Q_{max} (m^3/s)	Std Q_{max} (m^3/s)	Occurrence month (
3	Bécancour	235	814	446	134	2
4	Famine	13	299	163	57	7
5	Beaurivage	50	325	180	52	9
6	Etchemin	158	369	253	62	6
7	Matawin	60	240	153	41	2
8	Ouelle	87	427	218	82	2
9	Bras du Nord	63	277	156	48	0
10	Batiscan	295	837	563	141	0
11	York	50	280	141	47	0
12	Godbout	108	856	310	132	0

Table 5. Linear regression of flood runoff volume against water available for runoff (snowmelt and rainfall volumes) during the pre-flood period. Standardized regression coefficients (β) indicate the relative influence of snowmelt and rainfall volumes to interannual variability in flood volume. The adjusted coefficient of determination (R^2) indicates the strength of the relationships.

ID	Basin	β1: rainfall	β2 : snowmelt	Adjusted R^2
1	Acadie	0.6	0.6	0.83
2	Nicolet	0.5	0.6	0.81
3	Bécancour	0.3	0.9	0.89
4	Famine	0.3	0.8	0.82
5	Beaurivage	0.3	0.8	0.67
6	Etchemin	0.2	0.7	0.72
7	Matawin	0.6	0.5	0.88
8	Ouelle	0.4	0.7	0.85
9	Bras du Nord	0.5	0.6	0.92
10	Batiscan	0.5	0.6	0.93
11	York	0.3	0.8	0.88
12	Godbout	0.4	0.7	0.72

Table 6. Results of stepwise multivariate regression of spring flow peak magnitude *Qmax* and the six antecedent factors (predictors) for the twelve. All Adjusted R^2 are significant with p-value < 0.01. Frequency: number of times a predictor is chosen in a model. Basins are ranked by latitude from south (Acadie) to north (Godbout). The color scale for the standardized regression coefficients ranges from blue ([?] -1) to red ([?]1).

Basin	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	R^2
	$Rain_{sum}$	$Rain_{int}$	$Melt_{sum}$	$Melt_{int}$	SWE_{max}	S_{mean}	$Rain_{int}$ max	$Melt_{int}$ max	
1) Acadie				0.75					0.6
2) Nicolet					0.41			0.81	0.4

Basin	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	Standardized regression coefficients	R^2
3) Bécancour	0.42				0.51	-0.71			0.7
4) Famine	0.39			0.43	0.31				0.4
5) Beaurivage				0.46					0.2
6) Etchemin				0.51	0.33				0.4
7) Matawin		0.33	0.51	0.28		0.24			0.5
8) Ouelle	0.52						1.16	0.44	0.5
9) Bras du Nord		0.59		0.41					0.4
10) Batiscan		0.29	0.59						0.2
11) York		0.49		-0.31		-0.31			0.5
12) Godbout	0.23	0.92	0.23						0.6
Mean absolute value	0.39	0.52	0.44	0.45	0.39	0.42	1.16	0.63	
Frequency	4	5	3	7	4	3	1	2	

Table 7. Results of stepwise multivariate regression of spring flow peak timing Q_{maxT} (DOY) and the six antecedent factors (predictors) for the twelve basins. All Adjusted R^2 are significant with p-value < 0.01. Basins are ranked by latitude from south (Acadie) to north (Godbout). The color scale for the standardized regression coefficients ranges from blue ([?] -1) to red ([?]1).

Basin	Standardized regression coefficients	Standardized regression coefficients	Standardized regression c
	$\mathrm{Rain}_{\mathrm{sum}}$	$\mathrm{Rain}_{\mathrm{int}}$	$\mathrm{Melt}_{\mathrm{sum}}$
1) Acadie		0.61	
2) Nicolet	-0.5		
3) Bécancour		1.17	0.72
4) Famine		-0.14	
5) Beaurivage	-0.54	0.55	0.44
6) Etchemin	0.54		
7) Matawin	0.52	-0.37	0.33
8) Ouelle		-0.34	-0.34
9) Bras du Nord	0.28		0.52
10) Batiscan	-0.49		
11) York	0.28		0.61
12) Godbout	0.3	-0.65	

Basin	Standardized regression coefficients	Standardized regression coefficients	Standardized regression c
Mean absolute value	0.43	0.55	0.49
Frequency	8	7	6

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Fig. 1. Studied basins (purple) and streamflow gauge (black dots) in southern Quebec province. 1: Acadie, 2: Nicolet, 3: Bécancour, 4: Famine, 5: Beaurivage, 6: Etchemin, 7: Matawin, 8: Ouelle, 9: Bras du Nord, 10: Batiscan, 11: York, 12: Godbout. Basins IDs are ranked from south to north according to the latitude of basin centroids.

Fig. 2. Spring flood window from March to June and pre-event analysis period. The thick vertical stippled lines indicate the automatically detected flood onset date the peakflow date. The pre-flood analysis period extends from the onset date to one day before the peakflow date, to account for transfer times. Black curve: streamflow; blue bars: rainfall (P); red line: snowmelt (M).

Fig. 3. Interannual variability of flood magnitude and timing observed in the 12 study basins. (a) Peak streamflow (Q_{max} , mm/day); (b) peakflow timing (Q_{maxT} , in day of year) Basins are ranked by latitude, from south (ID#1) to north (ID#12). 1: Acadie, 2: Nicolet, 3: Bécancour, 4: Famine, 5: Beaurivage, 6 : Etchemin, 7: Matawin, 8: Ouelle, 9: Bras du Nord, 10: Batiscan, 11: York, 12: Godbout

Fig. 4. Boxplots showing the distribution of (a) the snowmelt volume (black) and rainfall volume (grey) in the pre-flood period for each basin and (b) the relative contribution of these volumes to the total runoff volume during this period. Basins are ranked by latitude, from south (ID#1) to north (ID#12).

Fig. 5. Correlogram showing Pearson's linear correlation coefficient for all antecedent factors (columns) and spring flow peak magnitude (Q_{max}) for the twelve basins (rows). Significant correlations ($p < 0.05$) are highlighted in bold; blue colors indicate negative correlations and brown colors positive correlations.

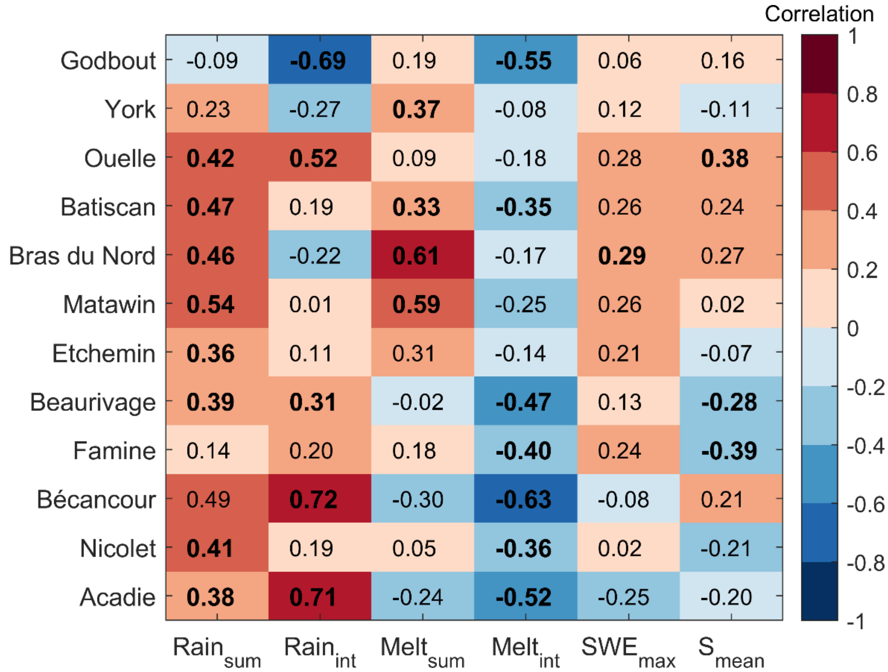

Fig. 6. Correlogram showing Pearson's linear correlation coefficient for all antecedent factors (columns) and day of occurrence (DOY) of peak spring streamflow Q_{max} for the twelve basins (rows). Significant correlations ($p < 0.05$) are highlighted in bold; blue colors indicate negative correlations and brown colors positive correlations.

Fig. 7. Sensitivity of peak spring flow (Q_{max}) to pre-flood rainfall (red symbols) and snowmelt (blue symbols) volume and intensity as a function of (a) latitude, (b) annual snowfall ratio, (c) forest cover. The sensitivity is equal to the standardized regression coefficients in Table 6.

References

Assani, A., Charron, S., Matteau, M., Mesfioui, M., and Quessy, J.-F.: Temporal variability modes of floods for catchments in the St. Lawrence watershed (Quebec, Canada), Journal of Hydrology, 385, 292–299, 2010a.

Assani, A., Landais, D., Mesfioui, M., and Matteau, M.: Relationship between the Atlantic Multidecadal Oscillation index and variability of mean annual flows for catchments in the St. Lawrence watershed (Quebec, Canada) during the past century, Hydrology Research, 41, 2010b.

Aygün, O., Kinnard, C., and Campeau, S.: Responses of soil erosion to warming and wetting in a cold Canadian agricultural catchment, CATENA, 201, 105184, 2021.

Aygün, O., Kinnard, C., Campeau, S., and Krogh, S. A.: Shifting Hydrological Processes in a Canadian Agroforested Catchment due to a Warmer and Wetter Climate, Water, 12, 739, 2020.

Aygün, O., Kinnard, C., Campeau, S., and Pomeroy, J. W.: Landscape and climate conditions influence the hydrological sensitivity to climate change in eastern Canada, Journal of Hydrology, 615, 128595, 2022.

Başağaoğlu, H., Chakraborty, D., Lago, C. D., Gutierrez, L., Şahinli, M. A., Giacomoni, M., Furl, C., Mirchi, A., Moriasi, D., and Şengör, S. S.: A Review on Interpretable and Explainable Artificial Intelligence in Hydroclimatic Applications, Water, 14, 1230, 2022.

Benoit, C., Demers, I., Roberge, F., Gachon, P., and Laprise, R.: Inondations des printemps 2017 et 2019 dans le bassin versant de la rivière des Outaouais (Québec, Canada), Les inondations au Québec: Risques, aménagement du territoire, impacts socioéconomiques et transformation des vulnérabilités, 2022. 2022.

Bergeron, J., Royer, A., Turcotte, R., and Roy, A.: Snow cover estimation using blended MODIS and AMSR-E data for improved watershed-scale spring streamfow simulation in Quebec, Canada, Hydrological processes, 28, 2014.

Bergeron , O.: Grilles climatiques quotidiennes du Programme de surveillance du climat du Québec, version 1.2 – Guide d'utilisation. Ministère du Développement durable, d. l. E. e. d. l. L. c. l. c. c., Direction du suivi de l'état de l'environnement (Ed.), Québec, 2015.

Brown, R. D.: Analysis of snow cover variability and change in Québec 1948–2005, Hydrological processes, 24, 1929–1954, 2010.

Buttle, J. M., Allen, D. M., Caissie, D., Davison, B., Hayashi, M., Peters, D. L., Pomeroy, J. W., Simonovic, S., StHilaire, A., and Whitfield, P. H.: Flood processes in Canada: Regional and special aspects, Canadian Water Resources Journal, 2016. 1918-1817 2016.

Coles, A. E., Appels, W. M., McConkey, B. G., and McDonnell1, J. J.: The hierarchy of controls on snowmelt-runoff generation over seasonally-frozen hillslopes, hydrology and earth system, 2016. 2016.

Curry, C. L. and Zwiers, F. W.: Examining controls on peak annual streamflow and floods in the Fraser River Basin of British Columbia, Hydrology and Earth System Sciences, 22, 2285-2309, 2018.

Dibike, Y. B., Shrestha, R. R., Johnson, C., Bonsal, B., and Coulibaly, P.: Assessing Climatic Drivers of Spring Mean and Annual Maximum Flows in Western Canadian River Basins, Water, 13, 1617, 2021.

Draper, N. R. and Smith, H.: Applied regression analysis, John Wiley & Sons, 1998.

Dyer, J.: Snow depth and streamflow relationships in large North American watersheds, Journal of geophysical research, 113, 2008.

Ellis, C., Pomeroy, J., Essery, R., and Link, T.: Effects of needleleaf forest cover on radiation and snowmelt dynamics in the Canadian Rocky Mountains, Canadian Journal of Forest Research, 41, 608-620, 2011.

Fang, X. and Pomeroy, J. W.: Impact of antecedent conditions on simulations of a flood in amountain headwater basin, hydrological process, 30, 2754–2772 2016.

Fortin, J.-P., Turcotte, R., Massicotte, S., Moussa, R., Fitzback, J., and Villeneuve, J.-P.: Distributed watershed model compatible with remote Sensing and gis data. I: description of model, Journal of hydrologic engineering, 6, 2001.

Foster, K., Uvo, C. B., and Olsson, J.: The development and evaluation of a hydrological seasonal forecast system prototype for predicting spring flood volumes in Swedish rivers, hydrology and Earth System Sciences, 22, 2953–2970, 2018.

Garvelmann, J., Pohl, S., and Weiler1, M.: Spatio-temporal controls of snowmelt and runoff generation during rain-on-snow events in a mid-latitude mountain catchment, hydrological process, 29, 3649–3664, 2015.

Gelfan, A., Pomeroy, J., and Kuchment, L.: Modeling forest cover influences on snow accumulation, sublimation, and melt, Journal of Hydrometeorology, 5, 785-803, 2004.

Koster, R. D., Mahanama, S. P. P., Livneh, B., Lettenmaier, D. P., and Reichle1, R. H.: Skill in streamflow forecasts derived from large-scale estimates of soil moisture and snow, Nature geoscience, 22, 2010.

Larue, F., Royer, A., De Seve, D., Langlois, A., Roy, A., and Brucker, L.: Validation of GlobSnow-2 snow water equivalent over Eastern Canada, Remote Sensing of Environment, 194, 264-277, 2017.

Li, H., Luo, L., Wood, E. F., and Schaake, J.: The role of initial conditions and forcing uncertainties in seasonal hydrologic forecasting, journal of geophysical research, 114, 2009.

Lin, H., Mo, R., Vitart, F., and Stan, C.: Eastern Canada Flooding 2017 and its Subseasonal Predictions, Atmosphere-Ocean, 57, 195-207, 2019.

Mahanama, S., Livneh, B., Koster, R., Lettenmaier, D., and Reichle, R.: Soil Moisture, Snow, and Seasonal Streamflow Forecasts in the United States, journal of hydrometeorology, 13, 2012.

Maurer, E. P. and Lettenmaier, D. P.: Predictability of seasonal runoff in the Mississippi River basin, Journal of Geophysical Research: Atmospheres, 108, 2003.

Mazouz, R., Assani, A. A., Quessy, J.-F., and Legare, G.: Comparison of the interannual variability of spring heavy floods characteristics of tributaries of the St. Lawrence River in Quebec (Canada), Advances in Water Resources, 35, 110-120, 2012.

Mccabe, G. J., Clark, M. P., and Hay, a. E.: rain-on-snow events in the western united states, american meteorological soceity 2007. 2007.

Merz, R. and Bloschl, G.: A process typology of regional floods, Water resources research, 39, 2003.

Mosavi, A., Ozturk, P., and Chau, K.-w.: Flood prediction using machine learning models: Literature review, Water, 10, 1536, 2018.

Musselman, K. N., Clark, M. P., Liu, C., Ikeda, K., and Rasmussen, R.: Slower snowmelt in a warmer world, Nature Climate Change, 7, 214–219, 2017.

Nied, M., Hundecha, Y., and Merz, B.: Flood-initiating catchment conditions: a spatio-temporal analysis of large-scale soil moisture patterns in the Elbe River basin, hydrology and earth system, 17, 1401–1414, 2013.

Nied, M., Pardowitz, T., Nissen, K., Ulbrich, U., Hundecha, Y., and Merz, B.: On the relationship between hydro-meteorological patterns and flood types, journal of hydrology, 519, 3249–3262, 2014.

Perrin, C., Michel, C., and Andreassian, V.: Improvement of a parsimonious model for streamflow simulation, Journal of Hydrology, 279, 275-289, 2003.

Pomeroy, J. W., Fang, X., and Marks, D. G.: The cold rain-on-snow event of June 2013 in the Canadian Rockies — characteristics and diagnosis, hydrological process, 30, 2899–2914, 2016.

Saad, C., Adlouni, S. E., St-Hilaire, A., and Gachon, P.: A nested multivariate copula approach to hydrometeorological simulations of spring floods: the case of the Richelieu River (Quebec, Canada) record flood, Stoch Environ Res Risk Assess 2015, 275–294, 2015.

Saint-Laurent, D., Mesfioui, M., and Evin, G.: Hydroclimatic Variability and Relation with Flood Events (Southern Quebec, Canada), Water Resources 36, 43–56, 2009.

Sena, N., Chokmani, K., Gloaguen, E., and Bernier, M.: Analyse multi chelles de la variabilit spatiale de l quivalent en eau de la neige EEN sur le territoire de l Est du Canada Hydrological Sciences Journal, 2016. 1-16, 2016.

Sui, J. and Koehler, G.: rain on snow induced flood events in Southern Germany journal of hydrology, 252, 205-220, 2001.

Tarasova, L., Merz, R., Kiss, A., Basso, S., Bloschl, G., Merz, B., Viglione, A., Plotner, S., Guse, B., and Schumann, A.: Causative classification of river flood events, Wiley Interdisciplinary Reviews: Water, 6, e1353, 2019.

Teufel, B., Sushama, L., Huziy, O., Diro, G. T., Jeong, D. I., Winger, K., Garnaud, C., de Elia, R., Zwiers, F. W., Matthews, H. D., and Nguyen, V. T. V.: Investigation of the mechanisms leading to the 2017 Montreal flood, Climate Dynamics, 52, 4193-4206, 2019.

Teufel, B., Sushama, L., Huziy, O., Diro, G. T., Jeong, D. I., Winger, K., Garnaud, C., Elia, R. d., Zwiers, F. W., Matthews, H. D., and Nguyen, V. T. V.: Investigation of the mechanisms leading to the 2017 Montreal flood, climat dynamics, 2018. 2018.

Turcotte, R., Filion, T.-C. F., Lacombe, P., Fortin, V., Roy, A., and Royer, A.: Simulation hydrologique des derniers jours de la crue de printemps: le probleme de la neige manquante, Hydrological Sciences Journal, 55, 872-882, 2010.

Valery, A.: Modelisation precipitations – debit sous influence nivale: Elaboration d'un module neige et evaluation sur 380 bassins versants, these de doctorat, Institut des Sciences et Industries du Vivant et de l'Environnement, AgroParisTech, Paris, 417 pp., 2010.

Valery, A., Andreassian, V., and Perrin, C.: 'As simple as possible but not simpler': What is useful in a temperature-based snow-accounting routine? Part 2 – Sensitivity analysis of the Cemaneige snow accounting routine on 380 catchments, Journal of Hydrology, 517, 2014b.

Wayand, N. E., Lundquist, J. D., and Clark, M. P.: Modeling the influence of hypsometry, vegetation, and storm energy on snowmelt contributions to basins during rain-on-snow floods, water ressources research, 51, 8551–8569, 2015.

Webb, R. W., Fassnacht, S. R., and Gooseff, M. N.: Hydrologic flow path development varies by aspect during spring snowmelt in complex subalpine terrain, The Cryosphere, 12, 287–300, 2018.

Wever, N., Comola, F., Bavay, M., and Lehning, M.: Influence of snow surface processes on soil moisture dynamics and streamflow generation in alpine catchments, hydrology and earth system sciences, 2017. 2017.

White, C. J., Carlsen, H., Robertson, A. W., Klein, R. J. T., Lazo, J. K., Kumar, A., Vitart, F., Coughlan de Perez, E., Ray, A. J., Murray, V., Bharwani, S., MacLeod, D., James, R., Fleming, L., Morse, A. P., Eggen, B., Graham, R., Kjellstrom, E., Becker, E., Pegion, K. V., Holbrook, N. J., McEvoy, D., Depledge, M., Perkins-Kirkpatrick, S., Brown, T. J., Street, R., Jones, L., Remenyi, T. A., Hodgson-Johnston, I., Buontempo, C., Lamb, R., Meinke, H., Arheimer, B., and Zebiak, S. E.: Potential applications of subseasonal-to-seasonal (S2S) predictions, Meteorological Applications, 24, 315-325, 2017.

Zhang, F.-Y., Li, L.-H., Ahmad, S., and Li, X.-M.: Using path analysis to identify the influence of climatic factors on spring peak flow dominated by snowmelt in an alpine watershed, Journal of Mountain Science, 11, 990-1000, 2014.