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ANALYSE FRÉQUENTIELLE RÉGIONALE NON STATIONNAIRE DES CRUES À DES SITES NON JAUGÉS

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SECTION 1

LA SYNTHÈSE

RÉSUMÉ

L'analyse fréquentielle régionale des crues est couramment utilisée pour estimer le risque de crue à un site où peu ou pas d'information est disponible sur les débits de pointe. Cette approche nécessite l'hypothèse de stationarité des crues. Dans ce mémoire, une nouvelle méthode est présentée afin de procéder à une analyse fréquentielle régionale des crues à des sites non jaugés lorsque l'hypothèse de stationarité n'est pas vérifiée. Des modèles locaux non stationnaires sont utilisés pour estimer le risque de crue aux sites jaugés. Cette information est ensuite utilisée de pair avec les caractéristiques physiographiques et météorologiques des bassins versants de façon à définir un voisinage hydrologique pour le site non jaugé par l'analyse canonique des corrélations (ACC). Un modèle de régression multiple est développé à l'intérieur de ce voisinage. La méthode proposée a été testée à partir d'un groupe de stations de jaugeage des débits situées dans le sud-est du Canada et le nord-est des Etats-Unis et qui présentent un signal de non stationarité. Les résultats indiquent que le développement d'un modèle de régression multiple au moyen de 2 variables explicatives (incluant l'aire du bassin versant) mène à de bonnes estimations des quantiles de crue régionaux et non stationnaires de temps de retour 5 et 100 ans pour la fin de la période d'observation historique (racine de l'erreur quadratique relative moyenne de 38.2 % et 60.8 % respectivement). L'utilisation de l'ACC pour la définition du voisinage hydrologique n'a pas donné de meilleurs résultats. Le nombre total de sites (29) est faible et, conséquemment, la taille des voisinages hydrologiques est trop petite pour développer de bons modèles de régression à l'intérieur de ceux-ci. La comparaison des quantiles de crue régionaux et non stationnaires avec les résultats stationnaires montre que le fait d'ignorer une tendance des crues printanières d'un site non jaugé peut mener à une sous-estimation ou surestimation considérable des quantiles de crue pour ce site.

Étudiant | Directeur de recherche

Note : Ce résumé sert aussi de résumé en français pour l'article de la section 2.

REMERCIEMENTS

Je remercie :

- Mon directeur de recherche, monsieur Taha Ouarda, pour le support et la confiance qu'il a manifesté à mon égard pendant mes deux années de maîtrise en sciences de l'eau;

- Mes camarades étudiantes et étudiants à la maîtrise, pour la richesse des discussions et des expériences vécues depuis le stage de terrain de septembre 2004 jusqu'à aujourd'hui. Je tiens à souligner particulièrement l'aide de Véronique Jourdain avec qui j'ai travaillé en étroite collaboration tout au long de ma recherche;

- Monsieur Salaheddine El Adlouni, associé de recherche dans l'équipe de mon directeur, pour l'aide fournie au niveau de l'analyse fréquentielle locale non stationnaire.

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INTRODUCTION

Le présent projet de maîtrise consiste à développer une méthode d'estimation des crues de récurrence donnée (par exemple 100 ans, c'est-à-dire susceptible de se produire en moyenne une fois au cours d'une période de 100 ans) dans le cas d'un bassin versant non jaugé (ne disposant pas de station de mesure des débits en rivière) dont le régime hydrologique varie dans le temps (c'est-à-dire est non stationnaire). L'estimation des crues de récurrence est importante à des fins, par exemple, de construction d'un barrage hydroélectrique ou de cartographie des zones inondables. Depuis les premiers travaux de Dalrymple (1960) dans le domaine, plusieurs méthodes se situant en dehors du cadre non stationnaire ont été préconisées. L'originalité du projet est de situer l'analyse à l'intérieur de ce contexte.

Clairement, le projet vise à répondre à la question suivante : Comment estimer les quantiles de crue d'un bassin versant non jaugé dans un cadre non stationnaire?

Une revue de littérature a d'abord été réalisée afin d'identifier les méthodes existantes d'analyse régionale non stationnaire des crues. Cette revue a nourri la réflexion vers le développement d'une méthode dans le cas d'un bassin versant non jaugé. Le modèle retenu pour le présent projet est une extension directe au cadre non stationnaire d'une procédure d'estimation régionale existante pour les sites non jaugés (voir Girard et al., 2000; Ouarda et al., 2001). Des bases de données hydrométriques, météorologiques et physiographiques décrivant les caractéristiques de bassins versants du sud-est du Canada et du nord-est des États-Unis ont été développées afin de tester le nouveau modèle. Nous avons utilisé une procédure de validation croisée afin de comparer les quantiles de crue estimés localement avec ceux fournis par le modèle. Une procédure similaire a aussi été employée à des fins de comparaison du nouveau modèle avec le modèle traditionnel stationnaire.

Cette section « Synthèse » du mémoire de maîtrise est divisée de la façon suivante. Le chapitre 1 précise la contribution de l'étudiant par rapport aux travaux ayant mené à l'article scientifique de la deuxième section. Le chapitre 2 situe cette contribution par rapport à d'autres articles scientifiques traitant de l'analyse fréquentielle des crues.

CHAPITRE 1

CONTRIBUTION DE L'ÉTUDIANT

La revue de littérature du projet de maîtrise a été réalisée en entier par l'étudiant à l'hiver 2005. Les résultats de cette recherche sont présentés dans la partie « Introduction and literature review » de l'article de la deuxième section. Les articles de Cunderlik et Burn (2003) et de Cunderlik et Ouarda (2006) constituent, en effet, la liste exhaustive des méthodes d'analyse régionale non stationnaire des crues que la revue a permis d'identifier. Tel que précisé dans l'article, la revue de littérature a mené au constat de l'absence d'un exemple documenté d'analyse fréquentielle non stationnaire des crues à des sites non jaugés.

L'étudiant a travaillé au développement d'un nouveau modèle principalement à l'automne 2005. La décision finale quant au choix du modèle a été prise au début de l'hiver 2006, d'un commun accord entre l'étudiant et son directeur de recherche. Le modèle a été finalisé au printemps 2006, le processus allant de pair avec la sortie des résultats de la validation. La version finale du modèle est décrite dans la partie 3 « Non-stationary regional model » de l'article. Tel que mentionné en introduction, le modèle retenu est une extension directe au cadre non stationnaire d'une procédure d'estimation régionale existante pour les sites non jaugés. Ainsi, il utilise des méthodes décrites dans des articles scientifiques antérieurs. Ces méthodes sont présentées dans la partie 2 « Theoretical background » de l'article.

La première étape du modèle (partie 3.1 « Flood frequency analysis at gauged sites ») consiste à estimer localement les quantiles de crue d'un certain nombre de bassins versants jaugés. Pour ce faire, le modèle GEV (generalized extreme-value) non stationnaire de El Adlouni et al. (2006) est utilisé (voir partie 2.1 « Non-stationary at-site flood frequency analysis »).

L'étape 2 du modèle (partie 3.2 « Neighborhood identification using CCA ») correspond à l'identification d'un groupe de bassins versants jaugés ayant un régime hydrologique suffisamment similaire au site non jaugé. Cette identification se fait via l'analyse canonique des corrélations (ACC). Quant à l'étape 3 du modèle (partie 3.3 « Information transfer »), elle correspond à l'estimation des quantiles de crue au site non jaugé par transfert de l'information disponible via un modèle de régression multiple. Ces deux étapes sont similaires à celles qu'on retrouve dans le modèle traditionnel stationnaire. Ainsi, la théorie sous-jacente (voir partie 2.2 « Delineation of hydrologic neighborhoods ») est inspirée de l'article de Ouarda et al. (2001) dans lequel les auteurs ont appliqué le modèle traditionnel stationnaire à un ensemble de bassins versants du sud de l'Ontario. Il faut aussi mentionner que dans une recherche subséquente Girard et al. (2000) ont apporté une modification à ce modèle pour améliorer la définition du voisinage hydrologique. Le présent projet de maîtrise incorpore cette suggestion. En résumé, au niveau du modèle, la contribution de l'étudiant est d'avoir adapté le modèle traditionnel (Girard et al., 2000; Ouarda et al., 2001) en remplaçant les distributions statistiques stationnaires par le modèle GEV non stationnaire décrit par El Adlouni et al. (2006). Il en résulte que les étapes 2 et 3 du nouveau modèle, en plus d'être appliquées pour chaque temps de retour T doivent aussi l'être pour chaque pas de temps t étant donné que le risque hydrologique peut varier dans le temps. Les quantiles de crue pour le bassin versant non jaugé prennent donc la formulation suivante : $Q_T(t)$ (ils sont conditionnels au temps).

Le nouveau modèle a été testé à partir de données réelles. La méthodologie retenue par l'étudiant est décrite dans la partie 5 « Study methodology » de l'article. Les bases de données hydrométriques, météorologiques et physiographiques décrivant les caractéristiques de bassins versants du sud-est du Canada et du nord-est des États-Unis ont été développées conjointement par Véronique Jourdain, étudiante à la maîtrise en sciences de l'eau au centre ETE, et l'étudiant. Leurs projets de maîtrise respectifs nécessitant l'utilisation d'une telle base de données, ils ont jugé opportun de conjuguer leurs efforts. Madame Jourdain s'est occupée de recueillir et de traiter les données hydrométriques et physiographiques pour les bassins versants du sud-est du Canada et l'étudiant a fait de même pour les bassins versants du nord-est des États-Unis. L'étudiant s'est aussi chargé de recueillir et de traiter les données météorologiques pour l'ensemble du territoire à l'étude (incluant le couplage entre les stations hydrométriques et les stations météorologiques). Le travail de construction des séries de crues printanières et d'implémentation/application du test retenu pour la vérification des hypothèses du modèle a été réalisé conjointement par madame Jourdain et l'étudiant. Tous les faits saillants concernant la construction de la base de données sont décrits dans la partie 4 « Case study » de l'article. Quant au test pour la vérification des hypothèses du modèle, « trend-free pre-whitening

(TFPW) procedure » de Yue et al. (2002, 2003), il est décrit dans la partie 5 « Study methodology ». Il permet de vérifier les hypothèses d'indépendance et de non stationnarité de premier ordre des séries de crues printanières servant à tester le nouveau modèle. La non stationnarité de premier ordre signifie que seulement le paramètre de position des séries varie dans le temps. La variance et tous les autres moments d'ordre supérieur sont supposés constants.

L'analyse fréquentielle locale non stationnaire (étape 1 du nouveau modèle) étant nécessaire à leurs projets respectifs, madame Jourdain et l'étudiant ont maintenu leur association pour cette étape. Monsieur Salaheddine El Adlouni, associé de recherche dans l'équipe de monsieur Taha Ouarda, nous a aidés par ses commentaires et suggestions pour l'ajustement des paramètres du modèle GEV non stationnaire.

L'étudiant a produit seul les résultats pour les étapes 2 et 3 du modèle (identification du voisinage hydrologique et transfert d'information via une régression multiple), incluant tous les tableaux et graphiques se trouvant dans l'article. À des fins de comparaison du nouveau modèle avec le modèle traditionnel stationnaire, une analyse fréquentielle locale stationnaire utilisant la même base de données que celle mentionnée précédemment s'avérait nécessaire. L'étudiant a pu bénéficier du fait que Véronique Jourdain avait déjà effectué ce travail pour son propre projet de maîtrise. Il s'agit d'une procédure automatisée s'effectuant à l'aide de programmes informatiques. La contribution de l'étudiant au niveau de cette analyse se limite donc à une discussion et à une récupération des résultats auprès de madame Jourdain. Enfin, l'étudiant a produit seul les résultats de la comparaison entre le nouveau modèle et le modèle traditionnel stationnaire.

L'interprétation, la discussion et les conclusions de l'étudiant entourant l'ensemble des résultats se trouvent dans les parties 6 et 7 de l'article (« Results and discussion » et « Conclusions » respectivement). Les discussions que l'étudiant a eues avec son directeur de recherche lui ont permis de mieux préciser certains éléments de la conclusion.

La première version de l'article scientifique se trouvant dans la section 2 de ce mémoire a été rédigée entièrement par l'étudiant. Des corrections et modifications ont été apportées par le directeur de recherche.

Suite au dépôt initial du présent mémoire et à la lecture des rapports des examinateurs, l'étudiant prend bonne note des améliorations suggérées en vue de la publication de l'article dans le *Journal of Hydrology*.

Dans la partie 3.1 « Flood frequency analysis at gauged sites », l'algorithme MCMC (Monte Carlo par chaînes de Markov) est utilisé pour calculer des estimateurs des paramètres du modèle GEV non stationnaire. Afin de signaler la taille de la chaîne de Markov et le temps de chauffe utilisés, les phrases suivantes sont à ajouter : *« Markov chains of size 25,000 are constructed. The burn-in period is 10,000. »*. Elle s'insère au bas de la page 43 après la phrase : *« The MCMC procedure of El Adlouni et al. (2006) is used. »*

Au niveau de l'équation (15) (partie 3.3 « Information transfer », page 45), le terme de gauche de l'égalité, $Q_T(t)$, varie en fonction du temps t alors qu'aucune quantité du terme de droite ne varie explicitement en fonction du temps. À des fins de clarification, cette partie de l'article est à réécrire de la façon suivante à partir de la deuxième phrase :

The problem is typically described using the power-form equation

$$Q_T(t) = \gamma_0(t) \cdot X_1^{\gamma_1(t)} \cdot \ldots \cdot X_n^{\gamma_n(t)} \cdot e^{\varepsilon(t)} \tag{1}$$

where $\gamma_0(t), \gamma_1(t), \ldots, \gamma_n(t)$ *are model parameters and* $\varepsilon(t)$ *a random error term. Many different procedures are available to estimate the model parameters* $\gamma_i(t)$. *One common procedure is to linearize Equation (14) through a logarithmic transformation*

$$\log Q_T(t) = \log \gamma_0(t) + \gamma_1(t)\log X_1 + \ldots + \gamma_n(t)\log X_n + \varepsilon(t) \tag{2}$$

and then to estimate the model parameters in Equation (15) using an ordinary least-squares technique. This procedure is used here ***for each time step*** *t.*

Aussi, dans la même optique, l'avant-avant-dernière phrase de la partie 3.2 « Neighborhood identification using CCA » à la page 45 est à bonifier de la façon suivante : *« Some of those* *variables can reflect the presence of non-stationarity in flood characteristics* ***and vary through time (implicitly shown here:*** $X(t) = X$ ***).*** »

Enfin, il a aussi été suggéré d'ajouter les graphiques des quantiles $Q_5(t)$ estimés pour des sites autres que la station 01BH005 - Dartmouth (rivière) en amont du ruisseau du Pas de Dame, QC (voir figure 2, page 63, bas de la page 53 dans le texte de l'article). L'appendice A contient les graphiques correspondants pour les 29 sites de l'étude de cas (voir partie 4 « Case study » de l'article).

CHAPITRE 2

SITUATION DE LA CONTRIBUTION

La revue de littérature effectuée à l'hiver 2005 a permis de mettre en lumière que l'estimation des quantiles de crue pour un bassin versant non jaugé dans un cadre non stationnaire est un sujet n'ayant pas fait l'objet d'un article scientifique jusqu'à maintenant. La contribution de l'étudiant se concentre spécifiquement sur cette question.

Les articles scientifiques traitant de l'analyse régionale non stationnaire des crues sont peu nombreux. Deux ont été identifiés : celui de Cunderlik et Burn (2003) et celui de Cunderlik et Ouarda (2006). Cependant, dans chacun de ces articles, les études de cas présentées concernent des bassins versants pour lesquels des séries de débits mesurés sont disponibles localement. À l'intérieur de la méthodologie utilisée pour l'obtention des résultats, ces séries sont utilisées directement ou mises en commun avec celles de d'autres bassins versants de façon à améliorer l'estimation des quantiles au site d'intérêt. On ne présente pas de résultats pour un bassin versant non jaugé. En présentant de tels résultats avec une méthodologie associée, le projet de mémoire s'inscrit dans la continuité de ces articles.

De plus, l'étudiant apporte une contribution qui représente une extension par rapport aux travaux de El Adlouni et al. (2006) traitant de l'analyse fréquentielle locale non stationnaire des crues. En effet, l'article présenté dans le cadre du présent mémoire applique le modèle GEV non stationnaire dans le cadre régional.

Enfin, l'article de la deuxième section constitue aussi une adaptation au cadre non stationnaire de la méthode de Ouarda et al. (2001) d'estimation fréquentielle régionale des crues par l'analyse canonique des corrélations. En plus, l'article incorpore la définition révisée du voisinage hydrologique telle que proposée par Girard et al. (2000).

CONCLUSION

Les travaux du présent mémoire de maîtrise partent du constat de l'absence dans la littérature d'une méthode d'analyse régionale non stationnaire traitant spécifiquement du cas d'un bassin versant non jaugé. Lorsque l'hypothèse de stationnarité n'est pas vérifiée, des méthodes alternatives doivent être envisagées. En développant une nouvelle méthodologie, le projet de maîtrise vient résoudre ce problème. L'objectif poursuivi était d'estimer les quantiles de crue d'un bassin versant non jaugé dans un cadre non stationnaire.

L'approche proposée, qui incorpore une méthode d'analyse fréquentielle locale non stationnaire à une méthode d'estimation régionale existante, a été testée à partir d'une base de données réelles du sud-est du Canada et du nord-est des Etats-Unis. Les résultats de l'étude indiquent qu'en présence de non stationnarité, l'approche proposée performe mieux que la méthode traditionnelle d'analyse fréquentielle régionale des crues. Pour les quantiles de temps de retour 5 et 100 ans sur l'horizon $t = 2003$ (fin de la période d'observation historique), les résultats en termes de biais relatif moyen et d'erreur quadratique relative moyenne sont meilleurs pour l'approche proposée que pour le modèle traditionnel stationnaire. Le fait d'ignorer une tendance à la baisse des crues printanières d'un site non jaugé peut mener à une surestimation des quantiles de crue pour ce site. Le risque de crue estimé par le modèle traditionnel est alors supérieur au risque réel et correspond à un risque de crue qui a eu cours il y a plusieurs années dans le passé. Cet élément fait ressortir la nécessité de prendre en compte la non stationnarité en analyse fréquentielle régionale des crues.

Le modèle développé dans ce mémoire a été testé en utilisant des données de bassins versants jaugés considérés non jaugés. Aucune hypothèse de stationnarité ou de non stationnarité spatiale n'a été faite à l'égard de régions ou de sous régions du territoire à l'étude. La tâche de déterminer sous quels critères le régime hydrologique d'un site non jaugé doit être considéré stationnaire ou non dépasse le cadre du présent mémoire de maîtrise. La contribution du présent projet est d'établir une méthode d'analyse fréquentielle des crues pouvant être utilisée en présence de non stationnarité pour un bassin versant non jaugé. Cette contribution s'ajoute aux travaux déjà réalisés en analyse fréquentielle non stationnaire des crues pour un bassin jaugé. Elle ouvre la voie à de possibles raffinements, autant au niveau de l'analyse locale que de l'analyse régionale non stationnaire. En résumé, le présent mémoire de maîtrise fournit les outils d'analyse fréquentielle des crues pour un bassin versant non jaugé et ce, dans le cas spécifique d'un territoire à l'étude où la non stationnarité des régimes hydrologiques a été préétablie.

APPENDICE A

QUANTILES $Q_5(t)$ ESTIMÉS AUX 29 SITES DE L'ÉTUDE DE CAS

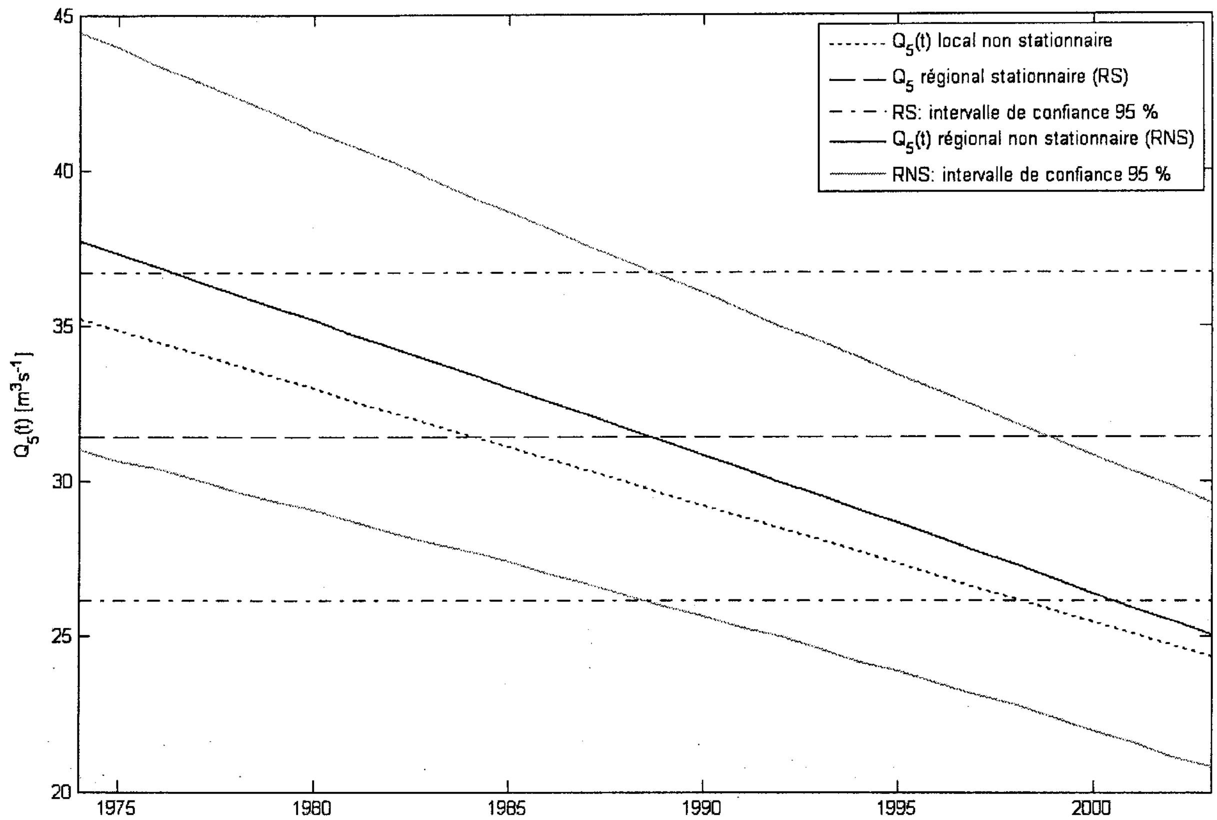


Figure 1. Quantiles $Q_5(t)$ estimés à Holland River at Holland Landing, ON (ID 02EC009)

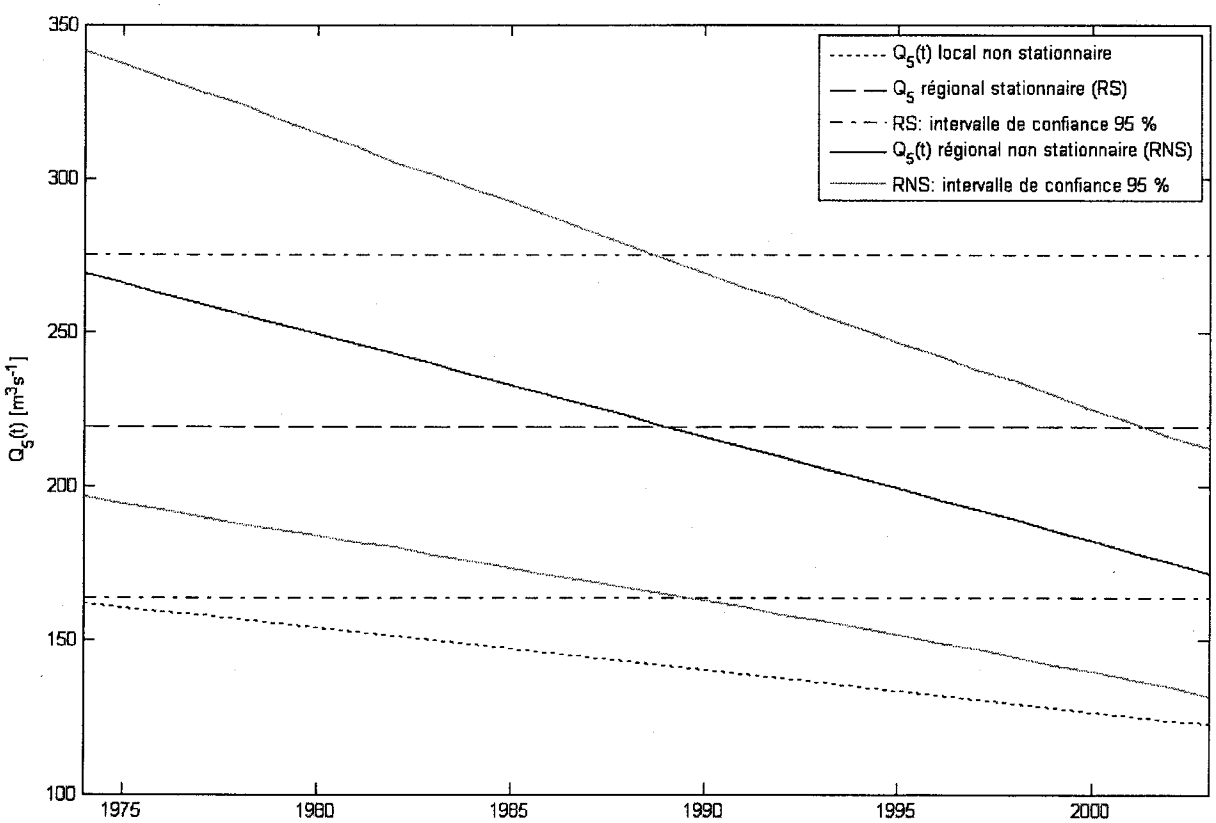


Figure 2. Quantiles $Q_5(t)$ estimés à Nottawasaga River near Baxter, ON (ID 02ED003)

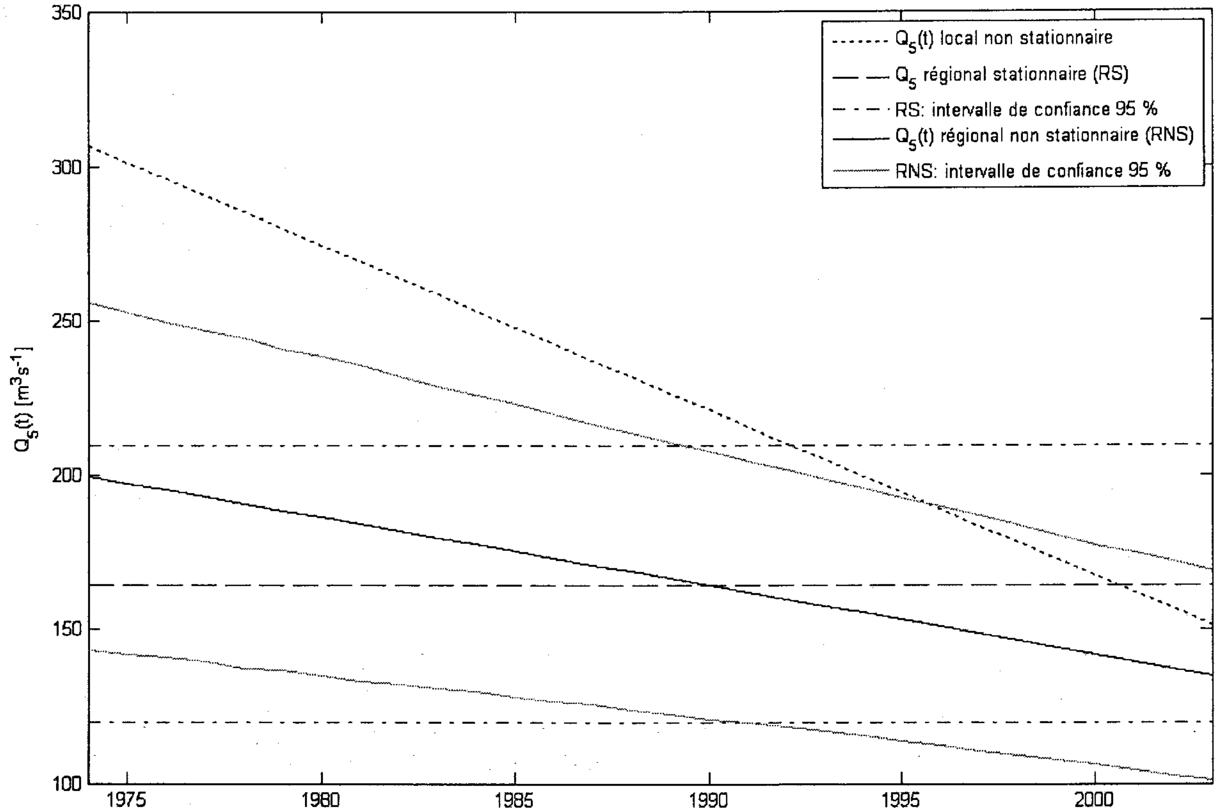


Figure 3. Quantiles $Q_5(t)$ estimés à Nith River near Canning, ON (ID 02GA010)

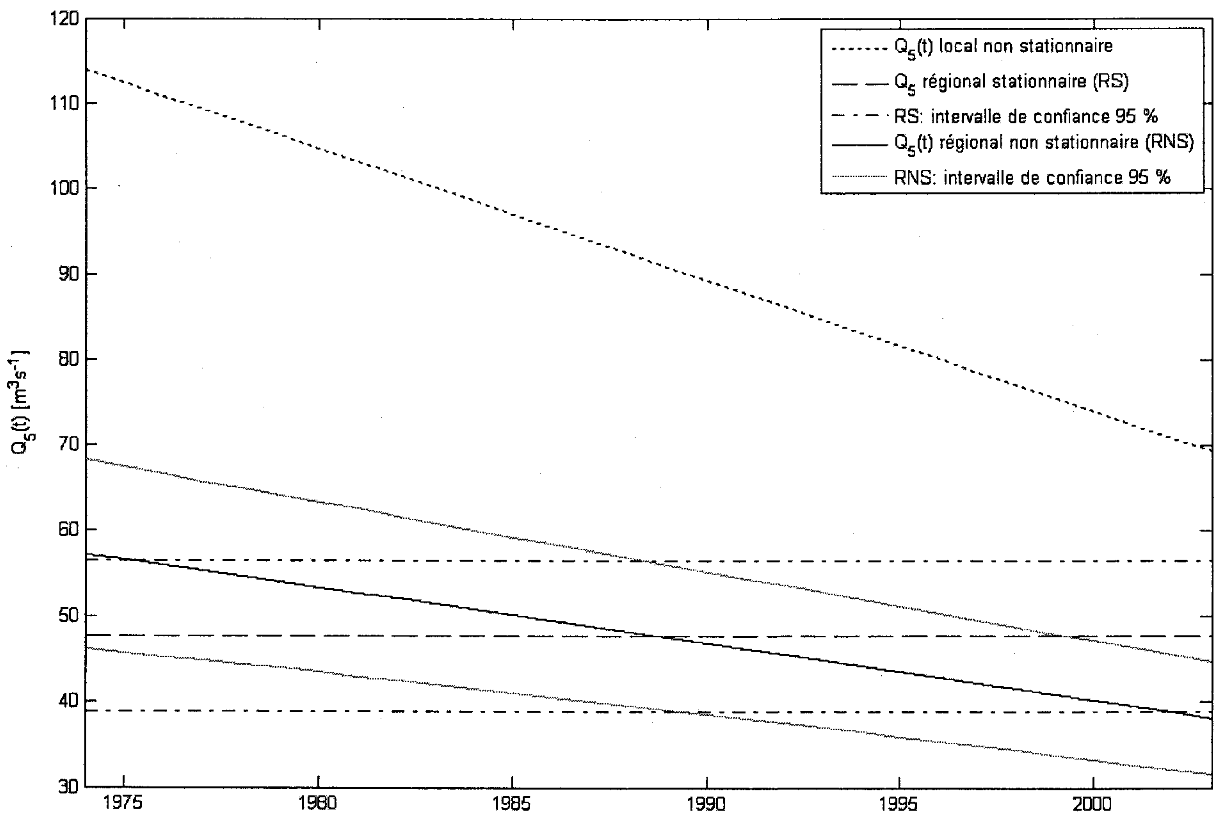


Figure 4. Quantiles $Q_5(t)$ estimés à Middle Thames River at Thamesford, ON (ID 02GD004)

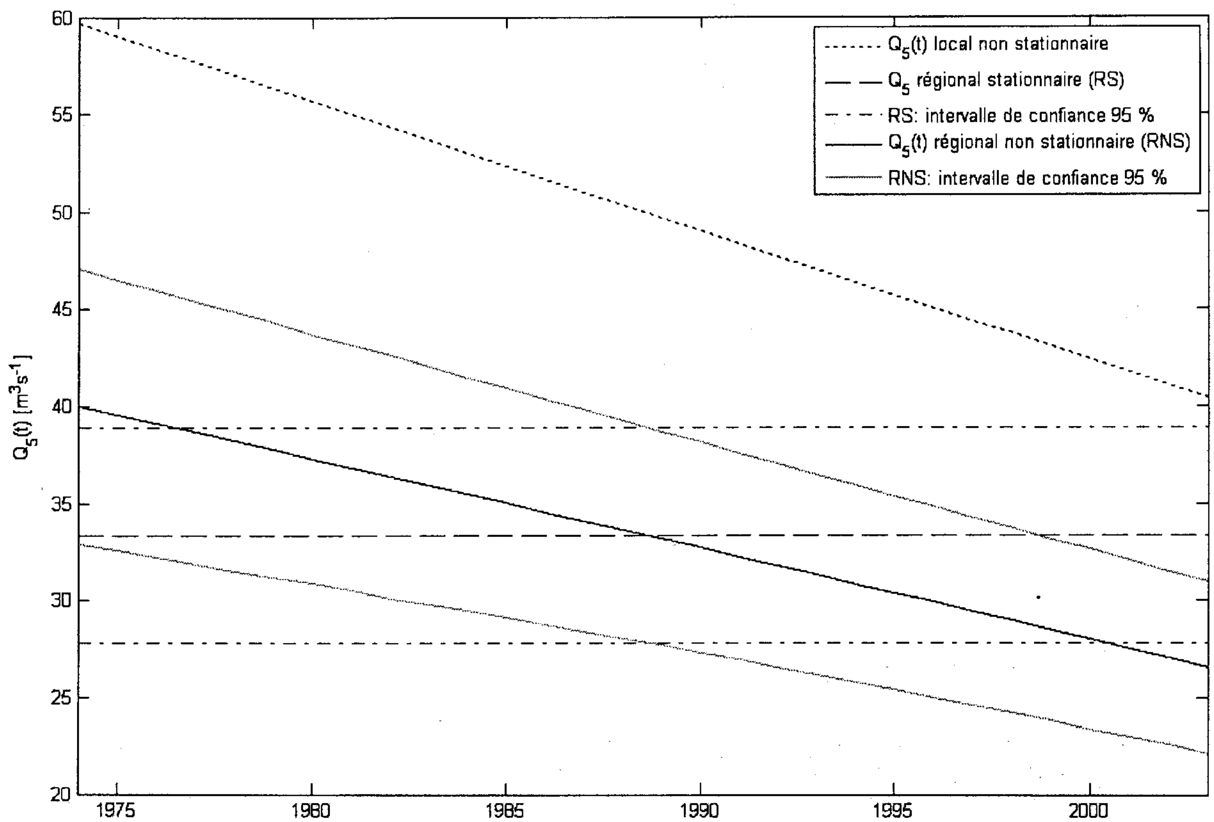


Figure 5. Quantiles $Q_5(t)$ estimés à East Oakville Creek near Omagh, ON (ID 02HB004)

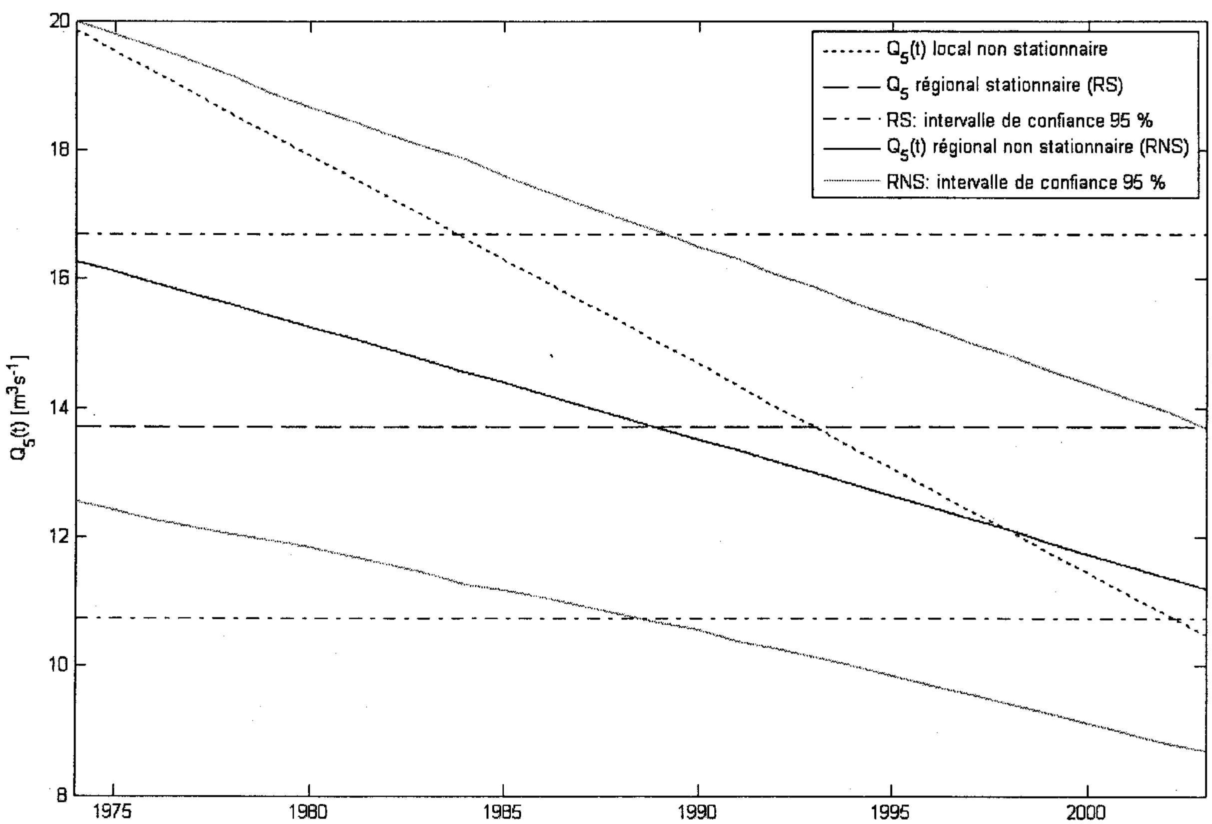


Figure 6. Quantiles $Q_5(t)$ estimés à Grindstone Creek near Aldershot, ON (ID 02HB012)

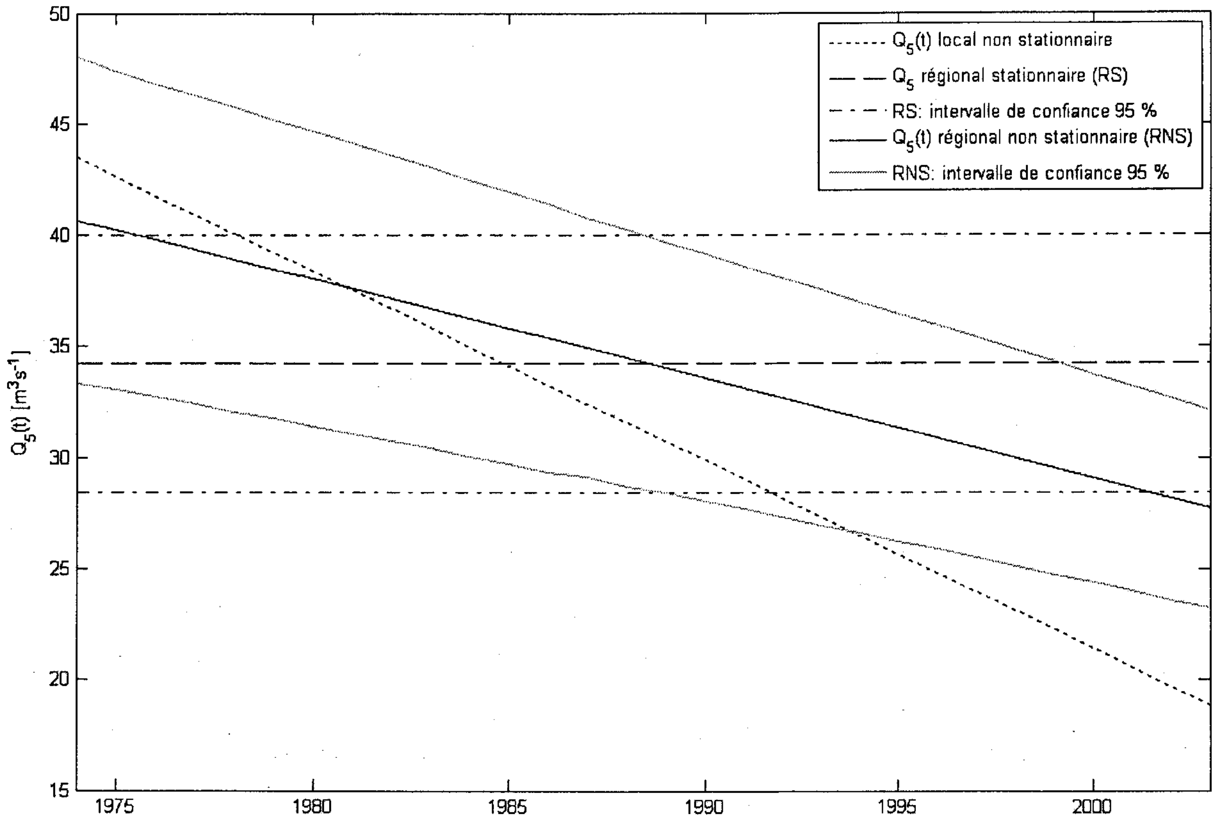


Figure 7. Quantiles $Q_5(t)$ estimés à East Humber River near Pine Grove, ON (ID 02HC009)

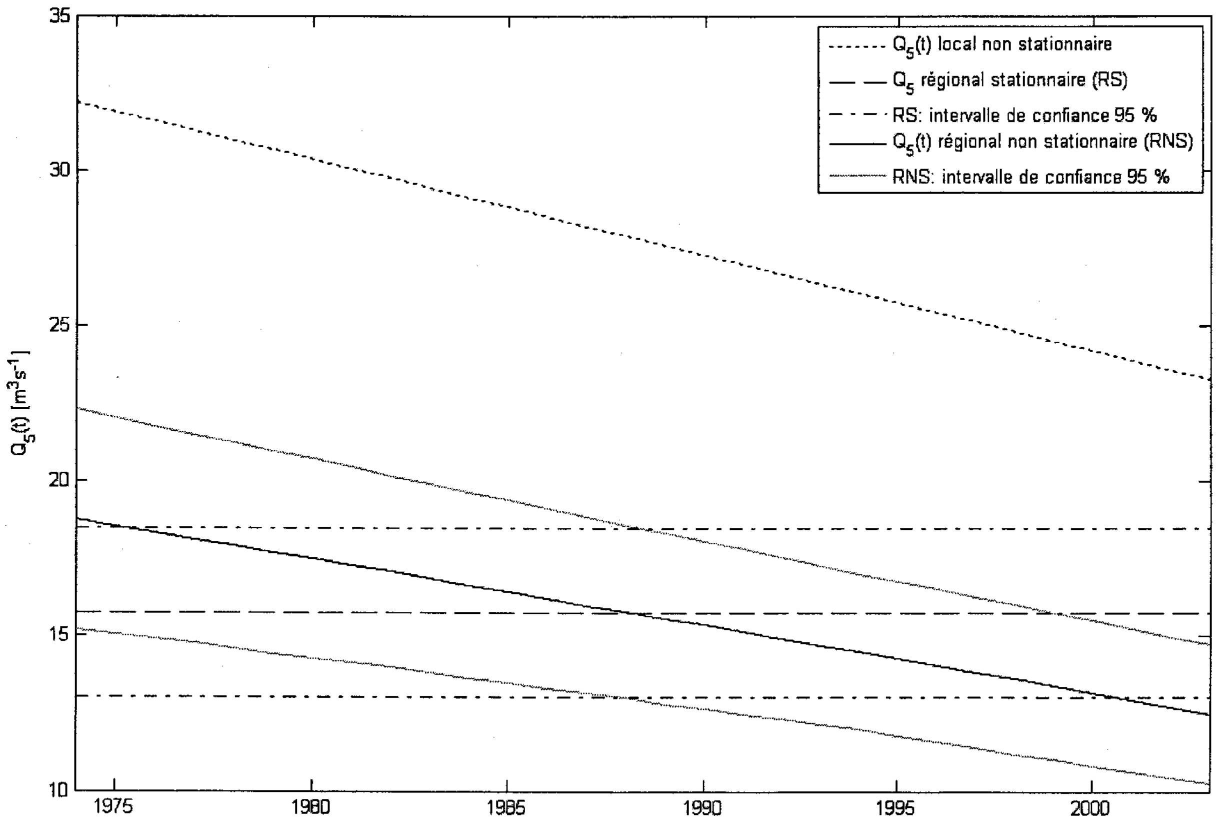


Figure 8. Quantiles $Q_5(t)$ estimés à Duffins Creek above Pickering, ON (ID 02HC019)

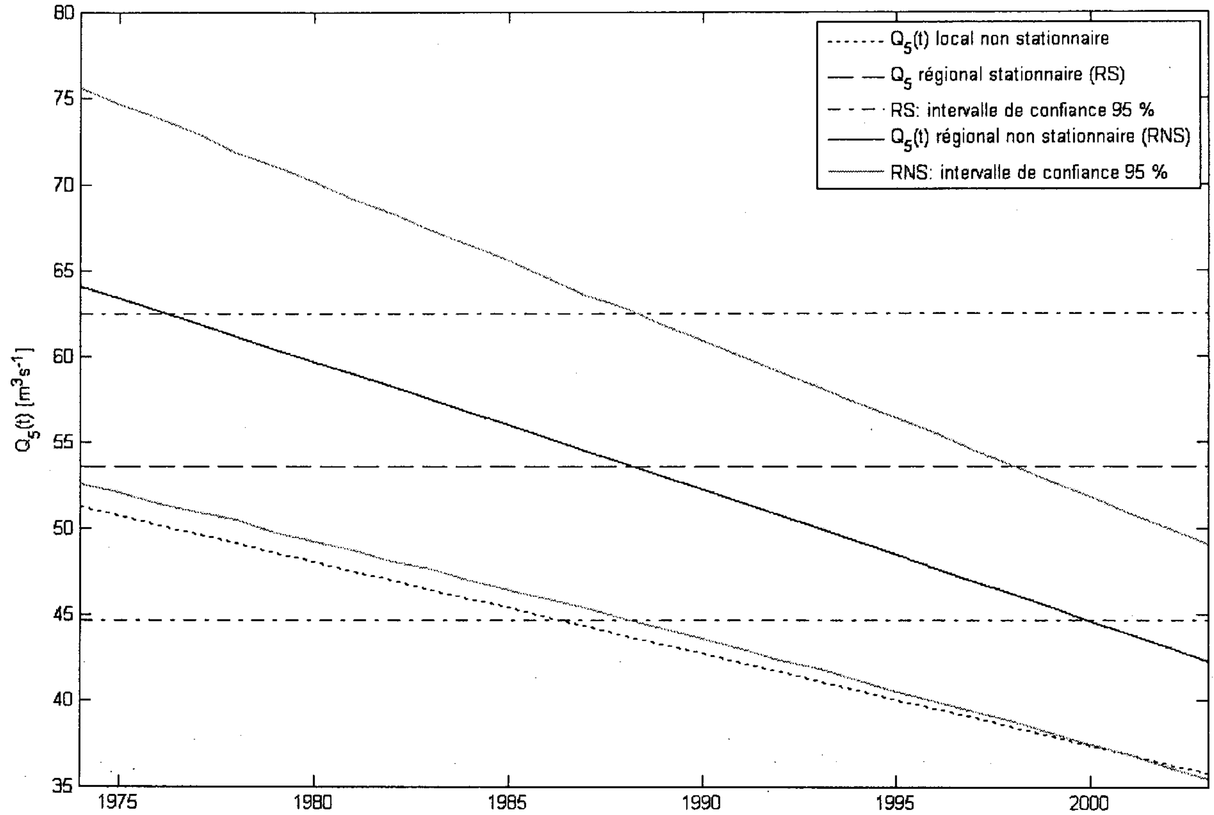


Figure 9. Quantiles $Q_5(t)$ estimés à Humber River at Elder Mills, ON (ID 02HC025)

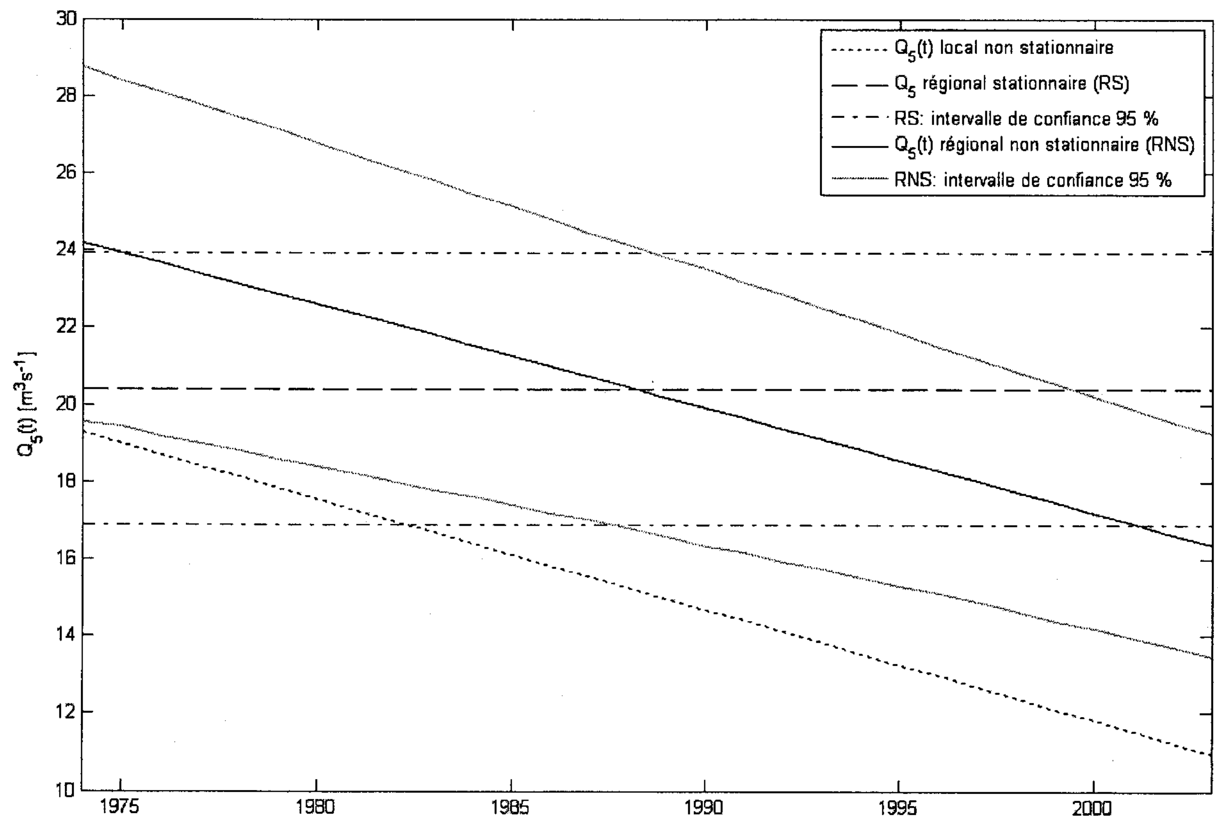


Figure 10. Quantiles $Q_5(t)$ estimés à Jackson Creek at Peterborough, ON (ID 02HJ001)

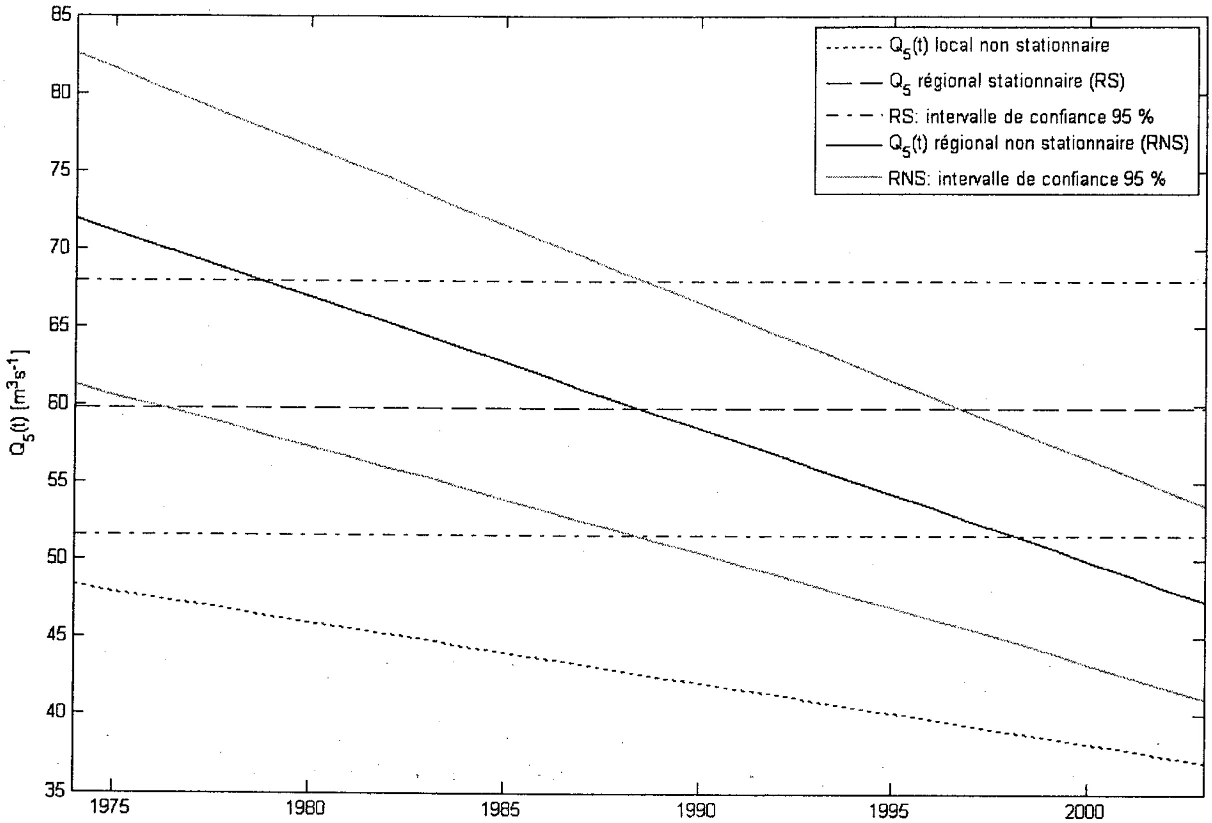


Figure 11. Quantiles $Q_5(t)$ estimés à Moira River near Deloro, ON (ID 02HL005)

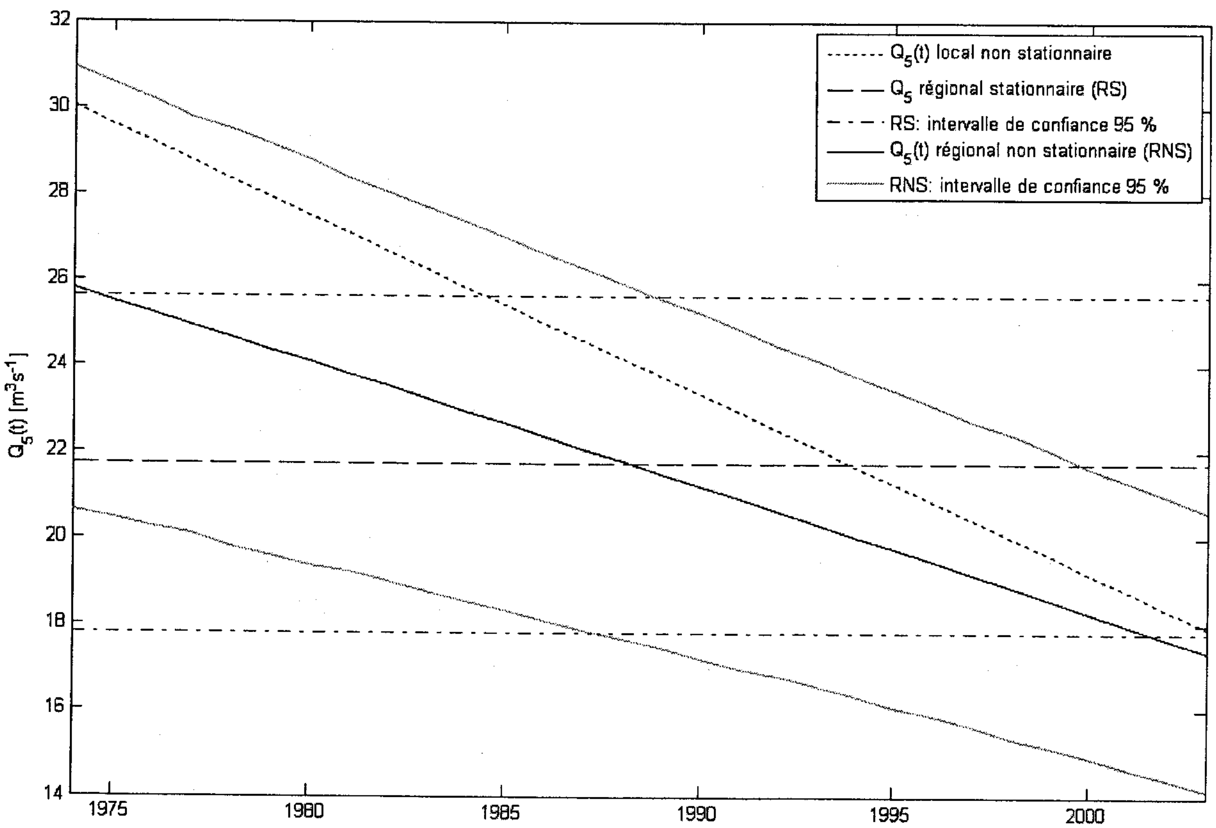


Figure 12. Quantiles $Q_5(t)$ estimés à Wilton Creek near Napanee, ON (ID 02HM004)

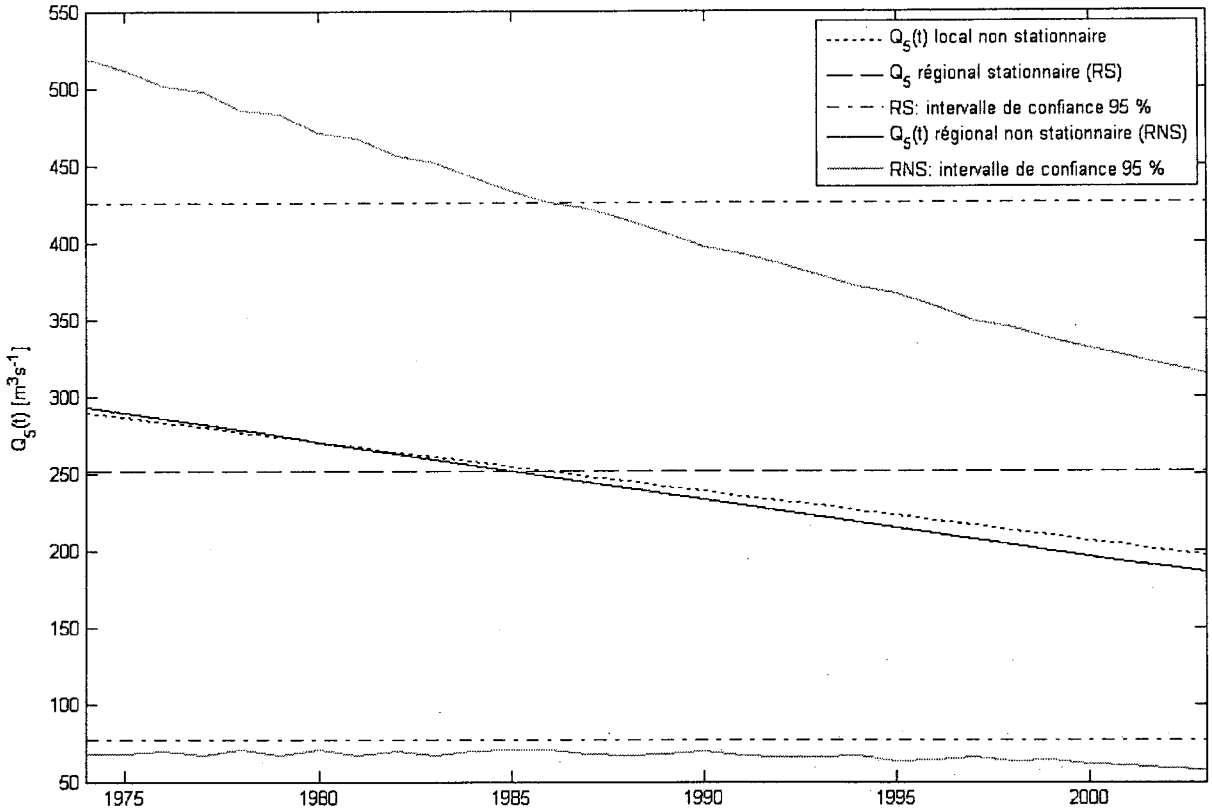


Figure 13. Quantiles $Q_5(t)$ estimés à Dartmouth (rivière) en amont du ruisseau du Pas de Dame, QC (ID 01BH005)

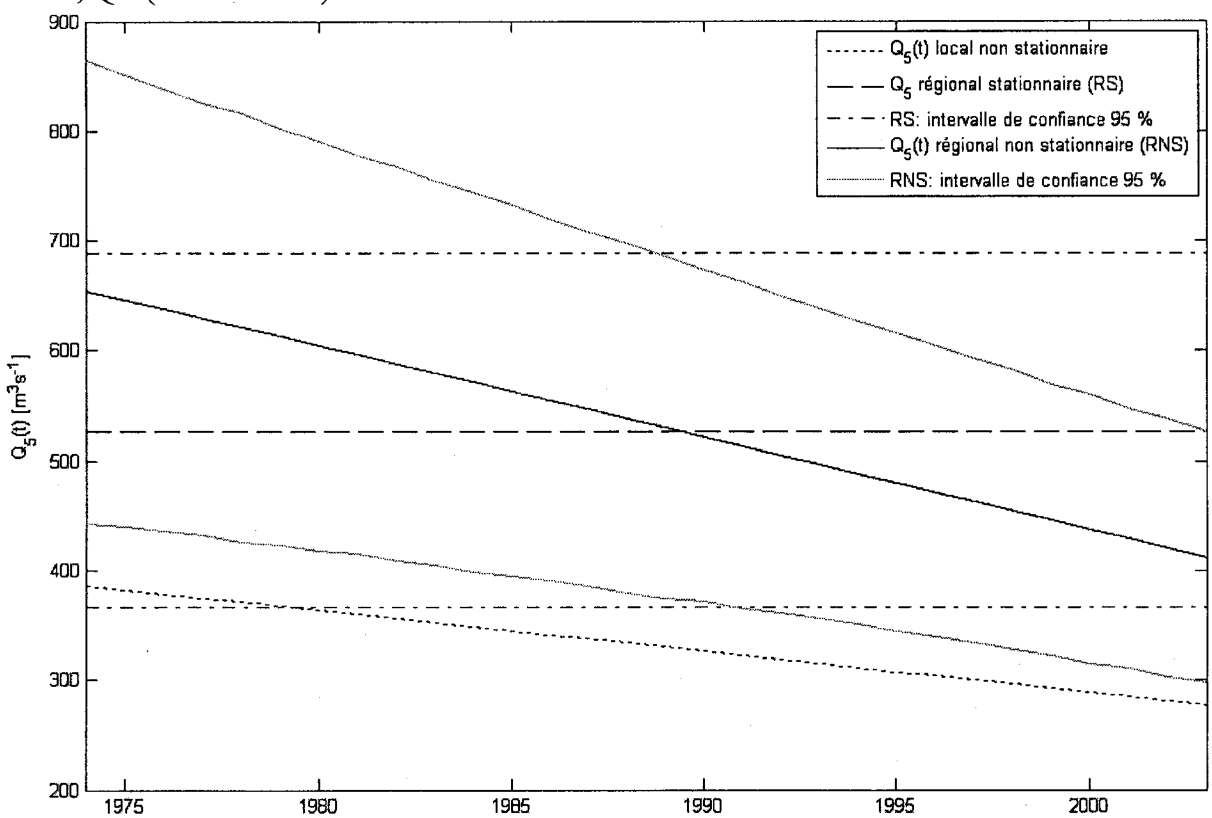


Figure 14. Quantiles $Q_5(t)$ estimés à Kinojevis (rivière) à Cléricy, QC (ID 02JB013)

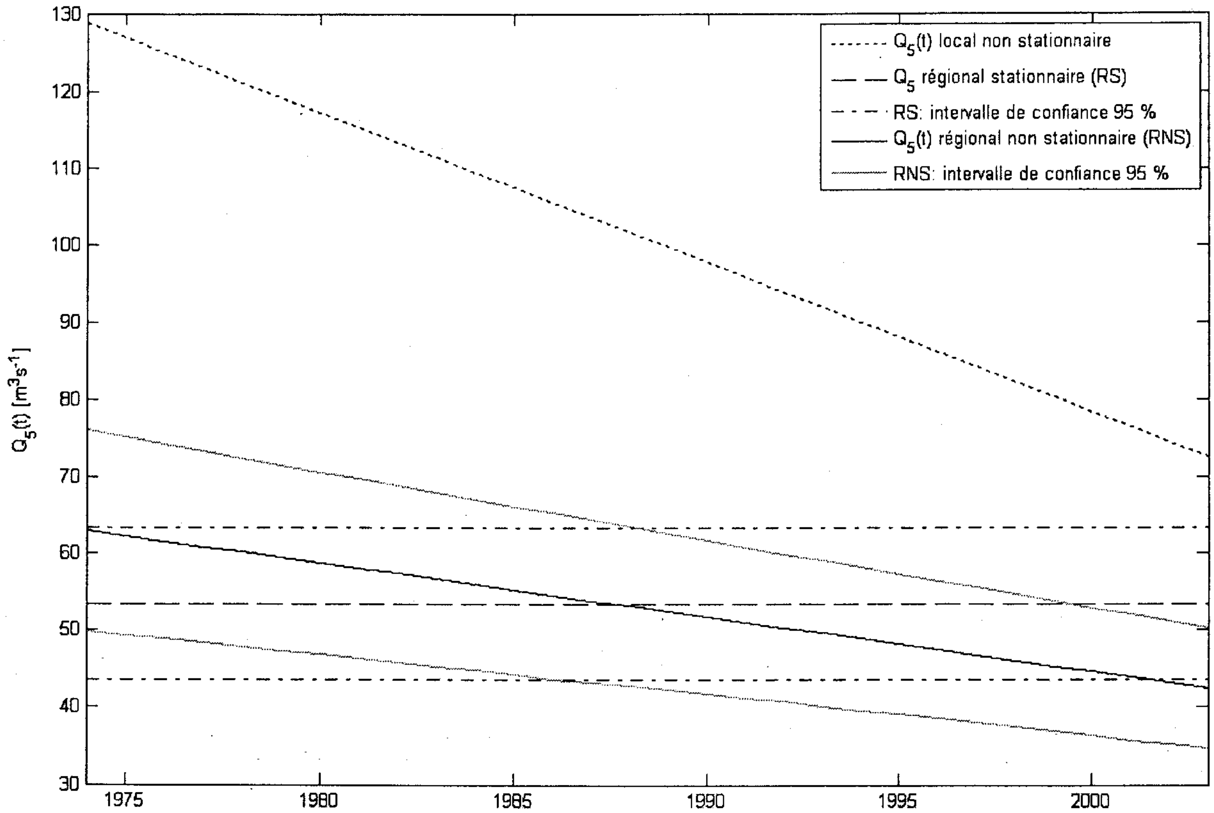


Figure 15. Quantiles $Q_5(t)$ estimés à North River at Shattuckville, MA (ID 01169000)

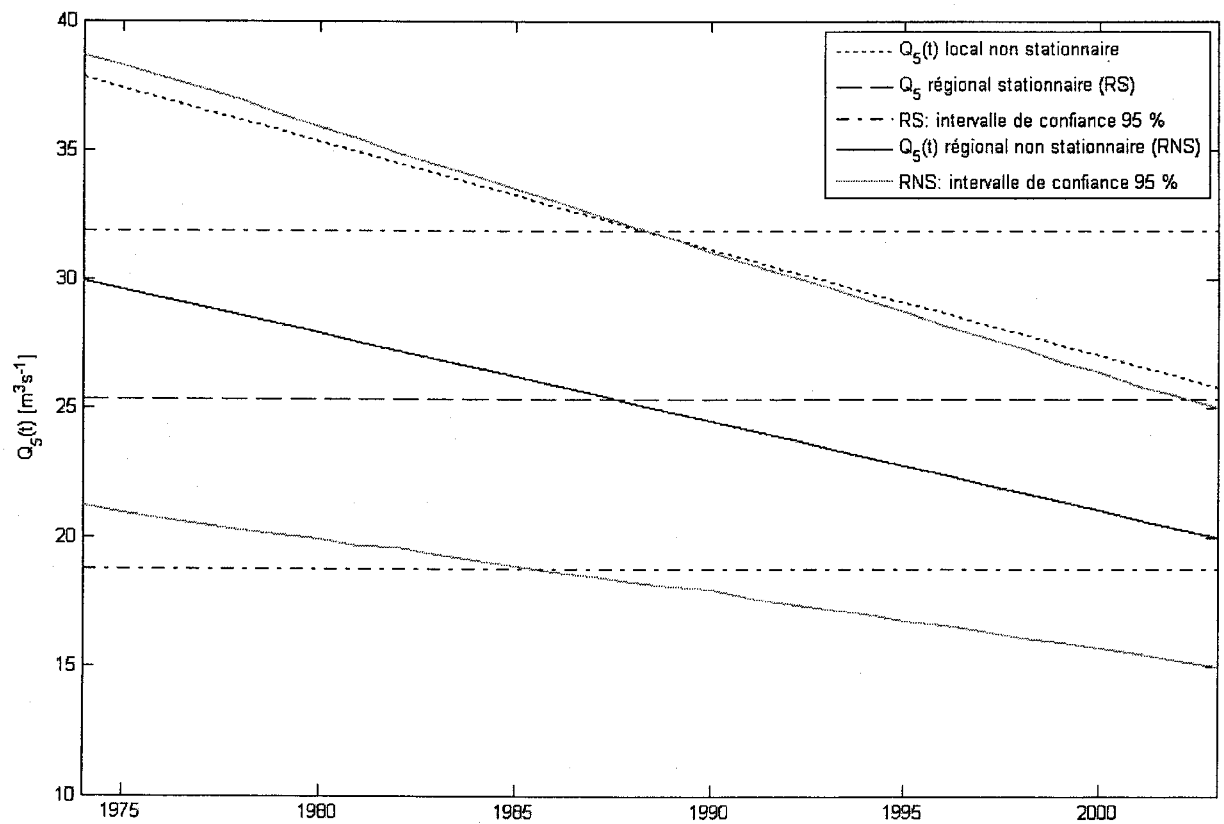


Figure 16. Quantiles $Q_5(t)$ estimés à Green River at Williamstown, MA (ID 01333000)

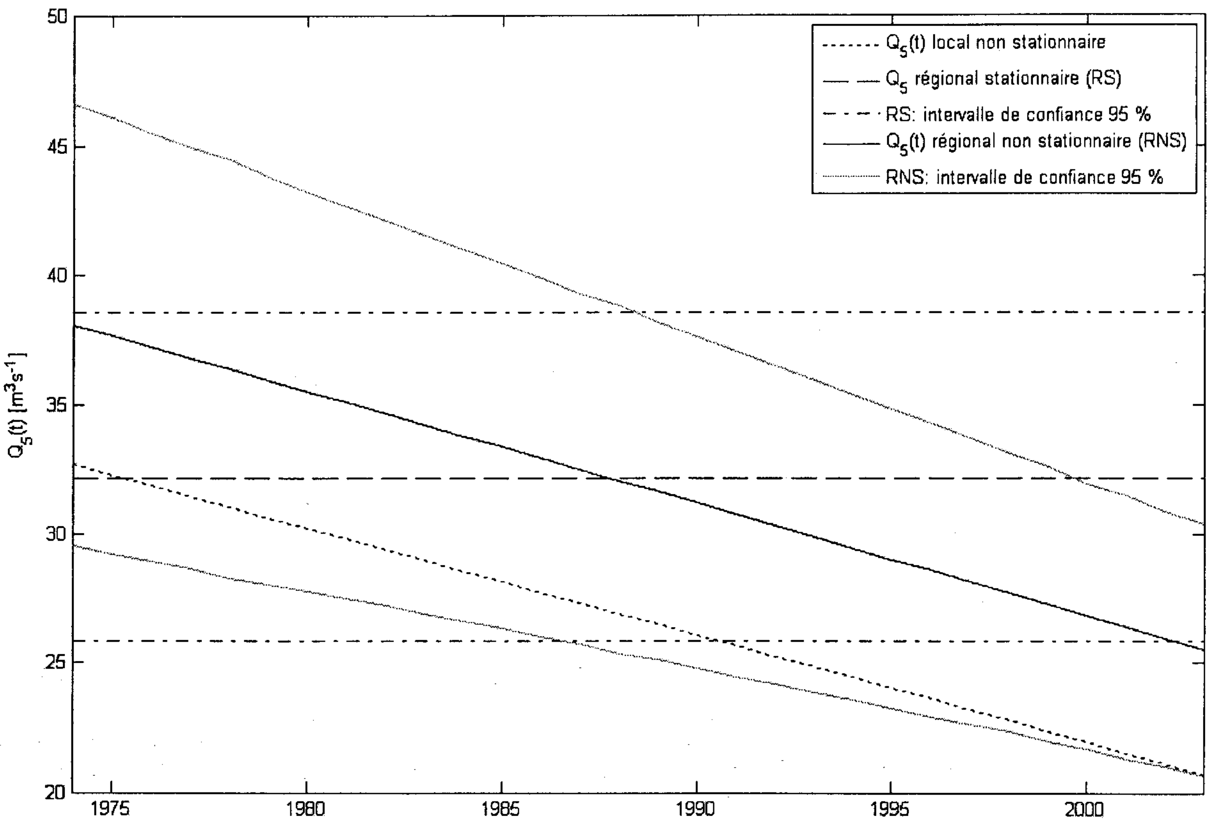
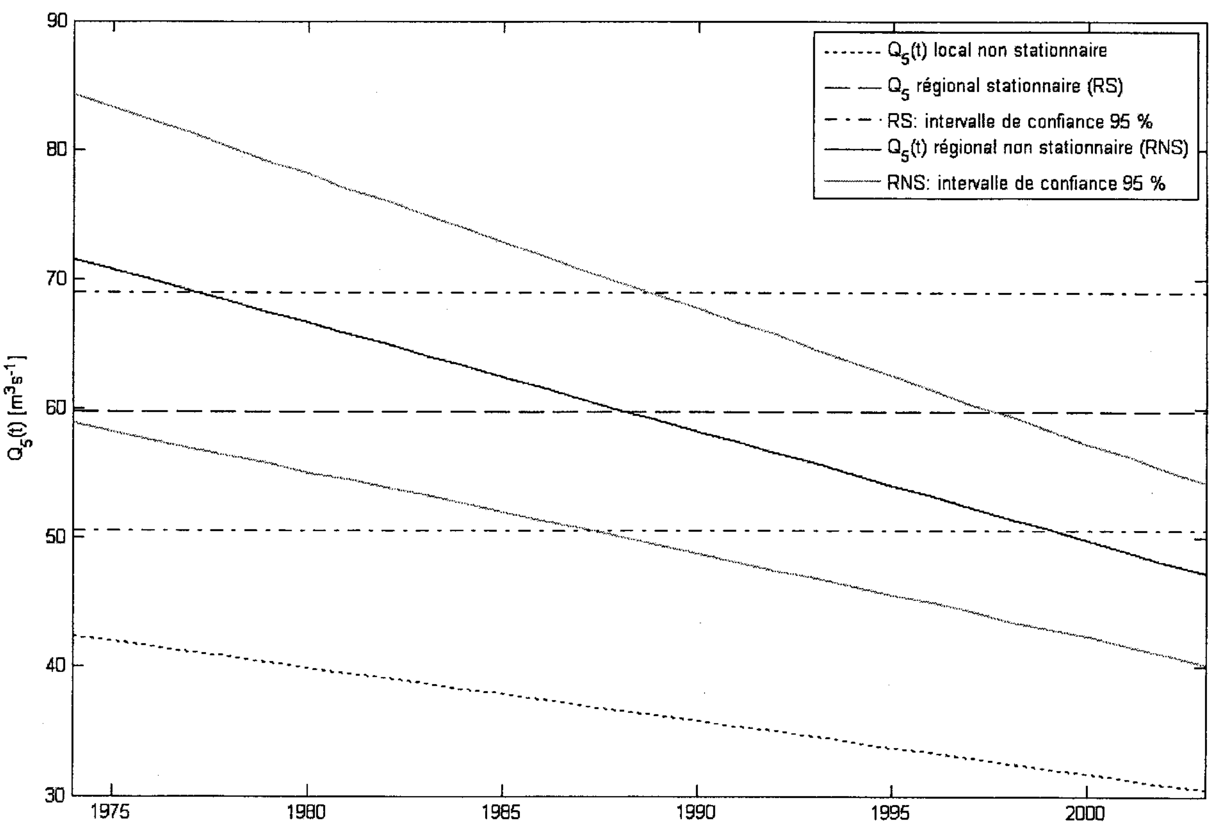


Figure 17. Quantiles $Q_5(t)$ estimés à Passaic River near Millington, NJ (ID 01379000)



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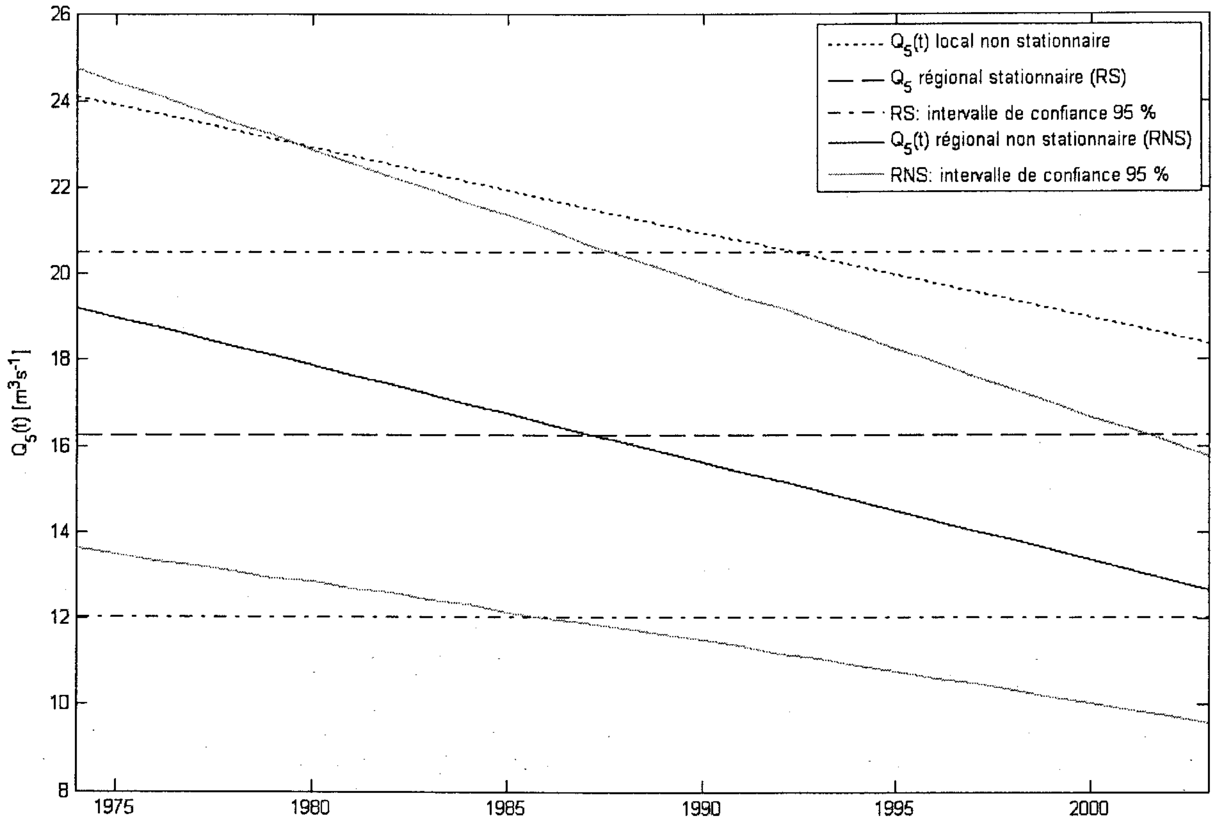

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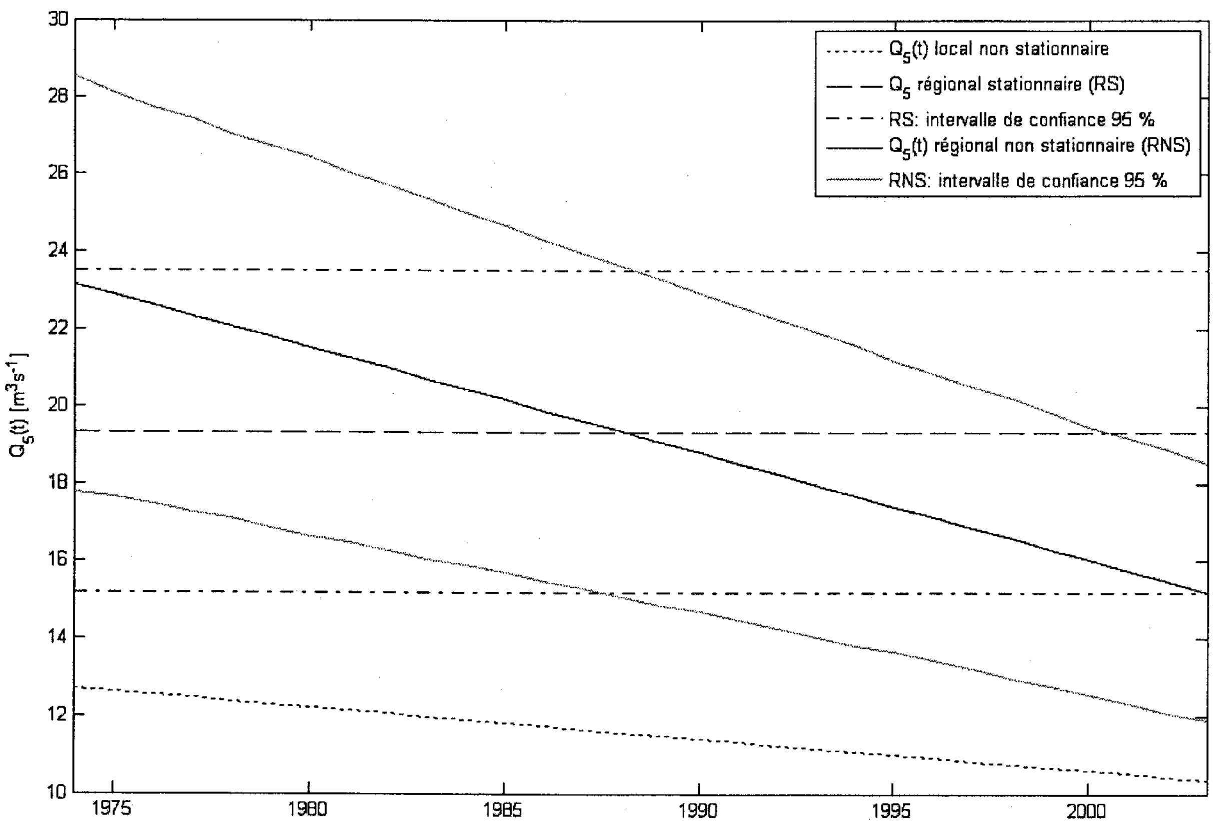

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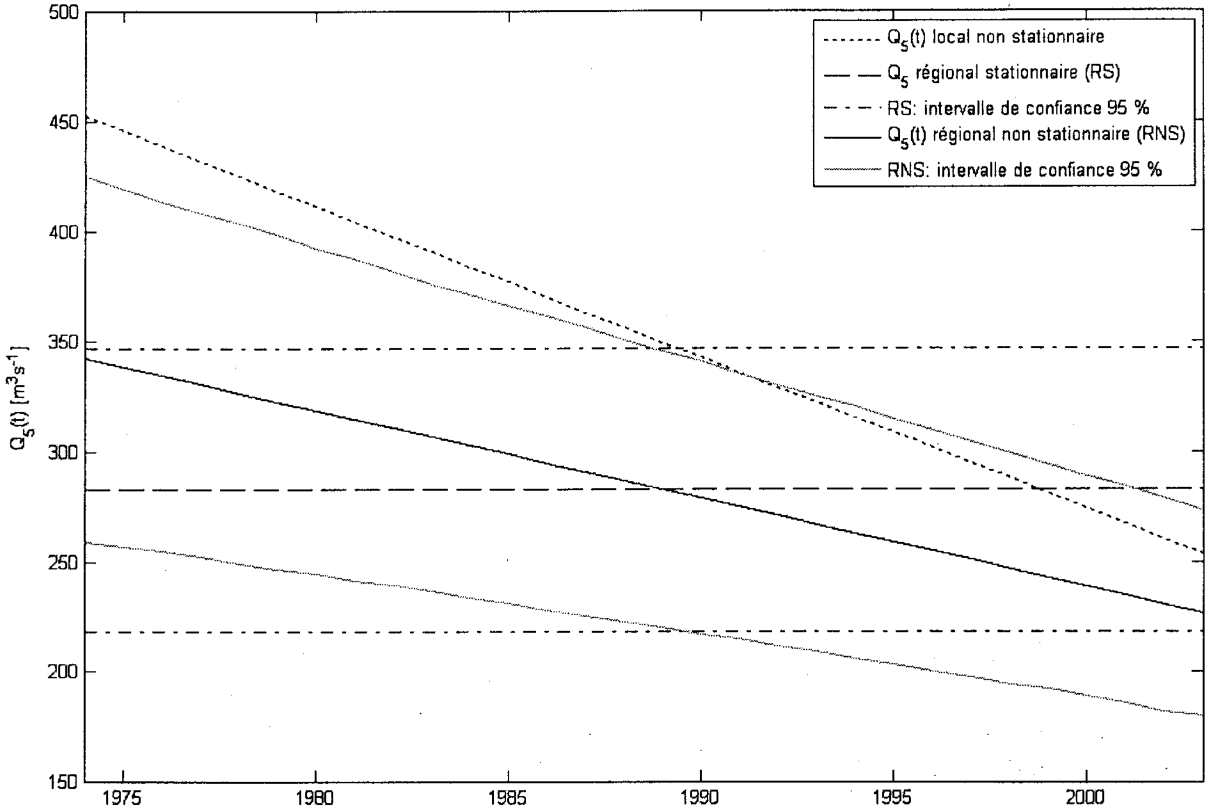

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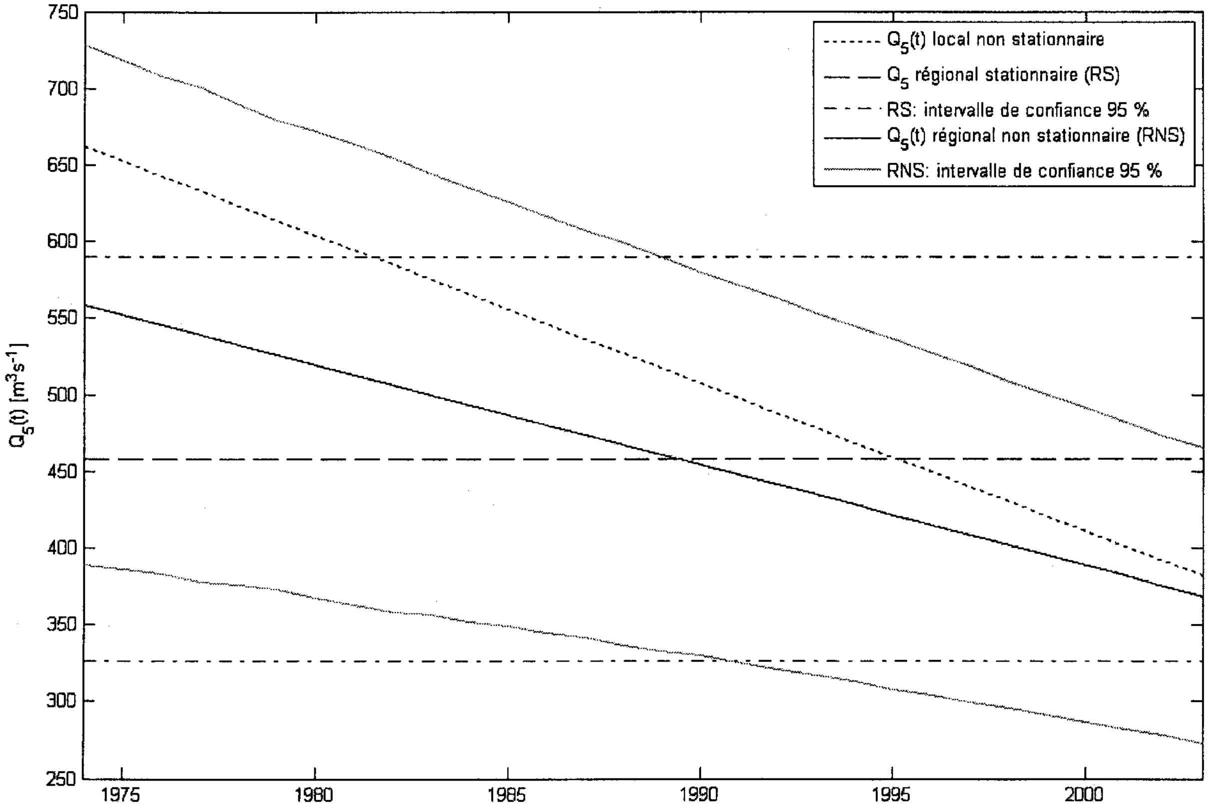

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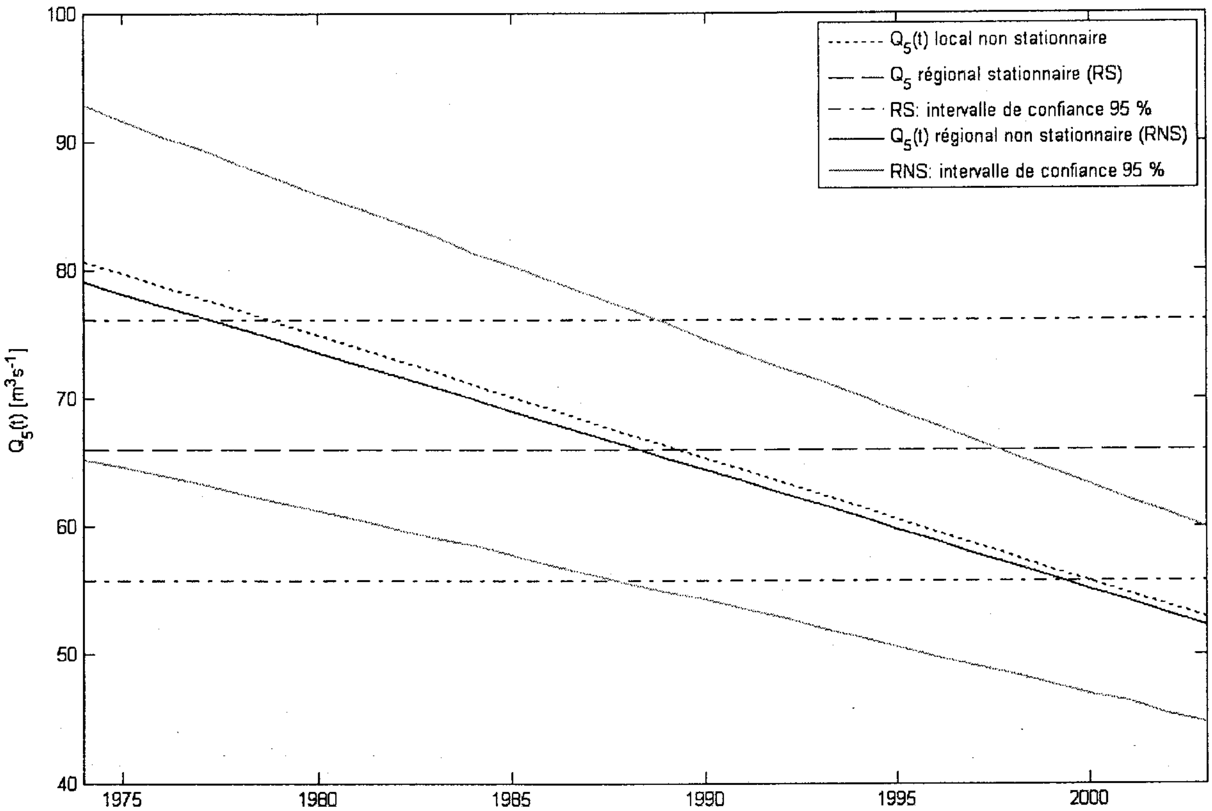

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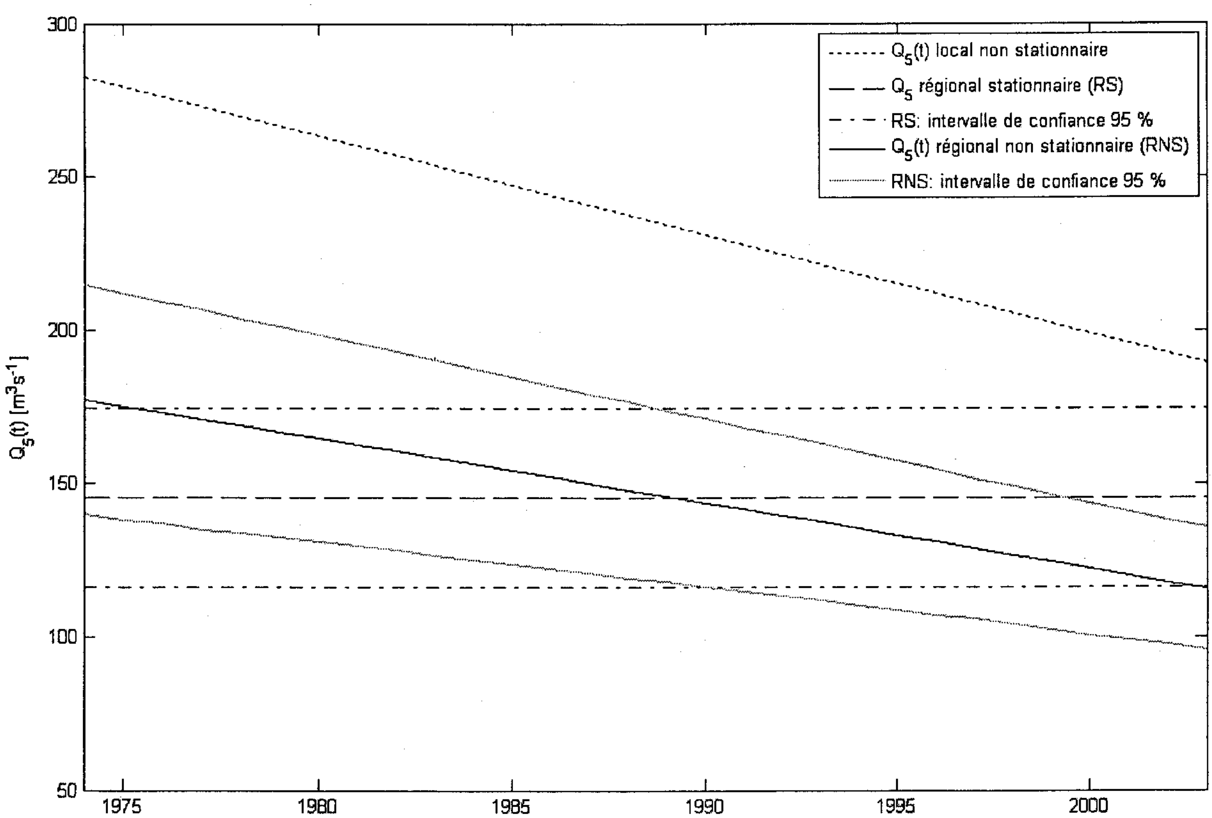

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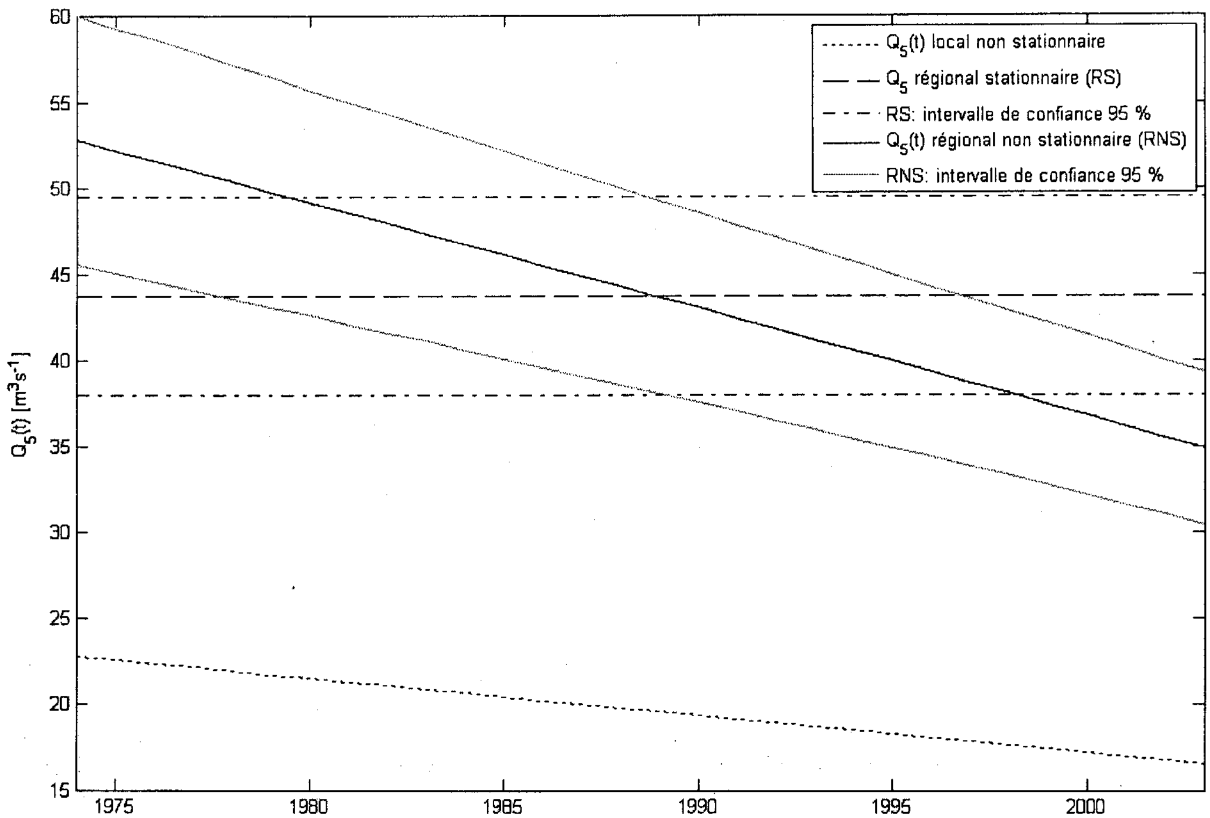

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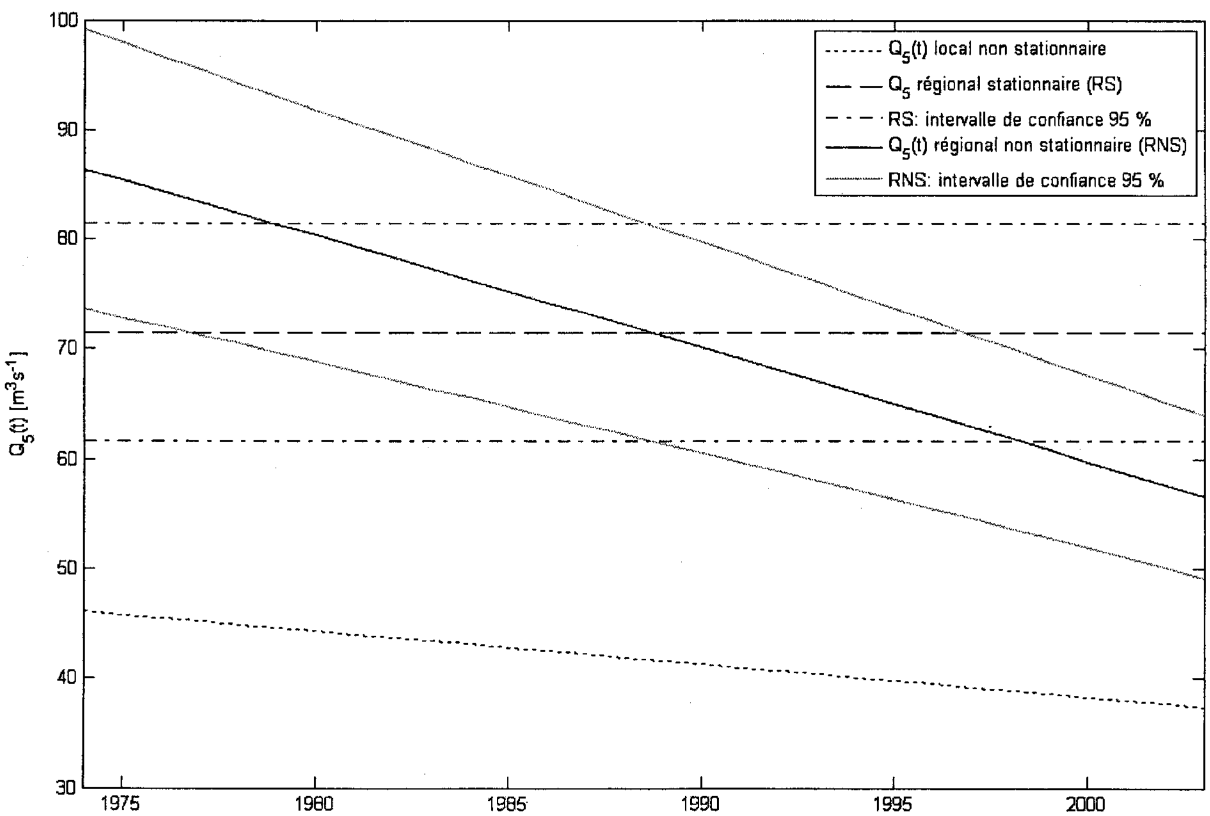

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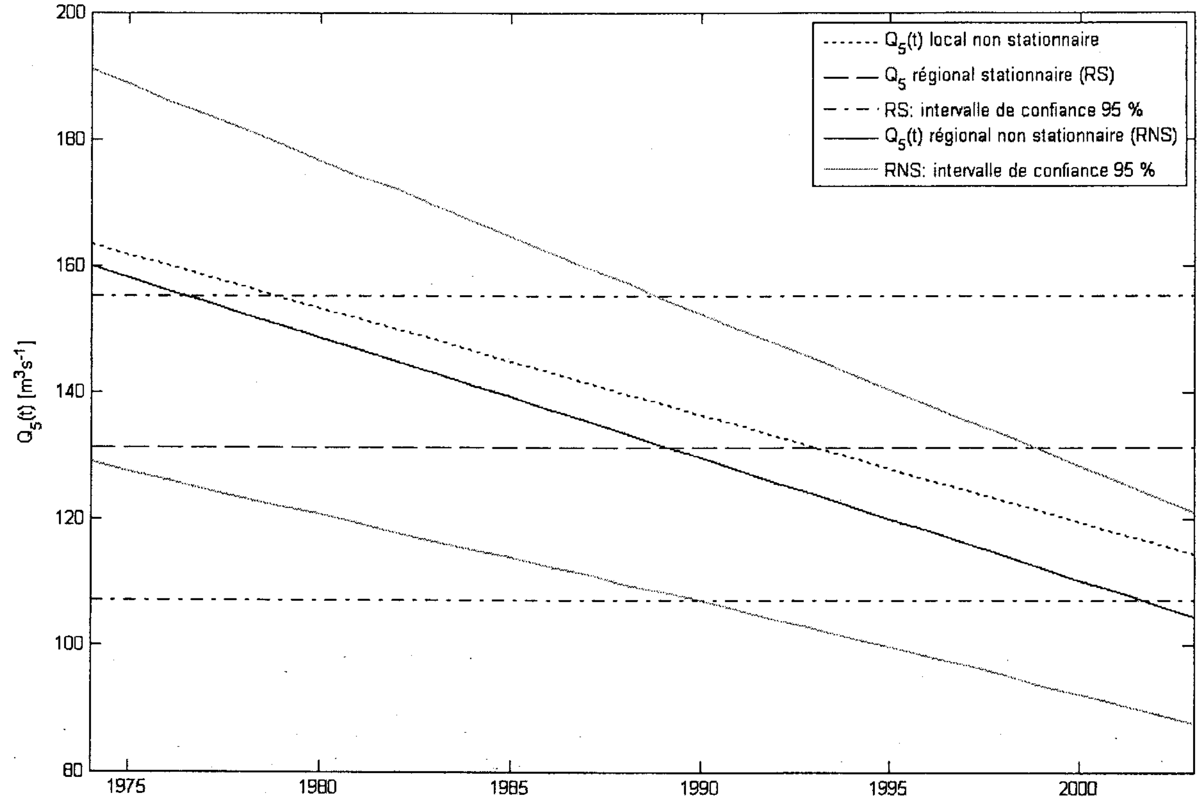

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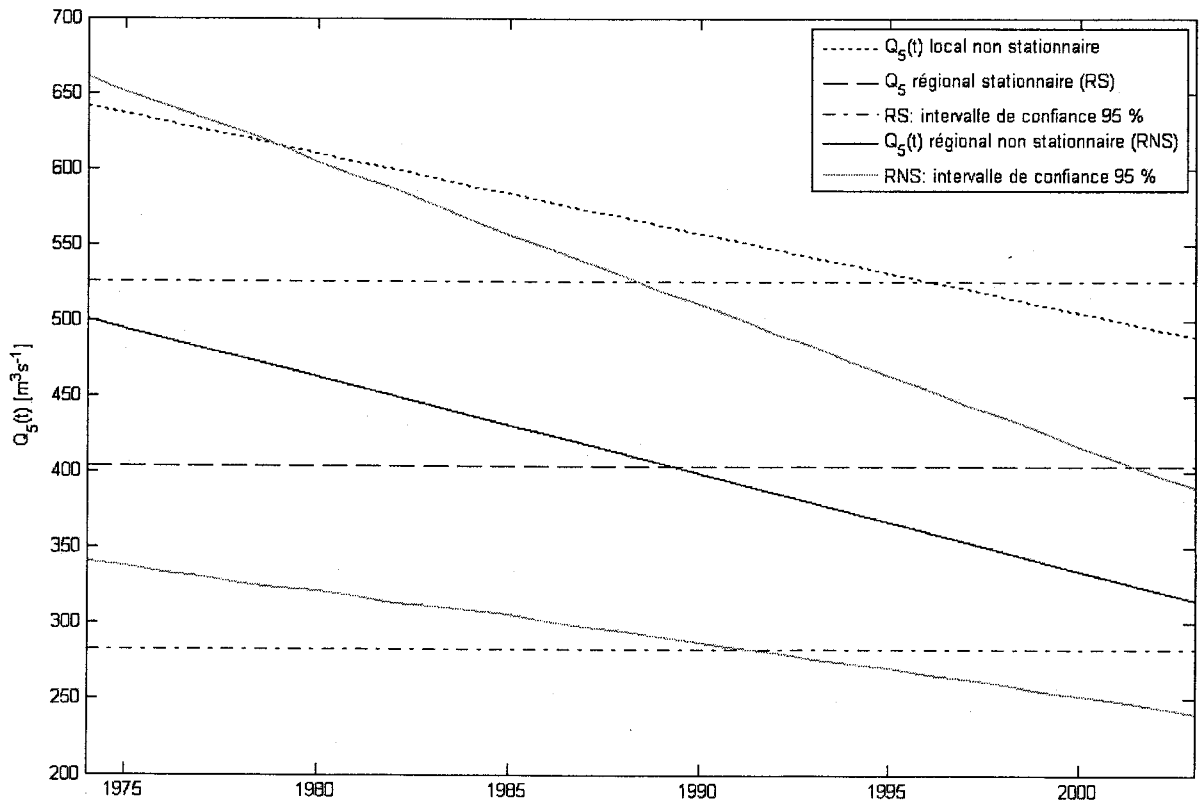

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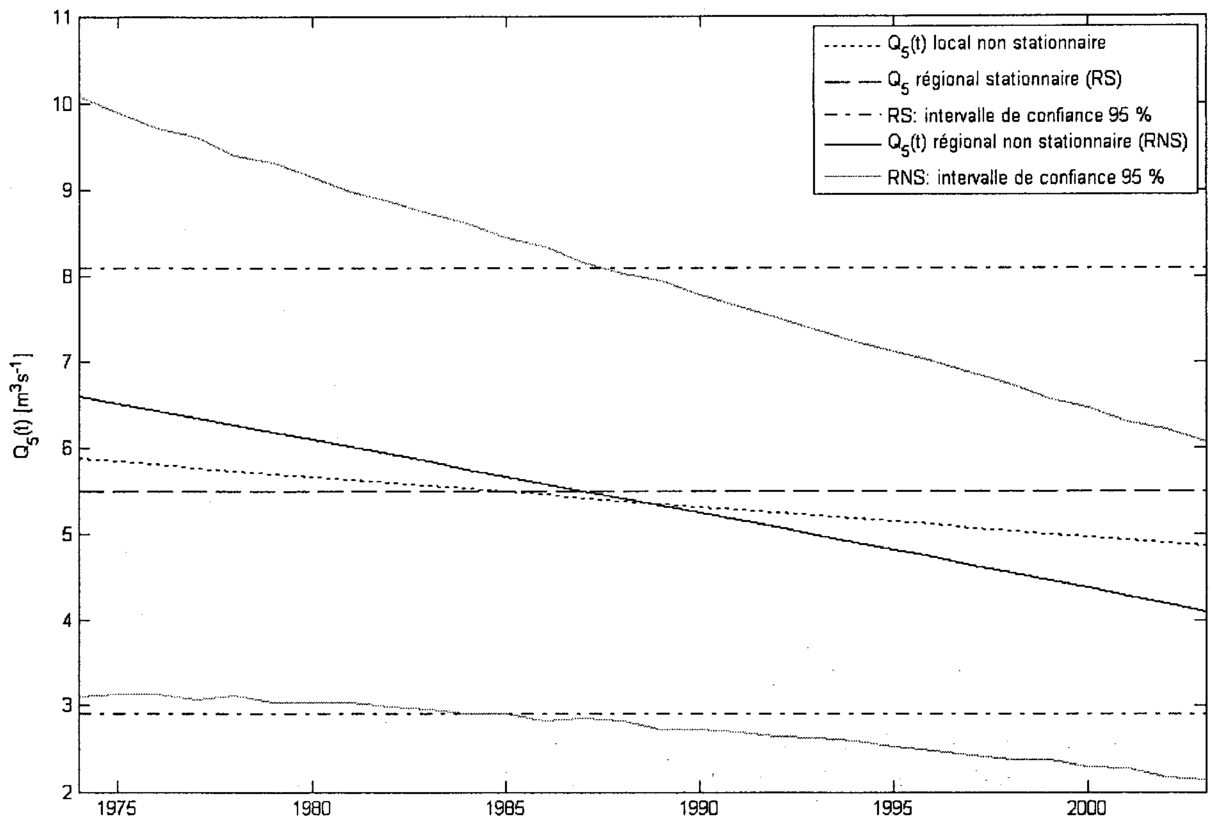

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SECTION 2

L'ARTICLE

RÉSUMÉ EN FRANÇAIS

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NON-STATIONARY REGIONAL FLOOD FREQUENCY ANALYSIS AT UNGAUGED SITES

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Abstract: Regional flood frequency analysis (FFA) is commonly used to estimate flood risk at a particular site where little or no information is available on peak flows. This approach requires the assumption of flood stationarity. In this paper, we present a method to perform regional FFA at ungauged sites when the assumption of stationarity is not valid. Non-stationary at-site models are used to estimate flood risk at gauged sites. This information can then be used along with meteorological and drainage basin characteristics to define a hydrologic neighborhood of the ungauged site by means of canonical correlation analysis (CCA). A multiple regression model is then developed within the hydrologic neighborhood. The proposed method was tested with a group of river flow gauging stations located in southeastern Canada and northeastern United States and which show a signal of non-stationarity. Results indicate that the development of a multiple regression model using 2 explanatory variables (including basin drainage area) leads to efficient estimation of the non-stationary regional flood quantiles $Q_5(t)$ and $Q_{100}(t)$ for the end of the historic observation period (relative root mean square error (RMSEr) of 38.2 % and 60.8 % respectively). The use of CCA for the definition of a hydrologic neighborhood did not lead to better results. This is explained by the fact that the total number of sites (29) is small and, consequently, the size of the hydrologic neighborhoods is too low to develop efficient regression models within each of them. Comparison with the stationary results show that ignoring a trend in the hydrologic regime of an ungauged site can lead to serious under- or overestimation of the quantile estimates for that site.

Keywords: Non-stationarity, Flood frequency analysis, Regional estimation, Canonical correlation analysis, At-site estimation, GEV model, Ungauged site

1 Introduction and literature review

Extreme events related to surface water runoff pose a significant risk to humans and to the environment. At the drainage basin scale consideration of this risk for, for example, hydraulic structure design or floodplain mapping requires an estimation of flood quantiles corresponding to various return levels. In the case of an ungauged site, the method commonly used is regional flood frequency analysis (FFA) which is usually based on the following two steps:

1. Identification of a group of gauged drainage basins with a hydrologic regime sufficiently similar to the ungauged site;
2. Estimation of flood quantiles at the ungauged site through information transfer from the sites identified in step 1.

Since the original work of Dalrymple (1960), almost all regional estimation methods presented in the literature consider that, for each gauged drainage basin and for the ungauged site, observations are independently and identically distributed. In other words, for each one of these basins, it is assumed that observations are independent, homogeneous and stationary. However, relatively recent studies carried out in various regions of the world question the assumption of flood stationarity (Changnon and Kunkel, 1995; Westmacott and Burn, 1997; Robson et al., 1998; Lins and Slack, 1999; Douglas et al., 2000). In that perspective, there is a need to focus on alternative approaches which do not require the assumption of stationarity.

The literature review carried out as part of the current research identified two studies that deal with non-stationary regional FFA. First, Cunderlik and Burn (2003) proposed a non-stationary pooled flood frequency model which assumes non-stationarity in the first two moments of the time series. However, the approach can only be used for a gauged site. Information from more than one location is pooled to improve the estimation of quantiles at that site. The flood frequency model separates the non-stationary pooled quantile function into a local time-dependent component, comprising the location and scale distribution parameters, and a regional component that can be regarded as time-independent under the assumption of second order non-stationarity.

One important note concerning the work of Cunderlik and Burn (2003) is that the site-focused pooling applied in the study (step 1 of traditional regional FFA) is based on the seasonality of annual maximum flood (AMF) series. The similarity measure between the target site and potential sites is defined as the root mean squared difference between relative frequencies of flood occurrence in each month. In order to adapt the model to the ungauged case, another similarity measure would have to be used.

More recently, Cunderlik and Ouarda (2006) proposed a non-stationary approach to regional flood-duration-frequency (QdF) modeling. The objective of the flood-duration-frequency analysis is to provide a continuous formulation of flood quantiles as an integrated function of return period and flood duration. QdF models are extensions of standard flood frequency models (Cunderlik and Ouarda, 2006). Similarly to Cunderlik and Burn (2003), the non-stationary regional QdF model assumes non-stationarity in the first two moments of the time series. The flood dynamics parameter, specific to the QdF model, is also assumed non-stationary. The non-stationary regional QdF model of Cunderlik and Ouarda (2006) is based on the index flood method (see Dalrymple, 1960). Thus, the non-stationary regional QdF quantile function can be separated into a local component, comprising the index flood and the flood dynamics parameter, and a regional component (dimensionless QdF growth curve). The index flood is a middle-sized flood often estimated as the mean or median value of the annual maximum or peaks-over-threshold flood series. In the case of an ungauged site, statistical modeling is used to estimate the index flood and the flood dynamics parameter from meteorological and drainage basin characteristics.

Cunderlik and Ouarda (2006) specify that a number of methods can be used for identification of a hydrologically homogeneous region (step 1 of traditional regional FFA). However, the group of drainage basins used in the case study was identified based on similarity in physiographic characteristics only. Hydrologic or meteorological variables such as flood quantiles or mean annual precipitation were not used.

The aim of the current study is to develop a method to perform non-stationary FFA at ungauged sites. The proposed approach for measuring similarity between an ungauged site and gauged drainage basins is canonical correlation analysis (CCA) using three types of descriptors: hydrologic, meteorological and physiographic variables. This approach has been successfully tested when used in traditional regional FFA under the assumption of stationarity (see Ouarda et al., 2000, 2001; Chokmani and Ouarda, 2004). The regional estimation method chosen for information transfer within each hydrologic neighborhood is multiple regression. Hydrologic variables from gauged drainage basins are obtained via at-site FFA using non-stationary generalized extreme-value (GEV) models.

Section 2 provides the theoretical background of the main approaches used in this study. The non-stationary regional model is fully described in section 3. A data set of gauged drainage basins from southeastern Canada and northeastern United States and the study methodology are presented in sections 4 and 5 respectively. Data-based validation of the proposed non-stationary approach and comparison with the stationary results are presented in section 6.

2 Theoretical background

2.1 Non-stationary at-site flood frequency analysis

The three-parameter GEV distribution, introduced by Jenkinson (1955), is commonly used for frequency analysis of extreme values such as flood peaks. It has been used in many studies on regional FFA (e.g. Ouarda et al., 2001; Cunderlik and Burn, 2003; Zhang and Hall, 2004;

Kumar and Chatterjee, 2005; Cunderlik and Ouarda, 2006). The cumulative distribution function of the GEV distribution is defined as:

$$
\begin{aligned}
F(x) &= \exp\left\{-\left[1-\kappa\frac{(x-\mu)}{\alpha}\right]^{1/\kappa}\right\} \qquad \kappa \neq 0 \\
&= \exp\left\{-\exp\left[-\frac{(x-\mu)}{\alpha}\right]\right\} \qquad \kappa = 0
\end{aligned}
\tag{3}
$$

where $\mu+\alpha/\kappa \leq x < \infty$ for $\kappa < 0$, $-\infty < x < \infty$ for $\kappa = 0$ and $-\infty < x \leq \mu+\alpha/\kappa$ for $\kappa > 0$. μ, α and κ are respectively the location, scale and shape parameters. It is the limit distribution of the maxima of a series of independent and identically distributed random variables. Thus, it appears that the GEV distribution cannot be used when the assumption of stationarity of the observations is not satisfied. In order to perform at-site frequency analysis of time series in presence of non-stationarity it is necessary to account for trends.

One common approach to do so is a direct extension of the GEV distribution. The distribution parameters are considered non-stationary but the choice of a distribution is time-invariant, so the problem reduces to the estimation of time-dependent parameters. Katz et al. (2002) gives an example of such an approach. The GEV distribution with a linear trend in the location parameter (i.e., $\mu_t = \beta_1 + \beta_2 \cdot t$) is fitted by maximum likelihood (ML) estimation to the sea level annual maxima at Fremantle, Western Australia (time period: 1897-1989). Even more recently, Nadarajah (2005) used the classic stationary GEV distribution along with non-stationary GEV models (linear and quadratic trends in the location parameter) to study annual maximum daily rainfall data for fourteen locations in West Central Florida (time period: 1901-2003). The ML method was applied to fit six different models to the data from each location.

The ML method is generally used in the literature for the parameter estimation of the GEV distribution. However, this method can lead to physically unacceptable κ estimates in small samples and a poor performance for quantile estimators. In order to eliminate these problems, Martins and Stedinger (2000) introduced the generalized maximum-likelihood (GML) method which uses a prior distribution $\pi(\kappa)$ to restrict estimated κ values to a statistically/physically reasonable range $[\kappa_L, \kappa_U]$. $\pi(\kappa)$ is used along with the likelihood function $L(\mu, \alpha, \kappa \mid x)$ to compute the generalized-likelihood (GL) function:

$$GL(\mu, \alpha, \kappa \mid x) = L(\mu, \alpha, \kappa \mid x)\pi(\kappa) \tag{4}$$

The generalized maximum likelihood estimators (GMLEs) of $\mu, \alpha,$ and κ can be identified by maximizing the generalized log-likelihood function. Martins and Stedinger (2000) used the Newton-Raphson method to compute them.

Within a non-stationary framework, El Adlouni et al. (2006) compared the ML and GML methods. Four GEV models with, respectively, 3, 4, 5 and 5 parameters were tested. In addition to the classic stationary model $\mathrm{GEV}_0(\mu,\alpha,\kappa)$, two models were considered in which the location parameter is respectively formulated as a linear and quadratic function of time: $\mathrm{GEV}_1(\mu_t = \beta_1 + \beta_2 \cdot t, \alpha, \kappa)$ and $\mathrm{GEV}_2(\mu_t = \beta_1 + \beta_2 \cdot t + \beta_3 \cdot t^2, \alpha, \kappa)$. The fourth model is the case with linear trend in both location and scale parameters: $\mathrm{GEV}_{11}(\mu_t = \beta_1 + \beta_2 \cdot t, \alpha_t = \eta_1 + \eta_2 \cdot t, \kappa)$.

El Adlouni et al. (2006) used numerical procedures to compute parameter estimators for the ML method. However, a Monte Carlo Markov Chain (MCMC) method was applied for the GML approach. Following this method, a Markov chain of size N is constructed via the Metropolis-Hastings algorithm (Metropolis et al., 1953; Hastings, 1970). Each state of the chain is a realization of the posterior distribution of the model GEV_i (i = 1, 2, 11). For each parameter, the GML estimator is equal to the mean of the parameter values obtained from the last $N - N_0$ realizations of the chain. N_0 is the number of runs associated to the burn-in period.

The main objective of the Monte Carlo simulation study carried out by El Adlouni et al. (2006) was to compare the performance of the ML and GML estimation methods for the following three values of the shape parameter: $\kappa = -0.1$, $\kappa = -0.2$ and $\kappa = -0.3$. The results of the simulation experiment showed that, in all cases, the GML method provides the best results with respect to bias and root mean square error (RMSE).

2.2 Delineation of hydrologic neighborhoods

The following subsection explains how CCA is commonly used for the identification of a group of gauged drainage basins $\{B_k\}$ hydrologically similar to an ungauged site B_0. Let $Y' = (Y_1, \ldots, Y_r)$ be a set of hydrologic variables representing flood characteristics, and let $X' = (X_1, \ldots, X_n), n \geq r$, be a set of variables representing the physiographic and meteorological characteristics of the drainage basins (e.g. drainage area, coordinates of the gauging station, mean annual precipitation). Y is unknown for B_0, while X is known for all B_k and for B_0.

First, the following two linear combinations are constructed:

$$\begin{aligned} V &= a_1 X_1 + \ldots + a_n X_n = a'X \\ W &= b_1 Y_1 + \ldots + b_r Y_r = b'Y \end{aligned} \tag{5}$$

The aim of CCA is to find two bases V and W of canonical variables for which the correlation matrix between the variables is diagonal and the correlations on the diagonal are maximized. In other words, CCA finds a coordinate system that is optimal for correlation analysis. Then, it allows one to infer on the values of the hydrologic canonical variables at the ungauged site B_0 knowing the values of the corresponding meteorological and physiographic canonical variables. To do so, the following optimization problem has to be solved for a and b:

$$
\begin{aligned}
&\max \operatorname{Corr}(W_i, V_i) = \lambda_i, \quad i = 1, \ldots, p \\
&\operatorname{Corr}(W_i, V_j) = 0, \quad i \neq j \\
&\operatorname{Var}(\mathrm{W_i}) = \operatorname{Var}(V_i) = 1, \quad i = 1, \ldots, p
\end{aligned}
\tag{6}
$$

The p solutions (λ_i, a_i, b_i) of this multidimensional problem can be obtained by means of the Lagrange multipliers technique. More details are given by Ouarda et al. (2001). p is equal to or less than r, which is the smallest dimensionality of the two variables Y and X ($\dim(X) = n$, $\dim(Y) = r$ and $n \geq r$). For each gauged drainage basin B_k, a hydrologic canonical score w_k is calculated:

$$w_k(i) = b_i' \cdot Y_k = b_{i1} Y_{k1} + \ldots + b_{ir} Y_{kr}, \quad i = 1, \ldots, p \tag{7}$$

Similarly, for the ungauged site B_0, a canonical score v_0 is computed using the meteorological and drainage basin characteristics X_0:

$$v_0(i) = a_i' \cdot X_0 = a_{i1} X_{01} + \ldots + a_{in} X_{0n}, \quad i = 1, \ldots, p \tag{8}$$

The problem is now to infer on the hydrologic canonical score w_0 of B_0, which means considering $W \mid V = v_0$, the conditional distribution of W given $V = v_0$. The following simplifying assumption is used in order to define a decision rule for including gauged drainage basins in the hydrologic neighborhood J_0 of the ungauged site:

$$\begin{pmatrix} W \\ V \end{pmatrix} \sim N_{2p}(0, L) \tag{9}$$

where L is the covariance matrix of the canonical variables:

$$L = \begin{pmatrix} I_p & \Lambda \\ \Lambda & I_p \end{pmatrix} \tag{10}$$

with $I_p = p \times p$ matrix identity and $\Lambda = \mathrm{diag}(\lambda_1, \ldots, \lambda_p)$. In practice, the original variables are transformed to ensure normality (Ouarda et al., 2001).

If Equation (7) is satisfied, it can be shown (Muirhead, 1982) that $W \mid V = v_0$ is p-normal:

$$(W \mid V = v_0) \sim N_p(\Lambda v_0, I_p - \Lambda\Lambda') \tag{11}$$

Λv_0 gives an estimate of the mean position of the ungauged site in the hydrologic canonical space. Thus, the gauged drainage basins to be included in J_0 are those for which the canonical scores w_k would be scattered around the mean position Λv_0 according to Equation (9). The quadratic form of the multivariate normal distribution of Equation (9) gives the equation for the distance D^2 to the mean position:

$$D^2 = (W - \Lambda v_0)' (I_p - \Lambda\Lambda')^{-1} (W - \Lambda v_0) \tag{12}$$

It can be shown (Muirhead, 1982) that D^2 , being a Mahalanobis distance, has a chi-square distribution with p degrees of freedom. Ouarda et al. (2001) used that property to include in J_0 all the gauged drainage basins for which D^2 is less than the $1-\phi$ quantile of a chi-square distribution with p degrees of freedom. A jackknife resampling procedure was used to identify a value for ϕ that corresponds to the optimal number of stations to include in the neighborhood.

However, in a subsequent research, Girard et al. (2000) proposed a revised definition of the decision rule which avoids the selection of an optimal value for ϕ. Equations (7) and (9) allow one to apply the Wald-Fisher rule of classification theory (see Anderson, 1984). Details are given in Girard et al. (2000). Finally, the decision rule is:

Include B_k in J_0 if :

$$(w_k - \Lambda v_0)' (I_p - \Lambda\Lambda')^{-1} (w_k - \Lambda v_0) \leq (w_k - 0)' I_p^{-1} (w_k - 0) + \ln\left(\frac{|I_p|}{|I_p - \Lambda\Lambda'|}\right) \tag{13}$$

In practice, the number of gauged drainage basins satisfying Equation (11) can be too small to perform information transfer to the ungauged site. Then, one option is to include in J_0 the m drainage basins with the smallest Mahalanobis distance D^2, without considering the threshold given by Equation (11). In that case, the optimal number m can be determined using a jackknife resampling procedure.

3 Non-stationary regional model

Considering that a common length of AMF time series is about 30-50 years long and given the large sampling variability involved in the estimation of higher moments from such series, non-stationarity is only assumed in the first moment (location parameter) in the proposed model. The form of non-stationarity is also assumed linear or quadratic. The assumption of independence is maintained.

3.1 Flood frequency analysis at gauged sites

The first step of the model is to perform non-stationary FFA at the K gauged sites B_k. Models $\mathrm{GEV}_0(\mu,\alpha,\kappa)$, $\mathrm{GEV}_1(\mu_t = \beta_1 + \beta_2 \cdot t, \alpha, \kappa)$ and $\mathrm{GEV}_2(\mu_t = \beta_1 + \beta_2 \cdot t + \beta_3 \cdot t^2, \alpha, \kappa)$ are considered. Parameter estimation of the stationary model GEV_0 is carried out using the ML method. The GML method has been selected for parameter estimation of the two models GEV_1 and GEV_2. The MCMC procedure of El Adlouni et al. (2006) is used. In order to compare the fit of the three models we use the deviance statistic U of Coles (2001). The statistic is based on the maximized log-likelihood l^* values and tests the validity of a model M_1 against another model M_0 such as $M_0 \subset M_1$. Model M_1 is significantly better than model M_0 if:

$$U = 2\left[l^*(M_1) - l^*(M_0)\right] > \chi^2_{1-\phi,\nu} \tag{14}$$

where $l^*(M)$ is the maximized log-likelihood value of model M and $\chi^2_{1-\phi,\nu}$ the $1-\phi$ quantile of a chi-square distribution with ν degrees of freedom. ν is the difference in the number of parameters between the models M_0 and M_1. The validity of the GEV_1 model is first tested against GEV_0. If GEV_1 is significantly better than GEV_0, then GEV_1 is tested against GEV_2 and the best model is identified. If not, GEV_0 is considered to be the best model.

For a given return period T, flood quantiles corresponding to the best fit GEV model are given by:

$$Q_T(t) = \mu_t + \frac{\alpha}{\kappa}\left\{1 - \left[-\log\left(1 - \frac{1}{T}\right)\right]^{\kappa}\right\} \tag{15}$$

where $\mu_t = \mu$ for the GEV_0 model, $\mu_t = \beta_1 + \beta_2 \cdot t$ for the GEV_1 model and $\mu_t = \beta_1 + \beta_2 \cdot t + \beta_3 \cdot t^2$ for the GEV_2 model.

3.2 Neighborhood identification using CCA

As a result of at-site FFA, the initial group of K gauged drainage basins can be partitioned into three subgroups K_0, K_1 and K_2 according to the best fit GEV model, GEV_0, GEV_1 or GEV_2 respectively. At this step, we suppose that B_0, the ungauged site, can be classified as belonging to K_i, one of the three subgroups, according to auxiliary information such as drainage basin characteristics or climatology.

Using equation (13) one can obtain flood quantiles for the subgroup K_i of gauged drainage basins. Let $Y' = (Y_1, \ldots, Y_r)$ be the set of hydrologic variables representing those flood characteristics. As the flood quantiles can vary through time according to equation (13), the flood characteristics that may present the greatest interest are those that affect the prediction at the horizon t in the future. Let $X' = (X_1, \ldots, X_n), n \geq r$, be the set of physiographic and meteorological variables describing the gauged drainage basins and the ungauged site. Some of those variables can reflect the presence of non-stationarity in flood characteristics. Using vectors Y and X, we can proceed with step 2 of the model. The identification of the hydrologic neighborhood for B_0 is completed according to subsection 2.2.

3.3 Information transfer

Within the hydrologic neighborhood identified in the last subsection, multiple regression is applied to estimate values of time-variant flood quantiles $Q_T(t)$ based on knowledge of physiographic and meteorological variables (vector X), for which data are available at the ungauged site. The problem is typically described using the power-form equation

$$Q_T(t) = \gamma_0 \cdot X_1^{\gamma_1} \cdot \ldots \cdot X_n^{\gamma_n} \cdot e^{\varepsilon} \tag{16}$$

where $\gamma_0, \gamma_1, \ldots, \gamma_n$ are model parameters and ε a random error term. Many different procedures are available to estimate the model parameters γ_i. One common procedure is to linearize Equation (14) through a logarithmic transformation

$$\log Q_T(t) = \log \gamma_0 + \gamma_1 \log X_1 + \ldots + \gamma_n \log X_n + \varepsilon \tag{17}$$

and then to estimate the model parameters in Equation (15) using an ordinary least-squares technique. This procedure is used here. The logarithmic transformation applied to Equation (14) introduces an additional bias because

$$\mathrm{E}\left[Q_T(t)\right] = \mathrm{E}\left\{\exp\left[\log Q_T(t)\right]\right\} \neq \exp\left\{\mathrm{E}\left[\log Q_T(t)\right]\right\} \tag{18}$$

Methods exist to correct this bias in the prediction (see Hersel and Hirsch, 1992; Girard et al., 2004). However, no general rule exists. Evaluation of the additional bias in each specific situation is recommended.

4 Case study

The proposed model has been tested using data from 29 river flow gauging stations located in southeastern Canada (Maritime Provinces and St. Lawrence River major drainage basins) and northeastern United States (New England, Great Lakes, and northern part of Mid Atlantic USGS hydrologic regions). Figure 1 shows how the 29 gauging stations are distributed across southeastern Canada and northeastern United States. The stations, operated by the U.S. Geological Survey, Environment Canada and the Quebec Ministry of the Environment, have 30 continuous years of record on the period 1974-2003. Daily flows from these stations are relatively free of anthropogenic influences. Data were obtained from the USGS National Water Information System (U.S. Geological Survey, 2005), the Water Survey of Canada's (WSC) Hydrometric Database (Water Survey of Canada, 2005) and the Quebec Ministry of the Environment. Basin drainage area was also available for these stations. Table 1 provides the number (USGS or WSC) of each station along with the name, state/province and basin drainage area.

In order to meet the assumption of flood homogeneity, it is important to reduce as much as possible the mixing between the different processes that generate floods (e.g. rain-fed or snowmelt driven floods). Here, we focus on peak flows generated by snowmelt during the spring season. The winter/spring season is defined using the latitude of each gauging station. The start date is always the same (January 1st), but the end date varies as follows: May 31st (stations located below the 45th parallel), June 30th (between the 45th and 50th parallels) and July 30th (above the 50th parallel). This definition is consistent with the one used in other studies (see Javelle et al., 2003; Hodgkins et al. 2003). Finally, the annual winter/spring peak flow is defined as the largest daily mean flow during the winter/spring season.

The 29 annual winter/spring peak flow series meet the assumption of independence and first-order non-stationarity of the model. The testing method used is presented in subsection 5.1 (significance level: $\phi = 10\,\%$). According to that test, the trend in the central value of each peak flow series is a downward trend. The deviance statistic, as described in subsection 3.1, also shows that the best fit model for each peak flow series is the $\mathrm{GEV}_1\left(\mu_t = \beta_1 + \beta_2 \cdot t, \alpha, \kappa\right)$ model (significance level: $\phi = 10\,\%$). Here, it must be clear that the set of 29 series is used only for the application of the model within the leave-one-out cross-validation procedure. No general assumption is made about the stationary or non-stationary character of the whole region or subregions within the geographic area of study.

Monthly precipitation and air temperature data in northeastern United States for the period 1974-2003 were obtained from the U.S. Historical Climatology Network (USHCN) data set (Williams et al., 2005). Daily precipitation and air temperature data available for the same period were also obtained from Environment Canada (EC) (meteorological stations in Ontario, Quebec and Maritime Provinces only). Mean winter/spring precipitation amounts and mean winter/spring air temperatures (mean, maximum and minimum) were computed over the period 1974-2003. Meteorological stations with too many missing observations were rejected.

A meteorological station (USHCN or EC) was associated with each streamflow gauging station in order to perform CCA and multiple regression. In each case, the closest meteorological station to the gauging station was selected.

5 Study methodology

In order to test the non-stationary regional model and to demonstrate its advantages when the assumption of stationarity of annual flood series is not valid, a data-based validation is conducted and the resulting non-stationary regional flood quantiles are compared with the stationary results.

5.1 Test of data series

First, we test the assumption of independence and first-order non-stationarity of the model. The Mann-Kendall (MK) test (Mann, 1945; Kendall, 1975) can be used to determine whether the central value or median of a time series changes over time. No assumption of normality is required, but there must be no serial correlation for the resulting p-values to be correct (Hersel and Hirsch, 1992). Yue et al. (2002, 2003) proposed a trend-free pre-whitening (TFPW) procedure to eliminate the effect of serial correlation on the MK test. We use the first part of this procedure as we test the independence and first-order non-stationarity of the time series. The procedure is given below. Let C_t (t = 1, …, n) be an AMF time series.

1. The slope δ of a trend in C_t is estimated non-parametrically using Sen's robust slope estimator (Sen, 1968):

$$\delta = Med(S_{ij}); \qquad S_{ij} = \frac{C_i - C_j}{i-j}, \forall j < i \tag{19}$$

   where C_i and C_j are flood peaks at time i and j respectively.

2. The trend is assumed to be linear, and C_t is detrended by: $D_t = C_t - \delta \cdot t$

3. The lag-1 serial correlation coefficient r_1 of the detrended series D_t is computed (Salas et al., 1980):

$$r_1 = \frac{\frac{1}{n-1}\sum_{t=1}^{n-1}\left(D_t - \bar{D}_t\right)\left(D_{t+1} - \bar{D}_t\right)}{\frac{1}{n}\sum_{t=1}^{n}\left(D_t - \bar{D}_t\right)^2}; \qquad \bar{D}_t = \frac{1}{n}\sum_{t=1}^{n} D_t \tag{20}$$

4. The significance of r_1 is assessed using the following approximation (Salas et al., 1980). r_1 is not significantly different from zero if:

$$\frac{-1+z_{\phi/2}\sqrt{n-2}}{n-1} \le r_1 \le \frac{-1+z_{1-\phi/2}\sqrt{n-2}}{n-1} \tag{21}$$

where $z_{\phi/2}$ and $z_{1-\phi/2}$ are respectively the $\phi/2$ and $1-\phi/2$ quantiles of the standard normal distribution. If r_1 is significantly different from zero, the sample data are considered to be serially correlated. Otherwise, the MK test is applied to the original time series C_t.

The MK test is a nonparametric test based on ranks. The null hypothesis H_0 states that the sample data are independent and identically distributed. The alternative hypothesis H_1 is that a monotonic trend exists in C_t. The test statistic, Kendall's S, is computed as follows:

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \operatorname{sgn}\left(C_j - C_i\right); \quad \operatorname{sgn}(\theta) = \begin{cases} 1 & \text{if } \theta > 0 \\ 0 & \text{if } \theta = 0 \\ -1 & \text{if } \theta < 0 \end{cases} \tag{22}$$

Under the null hypothesis of no trend, S is approximately normally distributed (for large sample sizes n) with mean $\mathrm{E}(S)$ and variance $\mathrm{Var}(S)$ as follows:

$$\mathrm{E}(S) = 0; \quad \mathrm{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{n} t_i\, i(i-1)(2i+5)}{18} \tag{23}$$

where t_i is the number of ties of extent i. The standardized test statistic Z is given by:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\mathrm{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{\mathrm{Var}(S)}} & S < 0 \end{cases} \tag{24}$$

Z follows a standard normal distribution. In a two-sided test for trend at a significance level of ϕ, H_0 should be rejected if $|Z| \ge z_{\phi/2}$. A positive value of S indicates an upward trend; a negative value indicates a downward trend.

The set of AMF time series being tested can be either a set of upward or downward trends (S_U or S_D respectively). For illustration purposes, this set must be sufficiently large to perform the data-based validation (cross-validation experiment). If S_U and S_D are both large enough, the procedure can be applied separately to each of them. However, these sets cannot be merged as upward and downward trends clearly refer to different types of hydrologic regimes and non-stationarities.

5.2 Performance criteria

Meteorological and drainage basin characteristics associated to the 29 winter/spring peak flow series of the case study are used along with the flood quantiles corresponding to the GEV_1 model (best fit model according to the deviance statistic). The cross-validation (jackknife) experiment is performed on the resulting drainage basin data set. A given drainage basin is temporarily removed from the data set and treated as ungauged. Flood quantiles for this site are then estimated using the remaining drainage basins (through CCA and multiple regression). This operation is repeated for the whole data set. Then, the estimated values (regional estimates) are compared with the flood quantiles corresponding to the GEV_1 model (at-site estimates). To assess the performance of the model, the relative mean bias (BIASr) and the relative root mean square error (RMSEr) are computed:

$$\text{BIASr} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\hat{z}_i - z_i}{z_i}\right) \tag{25}$$

$$\text{RMSEr} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\hat{z}_i - z_i}{z_i}\right)^2} \tag{26}$$

where $\hat{z}_i$ and z_i are, respectively, the regional and at-site estimates of drainage basin i and N the size of the data set.

Regional flood quantiles resulting from the application of the non-stationary regional model are also compared with those obtained from a stationary regional model. This stationary model is analogous to the one described in section 3. The methods applied for neighborhood identification and information transfer are identical. The flood series, meteorological and drainage basin characteristics, and the cross-validation experiment used are the same. Only at-site FFA is different in these two models. Instead of using non-stationary GEV models, the regional stationary model uses two-parameter (Weibull, normal, lognormal 2, Gamma, Inverse Gamma, exponential, extreme value type I) and three parameter (GEV, Generalized Pareto, Pearson type III, log Pearson type III, Generalized Gamma, lognormal 3, Halphen (A, B, B^{-1})) stationary distributions. Three parameter estimation methods are considered for the log Pearson type III distribution: indirect method of moments, Sundry Averages Method, non-centered moments (see Bobée and Ashkar, 1991). The following three methods are used for the remaining distributions: ML, ordinary moments, probability weighted moments. The best fit model is selected using the Akaike information criterion (Akaike, 1974).

6 Results and discussion

Non-stationary at-site FFA was performed in order to fit the GEV_1 model to each of the winter/spring peak flow series. Using Equation (13), the 5-year $\left(Q_5(t)\right)$ and 100-year $\left(Q_{100}(t)\right)$ flood quantiles were computed for the prediction horizon $t = 2003$ which corresponds to the end of the historic observation period. That constitutes vector Y for CCA $\left(Y' = \left[Q_5(t=2003), Q_{100}(t=2003)\right]\right)$. The physiographic and meteorological variables available for construction of vector X are listed below.

- AREA, basin drainage area $\left(\mathrm{km}^2\right)$;
- LAT, gauging station latitude;

- LONG, gauging station longitude;
- PTMP, mean total winter/spring precipitation (mm);
- TXMP, mean winter/spring maximum air temperature $(°\mathrm{C})$;

Results of the cross-validation experiment for 5 different combinations of physiographic and meteorological variables are presented thereafter. The response variable is $Q_5(t)$. Results for the full model (CCA-MR) are compared with results for the model where only multiple regression is used (Tables 2 and 3, respectively). In such a model (MR only), for each gauging station treated as ungauged, all the remaining 28 sites are included in the hydrologic neighborhood. No CCA is performed. The 5 different vectors X used are those that give the best results for the MR model according to the RMSEr index. Results in terms of BIASr and RMSEr are always better with the MR model in comparison with the full version. It can be seen that the CCA-MR model provided estimates for a number of sites that varies from 24 to 28. This is due to the fact that for some stations the size of the hydrologic neighborhood is too small to perform multiple regression. It must also be noted that the mean size of the hydrologic neighborhood among the remaining stations is very low. That partly explains why full model estimates are less precise than MR model estimates. Tables 4 and 5 present similar results for the response variable $Q_{100}(t)$. In general, BIASr and RMSEr indices are much larger for larger return periods.

By including the m drainage basins with the smallest Mahalanobis distance in the hydrologic neighborhood without considering any threshold, as described at the end of subsection 2.2, we obtained better results than those presented in Tables 2 and 4 for the full model. This model will now be referred to as the MD model. Results using vector $X' = [\mathrm{LONG}, \mathrm{BV}]$ are presented in Table 6 for $Q_5(t)$ and $Q_{100}(t)$. It can be seen that with

$m = 25$, BIASr and RMSEr values are slightly lower than with $m = 28$ (MR model) for both quantiles. This gives an indication of the usefulness of CCA for the definition of the hydrologic neighborhood when the number of sites is large (much larger than 29). In such a case, there is a real trade-off between homogeneity of the neighborhood and amount of observations that has to be addressed.

Results of the stationary at-site FFA are as follows. Only two-parameter distributions were selected with the Gamma distribution being the most popular one (12 cases). We used Q_5 and Q_{100} quantiles for the cross-validation experiment. MR model with vector $X' = [\text{LONG}, \text{BV}]$ has been selected for the remainder of this study. BIASr and RMSEr values are 7.1 % and 40.6 % respectively for the response variable Q_5 and 8.1 % and 45.7 % for Q_{100}.

The next step is to compare the quantile estimates resulting from the non-stationary regional model with those resulting from the stationary regional model. Here, the quantile estimates obtained with the non-stationary at-site FFA are taken as the true values of the quantiles. Results in terms of BIASr and RMSEr for the $Q_5(t)$ and $Q_{100}(t)$ quantiles are given in Tables 7 and 8 respectively. Quantiles computed by both regional models are positively biased (overestimated). However, BIASr and RMSEr values are lower for the non-stationary regional model than for the stationary regional model. The bias difference between both models is 27.9 % and 4.1 % for $Q_5(t)$ and $Q_{100}(t)$ quantiles respectively.

Figure 2 illustrates results for $Q_5(t)$ at station WSC ID 01BH005 located on the Dartmouth River in the Province of Quebec, Canada. For the prediction horizon $t = 2003$, the stationary regional model overestimates $Q_5(t)$ by 27 % assuming that the non-stationary at-site quantile estimate is the true value. The bias is much lower with the non-stationary regional model (-6 %). The quantile obtained by the stationary regional model for the year 2003 represents conditions that occurred 17 years ago, in 1986, according to the non-stationary at-site FFA. These results show that ignoring a trend in the hydrologic regime of an ungauged site can substantially reduce the accuracy of the quantile estimates for that site.

7 Conclusions

Traditional methods for FFA at ungauged sites are built upon the assumption that the hydrologic regime does not vary through time (i.e. stationary) at the ungauged site and at gauged sites. This assumption is questioned by several recent studies. Non-stationarity in the hydrologic regime can be induced by changes in the climatology but also in the drainage basin characteristics. In order to obtain accurate quantile estimates for hydraulic structure design or floodplain mapping, alternative approaches that take non-stationarity into account are needed.

This paper presented a non-stationary regional model for FFA at ungauged sites. The model was tested with a group of streamflow gauging stations located in southeastern Canada and northeastern United States. To do so, a leave-one-out cross-validation procedure is used. A similar validation procedure was also carried out using the traditional stationary regional model. Quantile estimates from both validation procedures were then compared.

The results for the proposed non-stationary approach showed that the development of a multiple regression model using 2 to 4 explanatory variables (including basin drainage area) leads to efficient estimation of the non-stationary regional flood quantiles $Q_5(t)$ and $Q_{100}(t)$ for time horizon $t = 2003$. The use of CCA for the delineation of hydrologic neighborhoods did not lead to better results. The total number of sites (29) is small and, consequently, the size of the hydrologic neighborhoods is too small to develop efficient regression models within each one. In general, the approach with CCA should be used only if the total number of sites is larger than 50. Otherwise, the approach using multiple regression only must be preferred.

Comparison of the cross-validation results shows that the non-stationary regional model is better than the stationary regional model in terms of both BIASr and RMSEr when the non-stationary at-site quantile estimates are considered as reference values. Results indicate that ignoring a trend in the hydrologic regime can lead to serious under- or overestimation of quantile estimates.

It must be noted that in this study we only used the non-stationary GEV_1 model for the proposed non-stationary approach. The choice of a best fit distribution among several non-stationary distributions would eventually lead to better results for the non-stationary regional model.

The proposed model was tested using gauged drainage basins treated as ungauged. No general assumption was made about the stationary or non-stationary character of the whole region or subregions within the area of study. The application of the proposed model within an area where a true regional non-stationary signal is observed could lead to better results than those obtained in this study.

Future work should be directed towards the identification of climatological variables and drainage basin characteristics related to non-stationarity in annual peak flow series. Further work is also needed on non-stationary at-site FFA.

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Table 1. The 29 river flow gauging stations for the cross-validation experiment.

ID	Name and state/province	Area (km^2)
02EC009	Holland River at Holland Landing, ON	181
02ED003	Nottawasaga River near Baxter, ON	1,180
02GA010	Nith River near Canning, ON	1,008
02GD004	Middle Thames River at Thamesford, ON	306
02HB004	East Oakville Creek near Omagh, ON	199
02HB012	Grindstone Creek near Aldershot, ON	83
02HC009	East Humber River near Pine Grove, ON	197
02HC019	Duffins Creek above Pickering, ON	94
02HC025	Humber River at Elder Mills, ON	303
02HJ001	Jackson Creek at Peterborough, ON	110
02HL005	Moira River near Deloro, ON	308
02HM004	Wilton Creek near Napanee, ON	112
01BH005	Dartmouth (rivière) en amont du ruisseau du Pas de Dame, QC	630
02JB013	Kinojevis (rivière) à Cléricy, QC	2,575
01169000	North River at Shattuckville, MA	231
01333000	Green River at Williamstown, MA	110
01379000	Passaic River near Millington, NJ	143
01379500	Passaic River near Chatham, NJ	259
01381500	Whippany River at Morristown, NJ	76
01399500	Lamington (Black) River near Pottersville, NJ	85
01400500	Raritan River at Manville, NJ	1,269
01403060	Raritan River below Calco Dam at Bound Brook, NJ	2,033
01439500	Bush Kill at Shoemakers, PA	303
01541000	West Branch Susquehanna River at Bower, PA	816
01546500	Spring Creek near Axemann, PA	226
01547100	Spring Creek at Milesburg, PA	368
01547200	Bald Eagle Creek bl Spring Creek at Milesburg, PA	686
01643000	Monocacy River at Jug Bridge near Frederick, MD	2,116
04122100	Bear Creek near Muskegon, MI	43

Table 2. Results of the cross-validation experiment for the full model (canonical correlation analysis + multiple regression). The response variable is $Q_5(t = 2003)$.

Physiographic and meteorological variables used	Number of estimates	Mean neighborhood size	BIASr (%)	RMSEr (%)
LONG, BV	28	7.8	16.6	57.5
LAT, BV, PTMP, TXMP	24	7.8	14.4	59.3
LAT, BV, PTMP	25	7.9	15.8	53.4
LONG, BV, PTMP	25	8.0	13.2	47.1
LAT, LONG, BV, PTMP	25	7.9	47.0	171.4

Table 3. Results of the cross-validation experiment for the MR model (multiple regression only). The response variable is $Q_5(t=2003)$.

Physiographic and meteorological variables used	**Number of estimates**	**Mean neighborhood size**	**BIASr (%)**	**RMSEr (%)**
LONG, BV	29	28	6.0	38.2
LAT, BV, PTMP, TXMP	29	28	7.7	38.5
LAT, BV, PTMP	29	28	6.5	38.6
LONG, BV, PTMP	29	28	5.9	39.2
LAT, LONG, BV, PTMP	29	28	6.2	39.5

Table 4. Results of the cross-validation experiment for the full model (canonical correlation analysis + multiple regression). The response variable is $Q_{100}(t=2003)$.

Physiographic and meteorological variables used	**Number of estimates**	**Mean neighborhood size**	**BIASr (%)**	**RMSEr (%)**
LAT, BV	29	8.1	36.2	118.1
BV, PTMP	28	7.6	49.2	146.7
BV, TXMP	29	8.0	16.0	78.8
LONG, BV	28	7.8	27.2	80.6
LONG, BV, PTMP	25	8.0	33.7	92.7

Table 5. Results of the cross-validation experiment for the MR model (multiple regression only). The response variable is $Q_{100}(t=2003)$.

Physiographic and meteorological variables used	**Number of estimates**	**Mean neighborhood size**	**BIASr (%)**	**RMSEr (%)**
LAT, BV	29	28	12.9	59.6
BV, PTMP	29	28	13.5	60.7
BV, TXMP	29	28	14.1	60.7
LONG, BV	29	28	12.2	60.8
LONG, BV, PTMP	29	28	12.3	62.1

Table 6. Results of the cross-validation experiment for the MD model (canonical correlation analysis (modified) + multiple regression). The m value corresponds to the number of drainage basins included in the hydrologic neighborhood.

m	$Q_5(t=2003)$ BIASr (%)	$Q_5(t=2003)$ RMSEr (%)	$Q_{100}(t=2003)$ BIASr (%)	$Q_{100}(t=2003)$ RMSEr (%)
19	7.0	39.5	11.3	61.6
20	6.0	38.8	11.1	62.7
21	6.2	38.6	12.3	63.7
22	6.0	38.5	13.0	63.4
23	5.7	37.9	12.9	62.6
24	5.7	37.8	12.2	61.3
25	5.4	37.9	11.4	60.2
26	6.3	37.8	13.2	60.2
27	6.5	38.0	13.7	60.5
28	6.0	38.2	12.2	60.8

Table 7. Comparison of $Q_5(t=2003)$ quantiles estimated by the non-stationary and stationary regional models.

Performance Measure	Non-stationary at-site estimates BIASr (%)	Non-stationary at-site estimates RMSEr (%)
Stationary regional estimates	33.9	58.3
Non-stationary regional estimates	6.0	38.2

Table 8. Comparison of $Q_{100}(t=2003)$ quantiles estimated by the non-stationary and stationary regional models.

Performance measure	Non-stationary at-site estimates BIASr (%)	Non-stationary at-site estimates RMSEr (%)
Stationary regional estimates	16.3	61.6
Non-stationary regional estimates	12.2	60.8

FIGURE CAPTIONS

Figure 1. Location of the 29 river flow gauging stations across southeastern Canada and northeastern United States.

Figure 2. $Q_5(t)$ quantile estimates at Dartmouth (rivière) en amont du ruisseau du Pas de Dame, QC (WSC ID 01BH005).

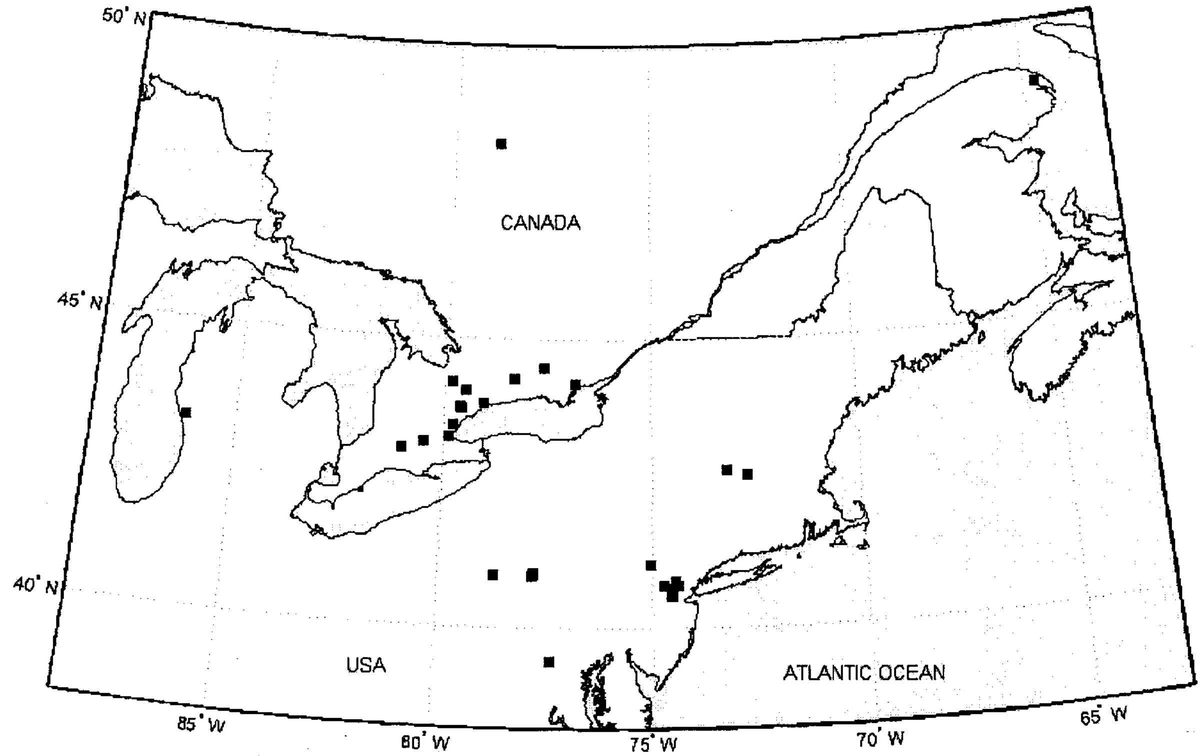

Figure 1.

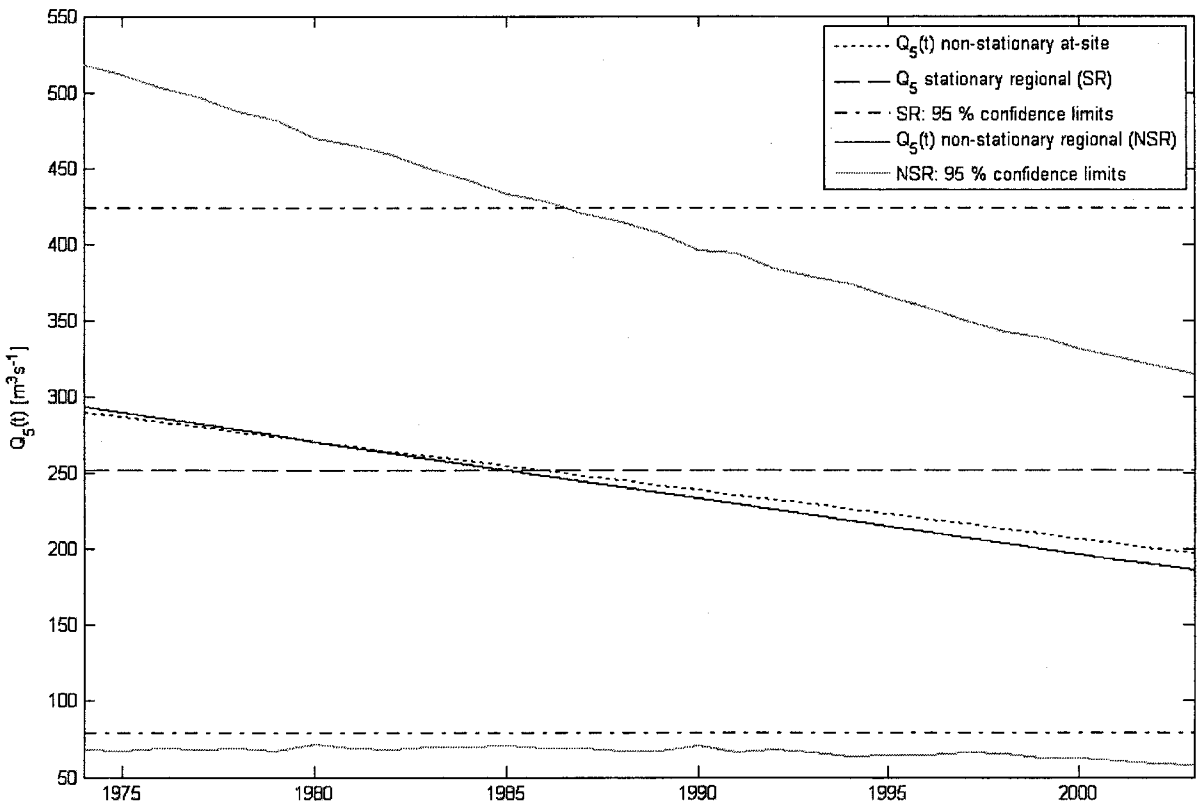

Figure 2.