

UNIVERSITÉ DU QUÉBEC À MONTRÉAL

IMPACTS DE L'UTILISATION DE QUANTITÉS AJUSTÉES DE PRÉCIPITATIONS SOLIDES  
DANS LE SYSTÈME CANADIEN D'ANALYSE DES PRÉCIPITATIONS

MÉMOIRE

PRÉSENTÉ

COMME EXIGENCE PARTIELLE

DE LA MAÎTRISE EN SCIENCES DE L'ATMOSPHÈRE

PAR

CATHERINE AUBRY

JANVIER 2024

UNIVERSITÉ DU QUÉBEC À MONTRÉAL  
Service des bibliothèques

Avertissement

La diffusion de ce mémoire se fait dans le respect des droits de son auteur, qui a signé le formulaire *Autorisation de reproduire et de diffuser un travail de recherche de cycles supérieurs* (SDU-522 – Rév.04-2020). Cette autorisation stipule que «conformément à l'article 11 du Règlement no 8 des études de cycles supérieurs, [l'auteur] concède à l'Université du Québec à Montréal une licence non exclusive d'utilisation et de publication de la totalité ou d'une partie importante de [son] travail de recherche pour des fins pédagogiques et non commerciales. Plus précisément, [l'auteur] autorise l'Université du Québec à Montréal à reproduire, diffuser, prêter, distribuer ou vendre des copies de [son] travail de recherche à des fins non commerciales sur quelque support que ce soit, y compris l'Internet. Cette licence et cette autorisation n'entraînent pas une renonciation de [la] part [de l'auteur] à [ses] droits moraux ni à [ses] droits de propriété intellectuelle. Sauf entente contraire, [l'auteur] conserve la liberté de diffuser et de commercialiser ou non ce travail dont [il] possède un exemplaire.»

## REMERCIEMENTS

Je tiens en premier lieu à exprimer ma profonde gratitude envers mes deux co-directeurs, Julie Thériault et Stéphane Bélair, qui m'ont accompagné, conseillé et guidé tout au long de cette aventure de maîtrise. Mes remerciements suivants vont à ceux qui ont été les fondements de ce parcours de deux ans. Leur amitié précieuse a non seulement enrichie mon mémoire, mais aussi mon quotidien. Une annonce de chips plus tard, ils sont devenus bien plus que de simples collègues. Je souhaite à tout le monde de rencontrer dans leur vie une Florence Beaudry et un Olivier Chalifour. Un remerciement tout particulier à Pei-Ning Feng et à Eva Mékis pour leur partage de connaissances et leur aide à travers ma découverte de CaPA et des fonctions de transfert. Je tiens également à exprimer ma reconnaissance envers les membres d'ECCC, particulièrement Franck Lespinas ainsi que Dikra Khedhaouria, pour leurs précieux conseils lors de nos rencontres hebdomadaires. À ma famille, je veux exprimer ma gratitude pour leur soutien tout au long de mes années d'études, et particulièrement durant ces deux dernières années. Votre présence est un pilier solide dans ma vie.

## TABLE DES MATIÈRES

REMERCIEMENTS .....	iii
TABLE DES MATIÈRES .....	iv
LISTE DES FIGURES .....	vi
LISTE DES TABLEAUX .....	viii
LISTE DES ABRÉVIATIONS, DES SIGLES ET DES ACRONYMES .....	ix
RÉSUMÉ .....	x
CHAPITRE I – INTRODUCTION .....	11
1.1 Aperçu de CaPA .....	12
1.2 Incertitudes pour les précipitations solides.....	14
1.3 Les fonctions de transfert.....	17
1.4 Les fonctions de transfert existantes.....	21
1.5 Objectifs.....	22
CHAPITRE 2.....	23
IMPACTS OF ADJUSTING SOLID PRECIPITATION AMOUNTS IN THE CANADIAN PRECIPITATION ANALYSIS SYSTEM.....	24
ABSTRACT .....	25
2.1 Introduction.....	26
2.2 Data and methodology .....	30
2.2.1 Domain of study and period.....	30
2.2.2 CaPA’s configuration.....	31
2.2.3 The hourly adjusted dataset.....	33
2.2.4 The Adjusted Daily Rainfall and Snowfall (AdjDlyRS) dataset .....	34
2.2.5 The transfer functions .....	35
2.2.6 Objective evaluation.....	39
2.2.7 Experiments setup .....	42
2.3 Evaluations of the different transfer functions .....	43
2.3.1 Impact of hourly data adjusted with UTF .....	43
2.3.2 Impact of hourly data adjusted with climate-specific transfer functions .....	45
2.3.3 Impact of hourly data with adjustment depending on snowfall intensity .....	46
2.3.4 Evaluation against AdjDlyRS .....	49

2.4 Discussion..... 51

    2.4.1 Sensitivity of CaPA’s results to various TFs based on air temperature ..... 51

    2.4.2 Interannual variability ..... 53

    2.4.3 Enhancement of the TF impact using snow intensity ..... 55

    2.4.4 Role of verification dataset and approach..... 56

2.5 Summary and conclusions ..... 59

CHAPITRE 3 - CONCLUSION ..... 61

RÉFÉRENCES ..... 66

## LISTE DES FIGURES

Figure 1: The domain of CaPA’s analyses is shown in grey, covering eastern British Columbia (BC), Alberta (AB), Saskatchewan (SK), Manitoba (MB), and western Ontario (ON). The domain extends from the north of United States to the south of the territories. The pink dots indicate the location of ECCC’s hourly automatic weather stations, and the black stars indicate the location of the Adjusted Daily Rainfall and Snowfall (AdjDlyRS) manual stations. .... 31

Figure 2: Catch efficiency for a single-alter as a function of wind speed for three different air temperatures ( $T_{air}$ ) and snowfall intensity (SI) for different sites: Marshall (red), Marshall SI (green), Haukeliseter (blue), Haukeliseter SI (pink), Batt’s Lake (grey) and Universal (black). Panel a):  $T_{air} = 0^{\circ}\text{C}$  and  $SI = 1.6 \text{ mm/h}$ . Panel b):  $T_{air} = -5^{\circ}\text{C}$  and  $SI = 1 \text{ mm/h}$ . Panel c):  $T_{air} = -10^{\circ}\text{C}$  and  $SI = 0.4 \text{ mm/h}$ . A wind threshold is applied for every transfer function (see Table 1). ..... 37

Figure 3: Objective evaluation metrics for CaPA’s analyses with the assimilation of unadjusted data (blue lines) and of data adjusted with UTF (orange lines). The evaluation is performed for winter 2019, from 1 December 2018 to 31 March 2019, and is valid over the entire study area shown in Figure 1: a) is for FBI-1 with a black line indicating no bias, b) is for ETS, c) is for POD, and d) is for FAR. The letter  $q$  provides the 6-hourly precipitation thresholds used for the evaluation (mm). White areas indicate that the differences between the two experiments are statistically significant at the 95 % confidence level, based on the bootstrap method; grey areas indicates that the differences are not statistically significant. .... 44

Figure 4: Same as Figure 3 but for the hourly adjusted data with the universal transfer function (orange) and the control run (black). ..... 45

Figure 5: Same as Figure 3 but for the hourly adjusted data with the Marshall transfer function depending on the air temperature (red) and the hourly adjusted data with the Marshall transfer function depending on the snowfall intensity (brown). ..... 47

Figure 6: Same as Figure 3 but for the hourly adjusted data with the Marshall transfer function depending on snowfall intensity (brown) and the control run (black). ..... 48

Figure 7: Objective evaluation metrics for CaPA’s analyses for the Control experiment (black lines) and with the assimilation of observations adjusted with MarTFsi (brown lines). The evaluation is performed against the AdjDlyRS dataset for winter 2019, from 1 December 2018 to 31 March 2019, and is valid over the entire study area shown in Figure 1: a) is for FBI-1 with a black line indicating no bias, b) is for ETS, c) is for POD, and d) is for FAR. The letter  $q$  provides the daily precipitation thresholds used for the evaluation (mm). Because the evaluation is for daily accumulations, the thresholds are different from previous figures. White areas indicate that the differences between the two experiments are statistically significant at the 95 % confidence level, based on the bootstrap method; grey areas indicate that the differences are not statistically significant. .... 50

Figure 8: Same as Figure 7 but for Hourly\_adj\_HaukTFsi. .... 51

Figure 9: Average total precipitation for the 138 stations in the domain using different transfer functions for the 2017, 2018, and 2019 winter seasons. The error bar shows the standard deviation of the average total precipitation. ....53

Figure 10: Evaluation with the LOOCV approach of CaPA for the Control run (black) and for the first guess (grey) for the frequency bias index FBI-1 with a black straight line indicating no bias valid for the study domain: a) is for winter 2017, b) is winter 2018 and c) is winter 2019. The letter q is the 6-hourly precipitation accumulation (mm). White areas mean that the differences between CTRL and FG are statistically significant at the 95 % confidence level, based on the bootstrap method; grey areas mean that the differences are not statistically significant. ....55

Figure 11: Case study of a precipitation event from 6 January 2019 at 1200 UTC to 7 January 2019 at 1200 UTC. Panel a) represents the precipitation accumulation (mm) with CaPA’s first guess superimposed with the location of the synoptic manual stations used for the LOOCV evaluation for that specific day. Panel b) is the same but with the location of the AdjDlyRS stations used for the evaluation. Panel c) represents observations from the hourly adjusted database that show the mean air temperature (°C) of the event. Panel d) represents observations from the hourly adjusted database that show the maximum wind speed ( $m s^{-1}$ ) of the event plotted at the stations. ....57

## LISTE DES TABLEAUX

Table 1: Coefficients and wind thresholds for the exponential transfer function (Equations 1 and 2) for different sites. Data are from Koltzow et al. (2020).....	38
Table 2: Experiments performed in CaPA for each winter (2017, 2018, and 2019) .....	42
Table 3: Absolute difference between universal transfer function (UTF) and more climate-specific transfer function (MARTF, BLTF HAUKTF) scores for FBI and ETS for winter 2019. White areas mean that the differences are statistically significant at the 95% confidence level, based on the bootstrap method; grey areas mean that the differences are not statistically significant. Numbers in bold represent differences that are statistically significant in favor of the more climate-specific transfer function.....	46



## LISTE DES ABRÉVIATIONS, DES SIGLES ET DES ACRONYMES

RDPS - The Regional Deterministic Prediction System - Le Système régional de prévision déterministe (SRPD)

HRDPS - The High Resolution Deterministic Prediction System (HRDPS) - Le Système à haute résolution de prévision déterministe (SHRPD)

GEM - The Global Environmental Multiscale *Model*

CMC - Centre Météorologique Canadien

ECCC - Environnement et Changement Climatique Canada

SMC - Service Météorologique du Canada

CaPA - Canadian Precipitation Analysis system – Système Canadien d’Analyse de Précipitations (Pas d’acronyme équivalent en français)

ETS Equitable Threat Score – Indice de Menace Équitable (pas d’acronyme équivalent en français)

FBI-1 Frequency Bias Index minus one – Indice de Biais catégoriel moins un (pas d’acronyme équivalent en français)

POD - Probabilité de détection

FAR - False Alarm Ratio - Ratio de fausse alarme

MBAG - Manitoba Agriculture (pas d’acronyme équivalent en français)

GRCA - Grand River Conservation Authority (pas d’acronyme équivalent en français)

TRCA - Toronto River Conservation Authority (pas d’acronyme équivalent en français)

SHEF - Réseau coopératif américain

QPE - Quantitative Precipitation Estimate – Estimation Quantitative de Précipitations

NWP – Numerical Weather Prediction – Modèle de prévision numérique du temps (PNT)

## RÉSUMÉ

Connaître la distribution spatio-temporelle des précipitations en temps quasi réel est essentiel pour diverses raisons, notamment les prévisions météorologiques et d'inondation, la surveillance de la sécheresse, la gestion de l'irrigation, la prévention des incendies de forêt et la production d'hydroélectricité. La gestion de ces activités peut être optimale lorsque les estimations de précipitations disponibles sont fiables. Le système Canadien d'Analyse de Précipitations (CaPA) est un projet développé et coordonné par Environnement et Changement Climatique Canada (ECCC). Ce système d'analyse vise à fournir une estimation des précipitations en temps quasi réel à l'échelle de l'Amérique du Nord. En hiver, la qualité des analyses de CaPA est limitée parce que de nombreuses observations automatiques de surface des précipitations solides ne sont pas assimilées en raison de la sous-captation de la jauge causée par le vent près de la surface. L'efficacité de collecte varie considérablement pour différentes vitesses de vents, pouvant par exemple diminuer son efficacité de collecte de près de 75 % à des vitesses de vents de plus de 7 m s<sup>-1</sup>. L'objectif de cette étude est d'évaluer la valeur ajoutée de l'ajustement des quantités de précipitations en fonction de la vitesse du vent dans CaPA. Pour ce faire, une nouvelle base de données horaires de précipitations provenant de stations automatiques à travers le Canada est d'abord incluse dans CaPA avec des quantités de précipitations ajustées sur la base de plusieurs types de fonctions de transfert. Dans l'ensemble, les résultats de cette étude suggèrent que l'ajustement des précipitations solides à l'aide d'une fonction de transfert qui dépend de l'intensité des précipitations solides plutôt que de la température de l'air près de la surface est plus susceptible d'améliorer les estimations de précipitations de CaPA pendant la saison hivernale.

## CHAPITRE I – INTRODUCTION

Les précipitations sont l'une des variables les plus importantes en météorologie. Les mesures des précipitations sont utilisées par un large éventail de professionnels, notamment les hydrologues, les gestionnaires de bassins versants et les agriculteurs pour quantifier et distribuer l'eau disponible afin de répondre aux besoins de la société. Elles sont essentielles pour assurer la sécurité publique dans divers domaines tels que le contrôle des avalanches et les opérations de dégivrage des avions, mais elles sont également utiles pour améliorer les modèles climatiques et météorologiques (Kochendorfer et al., 2017). La distribution spatio-temporelle des précipitations en temps quasi réel est en outre importante pour la prévision des inondations, la surveillance de la sécheresse et certaines applications telles que la gestion de l'irrigation et la production d'énergie hydroélectrique (Barnett et al., 2005; Pomeroy et al., 2007). Ces activités sont mieux gérées lorsque les estimations des précipitations disponibles sont fiables. Malgré une longue historique de surveillance, les observations de précipitations souffrent encore de biais et d'erreurs notables (Kochendorfer, 2017). Pour les régions éloignées, la couverture d'observations demeure d'ailleurs incomplète (Wang et al., 2017).

En raison de sa vaste étendue, l'obtention d'une couverture d'observation exhaustive, englobant l'intégralité Canada est une tâche difficile. La faible densité de stations météorologiques dans le pays constitue un obstacle important et, en hiver, les mesures prises avec des pluviomètres sont sensibles aux effets du vent, ce qui réduit leur efficacité de capture (Sevruk et al., 1991; Goodison et al., 1998). Un entretien régulier peut limiter ces problèmes de mesure, mais le coût associé peut être élevé si les stations sont éloignées ou d'accès limité (Lespinas et al., 2015). Les radars météorologiques peuvent également fournir des estimations spatiales et en temps quasi réel des

précipitations. Cependant, il existe de nombreuses imprécisions documentées avec les radars, telles que les effets de portée ou les échos du sol (Lespinas et al., 2015; Jameson et Kostinski 2002). La couverture spatiale est par ailleurs limitée au sud du Canada. (Lespinas et al., 2015). Les données satellitaires peuvent également être utilisées pour obtenir une estimation des précipitations en temps quasi réel. Encore dans ce cas, il y a des incertitudes pour la prédiction des quantités de précipitations. Elles proviennent des limites des algorithmes satellitaires qui établissent un lien entre les observations et les taux de précipitations de surface, ainsi que du sous-échantillonnage spatial et temporel des données micro-ondes passives (Ebert et al., 2007 ; Lespinas et al., 2015).

## 1.1 Aperçu de CaPA

Jusqu'au début des années 2000, aucune estimation quantitative des précipitations (QPE) en temps quasi réel n'était disponible au Canada, car le pays est vaste et les réseaux de surveillance météorologique de surface couvrent une zone limitée (Fortin et al., 2018). L'objectif global du système Canadien d'Analyse de Précipitations (CaPA) est d'offrir un produit de précipitations en temps quasi réel qui aurait de multiples applications comme l'initialisation des modèles d'Environnement et Changement climatique Canada (ECCC), la vérification de leurs prévisions météorologiques et le soutien des services climatiques (Fortin et al., 2018). CaPA est un projet national coordonné par la Division de la recherche météorologique de ECCC. Le projet a été initié en novembre 2003 et sa première version opérationnelle a été mise en place en avril 2011 au Centre Météorologique Canadien (CMC) (Fortin et al., 2018 ; Mahfouf et al., 2007). Il produit des accumulations de précipitations pour l'Amérique du Nord à fine résolution temporelle (6 heures et 24 heures) et spatiale (grille de 15 km et une grille de 2.5 km) (Khedhaouria et al., 2020).

Pour compenser la faible densité de stations météorologiques au Canada, CaPA combine les observations de précipitations in situ et radar avec un champ d'essai obtenu par une prévision météorologique numérique à court terme générée par le modèle GEM (Global Environmental Multiscale) d'ECMC (Lespinas et al., 2015 ; Côté et al., 1998; Milbrandt et al., 2016). En outre, dans les régions montagneuses, les stations météorologiques ne représentent pas avec précision les effets orographiques sur les précipitations, en raison de leur position dans les vallées (Lespinas et al., 2015). L'utilisation du modèle GEM, qui prend en compte les informations topographiques, permet de résoudre en partie ce problème (Mailhot et al., 2006). Les observations assimilées dans CaPA sont fournies par différents réseaux tels que les stations synoptiques manuelles et automatiques (SYNOP), les bulletins météorologiques de routine pour l'aviation (METAR), deux réseaux coopératifs : le Réseau Météorologique Coopératif du Québec (RMCQ) et le réseau coopératif météorologique américain appelé Standard Hydrometeorological Exchange Format (SHEF), le réseau géré par le British Columbia Wildfire Service (BCForest), celui géré par le ministère des Ressources naturelles et des Forêts de l'Ontario (OMNR), et le Manitoba Agriculture Network (MBAG) (Lespinas et al., 2015).

De nombreuses études utilisent CaPA comme source d'information sur les précipitations (Fortin et al., 2018). Un tel produit de précipitations maillées était nécessaire pour le Canada. Les produits CaPA sont utilisés dans les études hydrométéorologiques comme substitut pour comprendre les événements passés (Brimelow et al., 2014; Brimelow et al., 2015; Milrad et al., 2013; Milrad et al., 2015) ou pour évaluer la qualité des prévisions de précipitations et de débit (Cookson-Hills et al., 2017; Milrad et al., 2017; Teufel et al., 2016). Dans les études de modélisation de la surface du sol et de l'atmosphère, plusieurs études ont examiné les processus de surface de la saison chaude en utilisant les analyses CaPA pour obtenir un forçage des précipitations pour leur modèle de surface

du sol (Alavi et al., 2016; Carrera et al., 2015; Garraud et al., 2016; Garraud et al., 2017; Husain et al., 2016; Kornelsen et al., 2016; Xu et al., 2015). Certaines études de modélisation hydrologique ont également utilisé CaPA, notamment en raison de la disponibilité des produits couvrant le Canada et les États-Unis et de la facilité d'accès aux données (Deacu et al., 2012; Fry et al., 2014; Haghnegahdar et al., 2014). CaPA est un projet de plus en plus utile pour la communauté scientifique. Il est utile pour les applications de modélisation et utilisé comme proxy dans plusieurs études (Fortin et al., 2018). Toutefois, certains défis restent à relever. Il existe des incertitudes pour CaPA en ce qui concerne la mesure de la neige (Fortin et al., 2018). Les précipitations en hiver posent un problème en raison du niveau élevé d'incertitude de tous les types de mesures, y compris les jauges à neige (Mahfouf et al., 2007; Rasmussen et al., 2012).

Une procédure de contrôle de la qualité est incluse dans CaPA pour traiter et détecter les observations de précipitations solides. Actuellement, les stations automatiques sont exclues lorsque la température est en dessous de 0 °C et que la vitesse du vent dépasse 0,6 m/s à cause du problème de sous-captation par le vent (Feng et al., 2023). Pour les stations synoptiques manuelles, les critères d'exclusion sont une température inférieure à 0°C et une vitesse du vent supérieure à 3 m/s. En conséquence, cette procédure de contrôle de qualité entraîne le rejet de nombreuses stations en période hivernale.

## 1.2 Incertitudes pour les précipitations solides

Il est difficile de mesurer précisément la quantité de précipitations solides à l'aide de capteurs automatiques (e.g. Rasmussen et al. 2012). Dans des conditions froides et venteuses, les mesures de neige comportent des incertitudes et des biais importants (Milewska et al., 2019 ; Pan et al.,

2016 ; Kochendorfer et al., 2022). Les jauges de précipitations sous-estiment également la quantité de précipitations solides, principalement en raison des effets du vent (Kochendorfer et al., 2022). Seulement autour de 50% des précipitations sont mesurées lorsque le vent est d'environ 3-4 m/s (Wolff et al., 2015). Les hydrométéores qui tombent plus lentement sont plus susceptibles d'être déviés par l'air qui circule autour et au-dessus de la jauge (Thériault et al. 2012). La gravité de la déviation dépend de la hauteur de la jauge au-dessus de la surface, de la vitesse du vent à sa hauteur et de son profil (Sevruk et al., 1991). Les jauges créent un courant ascendant turbulent en amont qui empêche les flocons de neige de tomber dans l'orifice et d'être mesurés (Sevruk et al., 1989). Dans des conditions venteuses et froides, certaines erreurs de mesure des capteurs de précipitations peuvent dépasser 100 % des précipitations mesurées (Kochendorfer et al., 2018).

L'un des facteurs à prendre en compte est également le changement dans le réseau d'observation de surface au Canada. Le changement le plus important a été le passage de mesures manuelles à des mesures automatisées. Cette transition a commencé au début des années 1990, mais s'est accélérée au début des années 2000. Le changement d'une mesure manuelle des précipitations vers une mesure automatisée peut éventuellement entraîner des économies, mais il impose des restrictions et peut altérer la qualité des données (Mekis et al., 2018).

Pour atténuer l'influence des vents, des paravents comprenant un ou deux anneaux de lamelles métalliques sont installés autour des jauges. Il a été constaté que le paravent sur les jauges avait la plus grande importance dans la réduction du biais des précipitations. Les modèles conçus par Alter (1937) sont couramment utilisés et sont appelés paravent simple-Alter pour un seul anneau et paravent double-Alter pour un double anneau (Kochendorfer et al., 2022). Les configurations typiques de paravents utilisées sont sans paroi (UN), à simple paroi (SA), à double paroi (DA), à

double paroi Belfort (BDA) et à double paroi de référence pour l'intercomparaison (DFIR), tel qu'illustré dans l'article de Rasmussen et al. (2012). Une jauge à double paroi ne captera pas autant de flocons de neige que si elle se trouvait à l'intérieur d'une grande clôture double de forme octogonale, telle que la DFIR. La construction de grandes clôtures doubles entraîne un encombrement important, un coût élevé et nécessite un entretien. La double paroi (DA) semble être un compromis même si son installation entraîne un coût important et que son utilisation avec d'autres configurations de paravent complique l'homogénéité du réseau et des données (Smith, 2009). Le biais lié au vent varie considérablement en fonction de l'environnement et des caractéristiques du paravent, s'il y en a un, et du capteur de précipitations. L'homogénéisation des données n'est donc pas triviale. Il est nécessaire de disposer d'une référence avec laquelle comparer les données, car les types de jauges et les configurations des paravents sont affectés de manière différente par le vent. Le DFIR de l'Organisation météorologique mondiale (OMM) est la référence connue pour évaluer ce biais (Smith, 2009).

Lors d'une des campagnes de mesures sur le terrain par le WMO Solid Precipitation Intercomparison Experiment (SPICE) field measurement à Marshall, aux États-Unis, les séries chronologiques d'accumulation hivernale ont permis de mettre en évidence l'importance de ce paravent contre le vent. La jauge de précipitations avec un paravent DFIR a accumulé jusqu'à deux fois plus de précipitations qu'une jauge sans paravent pendant plusieurs mois d'hiver (Kochendorfer et al., 2022). En ayant plus de protection, comme une double clôture ou une double paroi, l'efficacité de collecte est augmentée (Smith, 2009). Les jauges de précipitations qui sont mal protégées ont également tendance à manquer les événements de faible accumulation dans des conditions venteuses. Il est recommandé de protéger la jauge pour réduire les effets de la sous-capture induite par le vent. Cependant, malgré l'installation d'un paravent, un biais dû au vent



persiste dans les mesures de neige (Wolff et al., 2015). C'est pourquoi les fonctions de transfert sont utilisées pour produire des données plus précises.

### 1.3 Les fonctions de transfert

Les fonctions de transfert ont d'abord été développées en fonction de la vitesse du vent et de la température de l'air pour les mesures automatisées des précipitations (Wolff et al., 2015; Kochendorfer et al., 2018). Elles servent à ajuster la sous-capture des mesures de précipitations induites par le vent. Les fonctions de transfert sont dérivées de mesures de précipitations sur des tests de terrain et décrivent l'efficacité de la collecte c'est-à-dire le rapport entre les précipitations accumulées et les précipitations accumulées de référence pour une certaine période pour un système de jauge et de paravent spécifique. Elles peuvent être appliquées pendant une courte période, de 30 à 60 minutes, alors que les mesures manuelles sont ajustées par observation pour une période de 12 ou 24 heures (Kochendorfer et al., 2018).

Les fonctions de transfert peuvent être utiles dans de nombreuses applications. La première est la validation des modèles météorologiques. Des études récentes reconnaissent que la sous-capture des précipitations solides est l'une des principales raisons pour lesquelles les précipitations solides mesurées et modélisées sont différentes (Kochendorfer et al., 2022). L'étude de Køltzow et al. (2020) a conclu que l'application de fonctions de transfert pour ajuster la sous-capture des précipitations solides induite par le vent fournit des informations utiles, réduit les erreurs de mesure des précipitations en donnant des valeurs de précipitations plus réalistes, et diminue les biais systématiques des prévisions. Une autre application concerne les biais de précipitations et l'hydrologie régionale. La sous-capture induite par le vent est également responsable des écarts entre les simulations des modèles et les observations hydrologiques. L'application d'une fonction

de transfert a permis d'améliorer la concordance entre l'ensemble des données maillées et les observations hydrologiques indépendantes (Kochendorfer et al., 2022).

Les performances des fonctions de transfert varient considérablement d'un site à l'autre, principalement en raison des différentes caractéristiques du vent. En raison de la diversité des conditions climatiques et des sites, chaque type de configuration capteur de précipitations-paravent doit avoir sa propre fonction de transfert. Toutefois, lorsque le même type de paravent est utilisé, la même fonction de transfert peut être utilisée pour différents types de jauges de précipitation (Kochendorfer et al., 2018). Kochendorfer et al. (2022) ont montré que les fonctions de transfert étaient indépendantes du type de jauges, mais dépendaient de la configuration du paravent. Les fonctions de transfert sont utiles, mais doivent être appliquées avec prudence. La connaissance du climat et de la météorologie locale est essentielle pour comprendre la sous-capture des précipitations et pour attribuer la bonne fonction de transfert à un site d'observation (Kochendorfer et al., 2022).

La variabilité de l'efficacité de capture peut s'expliquer par les différences de forme des cristaux de glace, la vitesse moyenne de chute des hydrométéores et la taille des hydrométéores qui peuvent varier de manière significative d'un site à l'autre (e.g. Thériault et al., 2012). Une topographie complexe peut également contribuer à la variabilité de l'efficacité de la collecte d'un site à l'autre. Les régions montagneuses avec des terrains complexes peuvent être sujet à des flux turbulents en raison de la rugosité accrue de la surface (Nitu et al., 2019). Les hypothèses faites pour des fonctions de transfert plus globales ne seront pas entièrement applicables dans ces cas, car cela affectera l'efficacité de capture de la jauge.

Pierre et al. (2019) ont évalué des fonctions de transfert accessibles développées dans différents régimes climatiques pour l'ajustement des mesures de précipitations solides sur un seul site (forêt Montmorency, Québec, Canada). L'étude a montré que les fonctions de transfert développées pour cette forêt spécifique affichaient des valeurs de biais et d'erreur plus faibles par rapport à d'autres fonctions non spécifiques, montrant l'importance du climat et des conditions du site dans la performance de la fonction de transfert. Cependant, l'identification de la fonction de transfert optimale pour un site spécifique est incertaine et les erreurs dues à l'application de toute fonction de transfert doivent être traitées avec précaution.

Nitu et al. (2019) a examiné des fonctions de transfert universelles qui peuvent s'appliquer à différents sites, en utilisant des données collectées à partir de huit emplacements distincts répartis dans 16 pays. Les résultats ont indiqué que l'utilisation de la vitesse du vent et de la température de l'air représentatives dans les fonctions de transfert réduit les biais. Cependant, leur performance a été affectée négativement lorsqu'elles ont été appliquées à des sites avec un terrain complexe (Nitu et al., 2019). Cette étude souligne également le potentiel des fonctions de transfert universelles pour une configuration spécifique de jauges de précipitation, pouvant être appliquée à des mesures dans divers climats.

Parallèlement, l'étude menée par Kochendorfer et al. (2018) a évalué un grand nombre de combinaisons de jauges et de paravents en utilisant des fonctions de transfert nouvelles et existantes. Pour la plupart des combinaisons, les fonctions déjà existantes se sont avérées aussi performantes que les nouvelles et plus spécifiques à l'instrument. L'utilisation de données provenant de plusieurs sites pour créer une fonction de transfert est préférable à l'utilisation de données provenant d'un ou deux sites seulement, en raison des biais liés aux sites. C'est pourquoi

il est possible qu'une fonction de transfert générique développée avec plusieurs sites soit plus universellement applicable à une jauge qu'une fonction de transfert spécifique à cette jauge (Kochendorfer et al., 2018).

Même si les fonctions de transfert sont efficaces, elles présentent certaines limites qui doivent être prises en compte. Le premier exemple concerne la poudrierie, source d'incertitudes dans les mesures opérationnelles dans certaines régions. Pour des vitesses de vent supérieures à  $9 \text{ m s}^{-1}$ , les fonctions de transfert peuvent entraîner des erreurs de mesure des précipitations très importantes. En effet, les conditions venteuses peuvent générer de la poudrierie qui peut être mesurée comme des précipitations tombantes par une jauge (Kochendorfer et al., 2022). Pour résoudre ce problème, une vitesse maximale du vent pour la fonction de transfert peut être appliquée pour exclure la poudrierie (Yang et Ohata, 2001 ; Yang et al., 2005 ; Kochendorfer et al., 2022).

La performance générale des fonctions de transfert dépend aussi d'autres facteurs qui doivent être pris en compte, comme les caractéristiques des cristaux de glace (Thériault et al., 2012) ou les particularités aérodynamiques qui affectent les mesures représentatives de la vitesse du vent. L'efficacité de collecte des cristaux de glace varient en fonction de leur forme, taille et de leur vitesse de chute (Thériault et al. 2012; Leroux et al. 2021). Vu que le taux de précipitation est relié à la distribution de taille, le taux de précipitation peut aussi être utilisé pour ajuster les précipitations solides (Colli et al. 2020).

#### 1.4 Les fonctions de transfert existantes

Plusieurs fonctions de transfert ont déjà été présentées et documentées dans la littérature. Elles ont été développées pour différents types de paravents et de conditions climatiques. Par exemple, les fonctions de transfert décrites dans Kochendorfer et al. (2017) sont basées sur huit sites d'observation : le Centre for Atmospheric Research Experiments (CARE), Ontario, Canada ; Haukeliseter, Norvège ; Sodankylä, Finlande ; Caribou Creek, Saskatchewan, Canada ; Weissfluhjoch, Suisse ; Formigal, Espagne ; Marshall, Colorado ; et Bratt's Lake, Saskatchewan, Canada exploités pendant deux hivers (Pierre et al., 2019). Des jauges Geonor T-200B chauffées et des jauges OTT Pluvio chauffées par orifice ont été utilisées avec et sans paravents pour développer les fonctions. Une fonction de transfert dite universelle a été définie à partir de ces sites, sigmoïdale pour la température de l'air et exponentielle pour la vitesse du vent à la hauteur de la jauge. Cette équation est un modèle tridimensionnel qui varie avec la température, elle ne nécessite donc pas de phase de précipitations (Smith et al., 2020).

Une autre approche, introduite par Colli et al. (2020), consiste à définir des fonctions de transfert en utilisant l'intensité des précipitations solides comme paramètre d'entrée au lieu de la température de l'air. Les jauges à neige ont tendance à recueillir sélectivement les particules les plus grosses, avec des vents forts, en raison de la plus grande vitesse à laquelle elles tombent. Par conséquent, ces particules peuvent traverser les lignes d'écoulement au-dessus des jauges de mesure et être collectées (Colli et al., 2020). Sur la base des résultats obtenus sur les sites d'observation de Marshall (Colorado, États-Unis), CARE (Canada) et Haukeliseter (Norvège), l'étude conclut que la sous-capture des jauges de précipitations solides causée par le vent est plus fortement corrélée à l'intensité des précipitations solides qu'à la température de l'air.

## 1.5 Objectifs

Il est nécessaire d'ajuster les mesures de précipitations solides des stations de surface assimilées dans CaPA pour compenser la sous-captation liée à la vitesse du vent. Comme montré par Feng et al. (2023), l'assouplissement des critères de contrôle de qualité basés sur le vent pour assimiler davantage d'observations de surface en hiver pourrait avoir un impact substantiel sur les biais d'analyse dus à la réduction des précipitations, qui peuvent alors être compensés par l'utilisation d'une fonction de transfert.

L'objectif principal de l'étude est d'évaluer l'amélioration de CaPA pour les précipitations solides en utilisant les fonctions de transfert pour ajuster les quantités de précipitation horaires. Pour ce faire, une nouvelle base de données horaire d'accumulation de précipitation (Smith et al., 2022) sera évaluée. Puis, plusieurs fonctions de transferts seront testées telles que la fonction de transfert universelle, des fonctions de transfert plus spécifiques au climat et une autre qui dépend du taux de précipitations solides. Les différentes expériences seront évaluées et comparées entre elles de façon systématique.

Ce mémoire est structuré comme suit. Le chapitre 2 regroupe, sous la forme d'un article scientifique, la méthodologie, les données, la configuration de CaPA utilisée dans cette étude, un résumé des résultats obtenus en incorporant les nouvelles données ajustées dans CaPA, une discussion plus détaillée des résultats ainsi que la conclusion principale. Le mémoire se conclut au chapitre 3, en offrant une conclusion plus exhaustive et complète.

## CHAPITRE 2

### IMPACTS DE L'UTILISATION DE QUANTITÉS AJUSTÉES DE PRÉCIPITATIONS SOLIDES DANS LE SYSTÈME CANADIEN D'ANALYSE DES PRÉCIPITATIONS

Ce chapitre est présenté sous la forme d'un article scientifique rédigé en anglais prêt à être soumis au *Journal of Hydrometeorology*. Il porte sur les impacts de l'utilisation de quantités de précipitations solides ajustées pour la sous-capture de la vitesse du vent sur le système canadien d'analyse des précipitations. Différentes fonctions de transfert seront utilisées pour l'ajustement, dont une fonction universelle et des fonctions plus spécifiques au climat qui dépendent soit de la température de l'air ou de l'intensité des précipitations solides.

# IMPACTS OF ADJUSTING SOLID PRECIPITATION AMOUNTS IN THE CANADIAN PRECIPITATION ANALYSIS SYSTEM

Catherine Aubry<sup>1</sup>, Stéphane Bélair<sup>2</sup>, Julie M. Thériault<sup>1</sup>, Eva Mekis<sup>4</sup>, Pei-Ning Feng<sup>1</sup>, Franck Lespinas<sup>3</sup>, Dikra Khedhaouiria<sup>2</sup> and Florence Beaudry<sup>1</sup>

<sup>1</sup> *Centre ESCER, Department of Earth and Atmospheric Sciences, Université du Québec à Montréal (UQAM), Montréal, Québec, Canada*

<sup>2</sup> *Environment and Climate Change Canada, Atmospheric Science and Technology, Dorval, Québec, Canada*

<sup>3</sup> *Canadian Centre for Meteorological and Environmental Prediction, Environment and Climate Change Canada (ECCC), Dorval, Quebec, Canada*

<sup>4</sup> *Environment and Climate Change Canada, Climate Research Division, Downsview, Ontario, Canada*

*Corresponding author: Catherine Aubry, aubry.catherine.2@courrier.uqam.ca*



## ABSTRACT

The spatiotemporal distribution of precipitation in near real-time is critical for various purposes, including weather and flood forecasting, monitoring drought, irrigation management, fire forest prevention, and hydroelectric production. The management of those activities can be optimal when precipitation estimates are reliable. The Canadian Precipitation Analysis (CaPA) is developed and coordinated by Environment and Climate Change Canada (ECCC). This analysis system aims to provide a near real-time North American-wide precipitation estimate. In winter, the quality of CaPA's analyses is limited because many automatic surface observations of solid precipitation are not assimilated due to the gauge undercatch caused by near-surface wind. The collection efficiency at specific wind speeds exhibits considerable variations. The objective of the study is to evaluate the added value of adjusting precipitation amounts considering the wind-induced undercatch in CaPA. A new database of hourly precipitation measurements from automatic stations across Canada is included in CaPA as part of this study, with precipitation amounts adjusted based on several types of transfer functions. Overall, results from this study suggest that increasing solid precipitation using a specific type of transfer functions that depend on snowfall intensity rather than near-surface air temperature is more likely to improve CaPA's precipitation estimates during the winter season.

## 2.1 Introduction

Precipitation is one of the most important variables in meteorology. It is essential for ensuring public safety in various domains such as avalanche control and aircraft de-icing operations, but it is also helpful to improve climate and weather models (Kochendorfer et al, 2017). The spatio-temporal distribution of precipitation in near real-time is in addition important for flood forecasting, drought monitoring, and some applications such as irrigation management and hydroelectric power generation (Lespinas et al., 2015). These activities are best managed when available rainfall and snowfall estimates are reliable. Despite a long history of monitoring, precipitation observations still suffer notable biases and errors, and their coverage across territories remains incomplete (Kochendorfer, 2017).

Up until the early 2000s, no near real-time nationwide quantitative precipitation estimate (QPE) was available in Canada, because of its large area and because surface weather monitoring networks cover only a limited portion of the country (Fortin et al, 2018). The Canadian Precipitation Analysis system (CaPA) is coordinated by Environment and Climate Change Canada (ECCC) and its objective is to offer near real-time gridded precipitation estimates. The project initiated in November 2003 implemented its first operational version in April 2011 at the Canadian Meteorological Centre (CMC) (Mahfouf et al, 2007; Fortin et al. 2018). CaPA produces precipitation accumulations over North America for two temporal (6-h and 24-h) and spatial resolution (15-km and 2.5-km grid spacing) in deterministic and ensemble modes (Lespinas et al. 2015, Khedhaouiria et al. 2020). To compensate for the low density of weather stations in Canada, CaPA combines precipitation observations from both meteorological stations and weather radar with a background field obtained from short-term numerical weather prediction (NWP) forecasts

generated by ECCC's Global Environmental Multiscale (GEM) model (Côté et al. 1998; Milbrandt et al. 2016).

The interest in analysis systems such as CaPA is growing in the scientific community, even though several challenges remain (Fortin et al., 2018). Some of these limitations are related to uncertainties regarding snowfall measurement. In CaPA's current configurations, quality control procedures lead to the rejection of many surface stations observations in winter. During cold and windy conditions, snow measurements are affected by include significant uncertainties and biases (Milewska et al, 2019; Pan et al., 2016; Kochendorfer et al, 2022). Precipitation gauges underestimate solid precipitation, primarily because of wind effects (Kochendorfer et al, 2022). The gauge deflects the environmental air, producing an updraft upstream of the gauge that prevents snowflakes from falling into the orifice and be measured (Sevruk et al., 1989). Hydrometeors that are falling slower are more prone to deflection by the air flowing around and over the gauge (Thériault et al. 2012). Under windy conditions, some precipitation gauge measurements errors can exceed 100% of the measured precipitation (Kochendorfer et al, 2018).

To mitigate the influence of wind effects, shields comprising one or two concentric rings of metal slats are often installed around the surface precipitation gauges. The shielding on the gauges has an important impact on bias reduction for precipitation measurement. Shield models designed by Alter (1937) are commonly used and named as single-Alter (SA) for a single ring and double-Alter (DBA) for double ring (Kochendorfer et al, 2022). However, wind-related biases remain for snowfall measurements even with this type of gauge shields (Wolff et al., 2015). For this reason, transfer functions are used to adjust precipitation measurements.

Transfer functions were first developed as a function of wind speed and air temperature for automated precipitations measurements (Wolff et al, 2015; Kochendorfer et al, 2018). Their formulation and calibration are derived from precipitation testbed measurements; they essentially provide an estimate of the collection efficiency for a specific gauge-shield system, i.e., the ratio of accumulated precipitation divided by the accumulated precipitation of a reference. Because the use of transfer functions can result in large precipitation measurement errors for wind speed greater than  $9 \text{ ms}^{-1}$ , a maximum wind speed threshold is set. Consequently, this helps to filter blowing snow, which, if considered as precipitation by automatic gauges, could lead to an overestimation of measured precipitation (Yang and Ohata, 2001; Yang et al, 2005; Kochendorfer et al, 2022).

Several transfer functions have already been presented and documented in the literature. They were developed for different types of shields and climate conditions. For instance, catch efficiency transfer functions described in Kochendorfer et al. (2017) are based on eight observational sites: the Centre for Atmospheric Research Experiments (CARE), Ontario, Canada; Haukeliseter, Norway; Sodankylä, Finland; Caribou Creek, Saskatchewan, Canada; Weissfluhjoch, Switzerland; Formigal, Spain; Marshall, Colorado; and Bratt's Lake, Saskatchewan, Canada (Pierre et al., 2019). A so-called universal transfer function has been defined out of those sites, sigmoidal for air temperature and exponential for wind speed at gauge height. These transfer functions depend mainly on the wind speed and air temperature. Air temperature is used as a proxy for the phase of the precipitation.

Even if transfer functions can adjust solid precipitation measurements, they are not always able to account for the scatter in the data at given wind speeds. For example, Rasmussen et al. (2001) showed that the collection efficiency can vary by more than 50% for a given wind speed. Thériault

et al. (2012) showed that the type of solid precipitation, hence the fall speed and the distribution size of precipitation, explains most of this scatter. Slower-falling particles tend to be deflected by the updraft upstream of the gauge while faster-falling particles fall in the gauge. Colli et al. (2020) proposed to use the snowfall intensity, linked to the distribution size, to adjust solid precipitation. Gunn and Marshall (1958) showed that the slope of the size distribution decreases with increasing snowfall intensity, leading to higher concentration of larger snowflakes. Hence, Colli et al. (2020) showed that the undercatch of solid precipitation gauges caused by wind is more strongly correlated with snowfall intensity than with air temperature.

There is a need to adjust surface stations solid precipitation measurements assimilated in CaPA to compensate for the gauge undercatch due to wind speed. As shown in Feng et al. (2023), relaxing wind-based quality control criteria to assimilate more surface observations in winter could have substantial impact on analyses biases reducing precipitation estimates, which can then be compensated with the use of a transfer function. The main objective of this study is to evaluate the added value of using an hourly precipitation database adjusted with transfer functions for wind speed undercatch into CaPA. Several transfer functions were then tested to see which one performs best, including the universal transfer function, climate-specific transfer functions, and transfer functions based on snowfall intensity.

This article is structured as follows. The methodology, data, and CaPA configuration used in this study are outlined in the following section. Section 3 provides a summary of the results obtained from incorporating the new adjusted data into CaPA, followed by a more detailed discussion of the results in section 4. A summary together with the main conclusion are provided in section 5.

## 2.2 Data and methodology

### 2.2.1 Domain of study and period

The analysis domain for this study covers Central Canada with a focus on the Canadian prairies (Figure 1). The domain extends from the eastern part of British Columbia to the western part of Ontario and from northern central United States to the southern portion of the Canadian territories. The benefit of studying this region is that it contains different landscapes such as the prairies, the Canadian shield, the Rocky Mountains, and the Boreal Forest (Evans, 2013). The analysis and results provided in this study capture geographical and large-scale weather influences on precipitation within the selected area. These outcomes related to CaPA's precipitation analysis improvements have relevance to a wide range of applications.

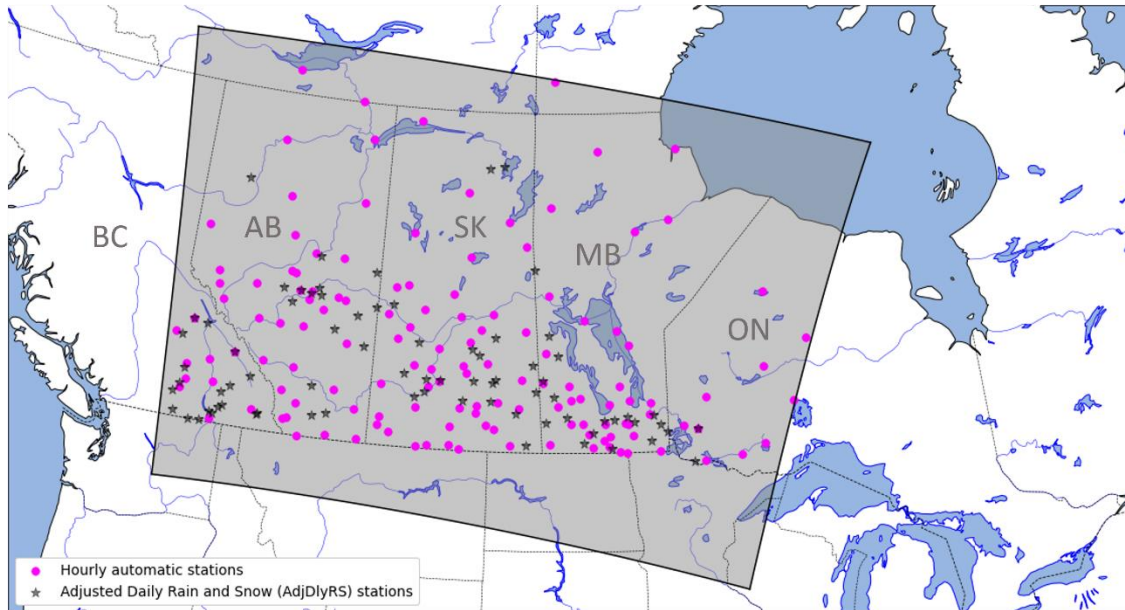


Figure 1: The domain of CaPA’s analyses is shown in grey, covering eastern British Columbia (BC), Alberta (AB), Saskatchewan (SK), Manitoba (MB), and western Ontario (ON). The domain extends from the north of United States to the south of the territories. The pink dots indicate the location of ECCC’s hourly automatic weather stations, and the black stars indicate the location of the Adjusted Daily Rainfall and Snowfall (AdjDlyRS) manual stations.

The study focuses on three winter seasons, i.e., 2016-2017, 2017-2018 and 2018-2019. These years were selected because a quality-controlled version of the hourly adjusted dataset used in this study is not available after 2019. Also, a new version of CaPA, along with an upgrade to the NWP system used to provide CaPA’s first guess, was operationally implemented in November 2016. To ensure consistency throughout the study, it was determined that a period during which the same version of CaPA would be utilized. Each winter season begins on December 1st and ends on March 31st. For simplicity, the three winter seasons are referred to as 2017, 2018 and 2019.

### 2.2.2 CaPA’s configuration

The CaPA precipitation analysis system has been developed in the last two decades at ECCC (see Mahfouf et al. 2007 for the first version). In CaPA, observations from surface stations, ground-

based weather radars, and space-based products are combined with background information from short-range forecasts produced by ECCC's GEM model (Côté et al. 1998; Milbrandt et al. 2016). It should be noted that the GEM model and the atmospheric assimilation system were not run for this study, with the analyses relying on data from de-archived operational databases. The precipitation analyses are produced with a two-dimensional optimal statistical interpolation, namely a simple kriging of innovations (also called simple residual kriging), as described in Fortin et al. (2015) and Lespinas et al. (2015). The error parameters associated with the first guess and observations are obtained from a variographic approach. Comprehensive quality control is used for all observation types ingested in CaPA (see Fortin et al. 2015 and Lespinas et al. 2015). In addition to quantitative precipitation estimates, CaPA also provides a confidence index, which informs on the contribution of the observations, in addition to what is already available from the first guess.

First implemented in November 2016, as explained in Fortin et al. (2018)'s review, several configurations of CaPA's are now operated at ECCC. Two of these configurations are based on deterministic versions of CaPA, for the regional and high-resolution prediction analyses produced on 10-km north American and 2.5-km pan Canadian domains (see Fortin et al. 2018). An ensemble version of the high-resolution (2.5-km) analyses has also been implemented, as described in Khedhaouria et al. (2020). In this study, the high-resolution 2.5-km deterministic CaPA configuration is used, except that the geographical domain of the analysis is smaller (Figure 1) and that weather radars are not assimilated, to solely evaluate the direct influence of transfer functions. Satellite products such as Integrated Multi-satellitE Retrievals (IMERG) for Global Precipitation Measurement mission (GPM) are not assimilated yet in CaPA's 2.5-km configurations.



Several networks of precipitation gauges are assimilated by CaPA before adding the new adjusted dataset. They include manual and automatic synoptic stations (SYNOP), automatic stations from ECCC, the legacy stations network from the Meteorological Service of Canada (MSC), the aviation routine weather reports (METAR), the US meteorological cooperative network [Standard Hydrometeorological Exchange Format (SHEF)], a network managed by the British Columbia Wildfire Service (BCForest), a network managed by the Ontario Ministry of Natural Resources and Forestry (OMNR), and the Manitoba Agriculture Network (MBAG).

### 2.2.3 The hourly adjusted dataset

The data used in this project are provided by ECCC and are publicly available (Smith et al., 2022). It is composed of hourly unadjusted and adjusted precipitation amounts, wind speed measured at 10-m or at gauge height, and 2-m air temperature from a set of 397 automated surface stations. Precipitation observations are adjusted using the universal transfer function to consider the bias related to the wind undercatch. The initial observing date is different for each station and depends on when automated precipitation gauges were installed. Measurements from some of these sensors start in 2001, but for most the data starts in 2004 or later. Quality control procedures were applied to the dataset. These include a range check against fixed thresholds for precipitation, removal of negative values, filtering of low noise thresholds, manual screening of outliers with climatologist guidance, and additional quality control measures for temperature and wind speed data to identify outliers and missing values (Smith et al., 2022).

Of the 397 stations included in the dataset, 150 stations are within the domain shown in Figure 1. Because much of this study's focus is related to reducing wind bias undercatch, near-surface wind speed measurements are of great importance. In the dataset, some stations report a 2-m wind speed

that is obtained by averaging four archived measurements each representing 15-minutes mean during the reporting hour (Smith et al., 2022). In contrast, specific stations provide a 10-m wind speed that is measured near the end of the hour without being averaged over the entire hour (Smith et al, 2022). Since wind speed thus appears to be better represented at 2-m for this dataset, it was decided to remove stations that only reported wind speed at 10-m height. With this criterion, the total number of observing stations within the analysis domain is 138, as shown in Figure 1.

Several adjustments are performed on the hourly precipitation observations prior to their assimilation into CaPA. These observations are first temporally aggregated to 6 h since CaPA only produces analyses at that temporal scale (or at the daily scale, which is not examined in this study). The adjustment based on the transfer functions (described below in this section) is performed at the hourly time scale prior to the temporal aggregation, with the appropriate observations for 2-m wind speed and air temperature. Also, surface stations from CaPA's traditional datasets that are located too close to stations from the hourly dataset are removed from the assimilation. The assumption is that observations from the new dataset are more accurate, especially when adjustment with transfer functions is performed.

#### 2.2.4 The Adjusted Daily Rainfall and Snowfall (AdjDlyRS) dataset

The AdjDlyRS dataset is presented in Mekis & Vincent (2011) and Wang et al. (2017). These data are used in this study to objectively assess the quality of CaPA's precipitation analyses, i.e., they are not assimilated in CaPA. They include stations with manual observations for daily rainfall and snowfall with sufficient metadata to perform the adjustment in Canada. All observations are made by human observers once a day. To generate the AdjDlyRS dataset, four major adjustments are implemented. These adjustments involve converting snowfall ruler measurements to their water

equivalent using the snow-water equivalent (SWE) ratio map by Mekis and Brown (2010), correcting for gauge undercatch and wind-induced evaporation (Mekis et Hogg, 1999; Devine et Mekis, 2008; Mekis et Vincent, 2011), assigning a small precipitation amount to each trace event (Mekis et Vincent, 2011), and adjusting daily precipitation data for other reported flags (Hutchinson et al., 2009). The validity time is taken as 1200 UTC each day. The location of the AdjDlyRS stations is shown in Figure 1.

### 2.2.5 The transfer functions

Multiple transfer functions were used in this study. First, the universal transfer function (UTF) from Kochendorfer et al. (2017) was applied:

$$CE = e^{-a(U)(1-\tan^{-1}(b(T_{air}))+c)} \quad (1)$$

in which  $CE$  is the gauge catch efficiency (or collection efficiency),  $U$  is the wind speed ( $\text{m s}^{-1}$ ),  $T_{air}$  is the air temperature ( $^{\circ}\text{C}$ ), while  $a$ ,  $b$  and  $c$  are empirical coefficients that depend on the specific type of gauge, shield type, and observation site.

Second, other transfer functions, more climate-specific, are also examined in this study. They are shown in Figure 2 and the values are given in Table 1. The selection is based on four criteria, namely whether these functions and their coefficients are published, the location of the site for which they were developed, the type of climate at these sites, and the amplitude of the collection efficiency. Transfer functions were selected from the list provided in Koltzow et al (2020), which depend on air temperature and are from different study sites with published coefficients. Some of these sites are in Canada, but very few are actually in the study area shown in Figure 1 which,

according to Pierre et al. (2019) has mostly a boreal climate with a small arid zone. The transfer functions evaluated in this study are:

- Bratt's Lake transfer function because it is in the study area. The Bratt's Lake observatory is positioned roughly 30 km southwest of Regina, Saskatchewan (Canada), in an area of open prairie with minimal topography, resulting in elevated exposure and correspondingly high wind speeds (Smith et al., 2019).
- Marshall site transfer function, because it is close to the study area, at the edge of the boreal zone, with an arid climate. The field site is situated on the eastern slopes of the Colorado Front Range, just outside Boulder, Colorado (US) and its elevation is approximately 1740 m above sea level. The site is mostly flat, and the absence of trees, large buildings, or other obstructions allows for unimpeded wind flow around the gauges (Kochendorfer et al, 2017).
- Haukeliseter transfer function, based on a site in Norway, because it has a collection efficiency much smaller than what is produced with the universal transfer function (see Figure 2). This large difference in collection efficiency will allow to see if the difference in the adjustment would have a significant effect in CaPA. The site is located at 59.812° N, 7.214° E, on a plateau at an altitude of 991 meters in the alpine region of southwestern Norway and has a boreal climate, like the domain of study (Kochendorfer et al, 2017).

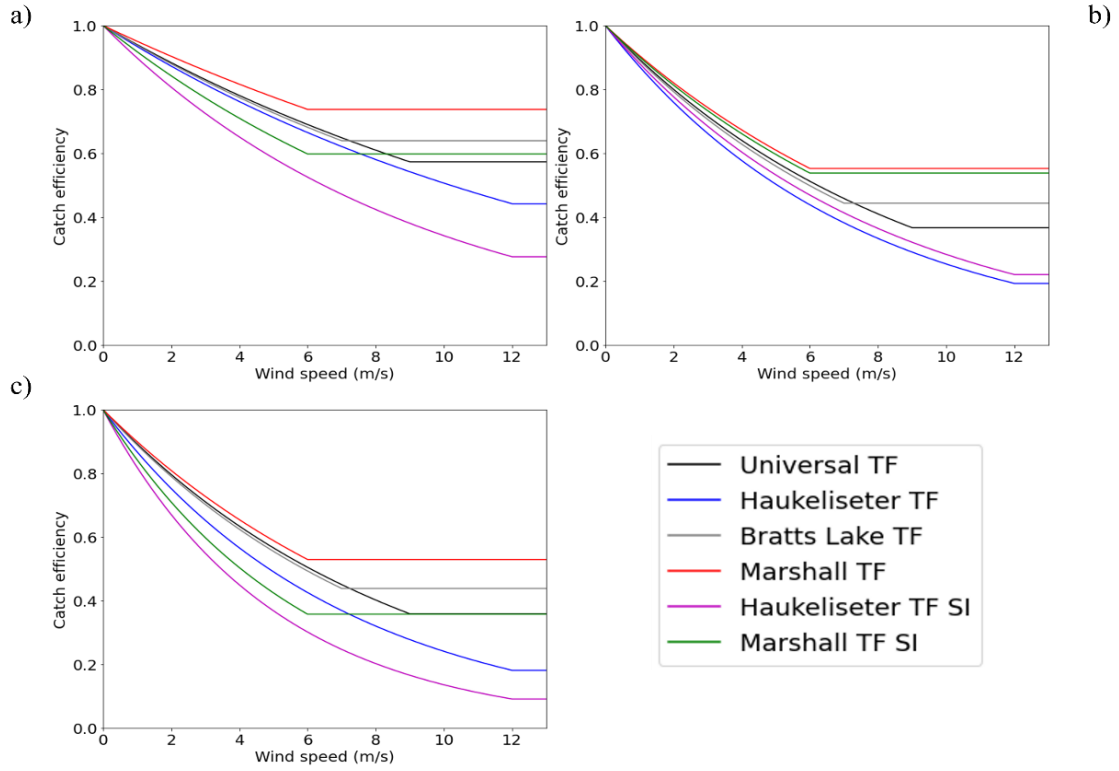


Figure 2: Catch efficiency for a single-alter as a function of wind speed for three different air temperatures ( $T_{air}$ ) and snowfall intensity (SI) for different sites: Marshall (red), Marshall SI (green), Haukeliseter (blue), Haukeliseter SI (pink), Bratt's Lake (grey) and Universal (black). Panel a):  $T_{air} = 0^{\circ}\text{C}$  and  $SI = 1.6 \text{ mm/h}$ . Panel b):  $T_{air} = -5^{\circ}\text{C}$  and  $SI = 1 \text{ mm/h}$ . Panel c):  $T_{air} = -10^{\circ}\text{C}$  and  $SI = 0.4 \text{ mm/h}$ . A wind threshold is applied for every transfer function (see Table 1).

Third, a transfer function based on snowfall intensity rather than air temperature is evaluated in this study. This formulation is introduced in Colli et al. (2020) for three different specific sites: Marshall, CARE and Haukeliseter:

$$CE = e^{-a(U)(1-\tan^{-1}(b(SI))+c)} \quad (2)$$

where  $a$ ,  $b$ , and  $c$  is a new set of numerical best-fit coefficients and  $SI$  is the snowfall intensity. In this study, the hourly precipitation rate from the Smith et al. (2022) database, is therefore use as a proxy for snowfall intensity. As the Marshall and Haukeliseter sites have already been chosen as

climate specific transfer functions in CaPA, it is relevant to test these same two sites also in CaPA to compare these two different types of functions as well.

Each of these transfer functions are only applied to measurements from gauges with a single Alter. It should be mentioned that in the new hourly database some of the stations changed from single Alter to Double Alter shield between 2016 and 2019. This was the case for 14 stations: 6 of which changed during the second winter (2018) and 8 during the third winter (2019). When precipitation is measured with a gauge using a double Alter-shield, precipitation is not adjusted.

The hourly precipitation data are adjusted for temperatures less than and equal to 5°C, as in Smith et al. (2022). Wind thresholds are also applied because precipitation measurements are small or non-existent at high mean wind speeds and transfer functions are inaccurate. The threshold depends on the transfer function and are given in Table 1, along with the function transfer coefficients.

Table 1: Coefficients and wind thresholds for the exponential transfer function (Equations 1 and 2) for different sites. Data are from Koltzow et al. (2020)

<b>Sites</b>	<b>a</b>	<b>b</b>	<b>c</b>	<b>Wind threshold</b>
<b>Universal</b>	0.0281	1.628	0.837	9.0 m s <sup>-1</sup> at 10-m wind speed and 7.2 m s <sup>-1</sup> at 2-m wind speed
<b>Bratt's Lake</b>	0.03548	1.955	0.8036	7.0 m s <sup>-1</sup> at 10-m wind speed
<b>Marshall</b>	0.04009	0.5159	0.2679	6.0 m s <sup>-1</sup> at 10-m wind speed
<b>Haukeliseter</b>	0.05068	0.9753	0.3435	12.0 m s <sup>-1</sup> at 10-m wind speed
<b>Marshall si</b>	0.4156	8.7795	-0.7062	6.0 m s <sup>-1</sup> at 10-m wind speed
<b>Haukeliseter si</b>	12.5937	338.0402	-0.5737	12.0 m s <sup>-1</sup> at 10-m wind speed

### 2.2.6 Objective evaluation

Two methods are used to objectively evaluate the CaPA analyses. The first is based on the leave-one-out cross validation (LOOCV) approach. This method is typically used to evaluate modifications proposed for operational implementation at ECCC (e.g., Fortin et al. 2018). Generally, when evaluating an analysis, a common protocol is to select a set of independent observations that were not used in the production of the gridded analyses and use them to compute verification metrics. However, due to the low density of the weather station network in Canada, it is not easy to select such independent stations. An alternative method is to select the most reliable weather stations that were assimilated into CaPA, eliminate them individually from the observation dataset, and estimate the analysis value at their respective locations based on the closest observations (see Lespinas et al, 2015). The resulting observations and LOOCV analyses values can then be used to compute the verification metrics (Lespinas et al, 2015). In this study, manual synoptic observations assimilated in CaPA are selected for the LOOCV objective evaluation. These observations are subject to CaPA's quality control and are rejected for meteorological situations with strong near-surface winds and cold conditions (i.e., with wind speed greater than  $3 \text{ m s}^{-1}$  and air temperature below  $0^{\circ}\text{C}$ ). The quality of CaPA's precipitation analyses might then be incorrectly estimated for strong wind events.

As a complement, the AdjDlyRS is used as another independent dataset for CaPA's evaluation. The objective evaluation done for daily precipitation is based on a direct comparison of CaPA's aggregation of 6-hourly analyses against observations from the AdjDlyRS dataset, taken as valid at 1200 UTC each day. The LOOCV approach is not needed in that case because observations from AdjDlyRS are not assimilated in CaPA.

Stationary block bootstrapping is employed to evaluate the uncertainty of the differences between the evaluation metrics for two specific experiments. The fundamental concept behind block bootstrapping is to preserve data structure by resampling contiguous blocks of observations rather than individual ones. This approach aims to replicate data correlation by resampling within data blocks, proving effective for model evaluation and validation in domains characterized by temporal or spatial correlation in the data. This statistical significance test uses confidence intervals for each precipitation threshold and is based on spatial and temporal correlations as well as the spatial density of stations (see section 3a in Lespinas et al. 2015). In the following figures, the white area indicates that the differences between the experiments are statistically significant at the 95 % confidence level based on the bootstrap method. The grey area is for differences that are not considered as statistically significant.

The four-evaluation metrics analyzed in this study are the frequency bias index (FBI), the equitable threat score (ETS), the false alarm ratio (FAR), and the probability of detection (POD). These metrics are obtained from observation and forecast/analysis values, spatially aggregated across all stations and temporally across all dates for selected thresholds of observed precipitation. This approach is giving an assessment of CaPA’s performance over the entire range of precipitation (Lespinas et al., 2015). The scores are determined by categorizing events as hits, false alarms, and misses. A hit occurs when CaPA accurately predicts the observation, while a miss happens when CaPA fails to capture an observed event. In contrast, a false alarm occurs when CaPA predicts an event that did not occurred.

The FBI is a measure of the bias. It calculates the frequency of forecast events over the frequency of observed events.

$$FBI = \frac{hits + false\ alarm}{hits + miss} \quad (3)$$



In this study, “FBI-1” is examined so that values are either positive (overestimation of precipitation) or negative (underestimation of precipitation). When the frequencies of observations and forecast are identical, the value equals 0 (perfect situation).

The ETS provides a measure of the analyses’ accuracy.

$$ETS = \frac{hits - random\ success}{hits + miss + false\ alarms - random\ success} \quad (4)$$

Where random success is:

$$random\ success = \frac{(hits + miss) \cdot (hits + false\ alarm)}{N} \quad (5)$$

with N representing the total number of events. The range varies from  $\frac{-1}{3}$  to 1, where 1 means a perfect forecast (Lespinas et al., 2015). Values under 0 indicates no skill.

The POD show the hit rate. It expresses the fraction of correct event forecasts with respect to the total number of events observed. POD varies from 0 to 1, with 0 being for no detection and 1 being for perfect detection.

$$POD = \frac{hits}{hits + miss} \quad (6)$$

The FAR provides a measure of the number of false alarms with respect to the total of event forecasts.

$$FAR = \frac{false\ alarm}{hits + false\ alarms} \quad (7)$$

It ranges from 0 at 1, with 0 being for the perfect situation (i.e., no false alarms).

## 2.2.7 Experiments setup

All the CaPA assimilation cycles examined in this study start on 1 November and end on 31 March for each of the three winter seasons evaluated. The objective evaluation, starting from December 1st each year, involves discarding the first cycle month to facilitate CaPA in establishing accurate error statistics through the variographic approach.

Two types of experiments were performed: a control experiment, which takes into consideration only the observation stations already present in CaPA, and experiments with new hourly stations adjusted based on different transfer functions. By comparing evaluation metrics for the control versus the various experiments, the effect of adding new observations (either adjusted or non-adjusted) to CaPA is determined. Table 2 summarizes the experiments conducted in the project.

Table 2: Experiments performed in CaPA for each winter (2017, 2018, and 2019)

<b>Name of the experiment</b>	<b>Experiment</b>
<b>Control</b>	Stations already present in CaPA
<b>Hourly_Unadj</b>	Stations already present in CaPA + Hourly data unadjusted
<b>Hourly_Adj_UTF</b>	Stations already present in CaPA + Hourly data adjusted with the universal transfer function
<b>Hourly_Adj_BLTF</b>	Stations already present in CaPA + Hourly data adjusted with the Bratt's Lake transfer function
<b>Hourly_Adj_MarTF</b>	Stations already present in CaPA + Hourly data adjusted with the Marshall transfer function
<b>Hourly_Adj_HaukTF</b>	Stations already present in CaPA + Hourly data adjusted with the Haukeliseter transfer function
<b>Hourly_Adj_MarTFsi</b>	Stations already present in CaPA + Hourly data adjusted with the Marshall transfer function depending on the snowfall intensity
<b>Hourly_Adj_HaukTFsi</b>	Stations already present in CaPA + Hourly data adjusted with the Haukeliseter transfer function depending on the snowfall intensity

## 2.3 Evaluations of the different transfer functions

Results from experiments using different transfer functions revealed that adjusting precipitation accumulations for wind-related undercatch effects did not have substantial impact on CaPA's precipitation analyses for the first two winter seasons considered in this study, i.e., 2017 and 2018. This interannual variability is discussed in detail later in this article, along with reasons that could explain these results. Therefore, emphasis is on results from the most recent winter season (i.e., 2019).

This section is organized as follows, with evaluation for i) the impact of adding the new hourly surface observations into CaPA with adjustment from UTF, ii) the impact from climate-specific transfer functions and iii) from adjustment based on snowfall intensity, and finally iv) the impact of adjustment by evaluating CaPA's analyses with the AdjDlyRS dataset.

### 2.3.1 Impact of hourly data adjusted with UTF

The first two experiments evaluated in this section are CaPA's cycles in which the Smith et al. (2022) database is added, without adjustment and with adjustment from UTF. These results are presented in Figures 3 and 4, for winter 2019.

As shown in Figure 3 in which the objective evaluation is performed for two CaPA assimilation cycles with the new hourly dataset, the UTF adjustment can only increase the amount of precipitation. The FBI-1 metric is thus slightly increased, especially for larger precipitation thresholds. This increase can be considered as an improvement for that specific year since the number of events is underestimated for all the thresholds. When the number of events is increased, the detection (as shown by POD) increases, which is an improvement, but the false detection (FAR)

increases, which is a deterioration. The overall impact on accuracy is an increase in ETS for larger thresholds, indicating that the adjustment with UTF improves the quality of the precipitation analyses for that specific winter season.

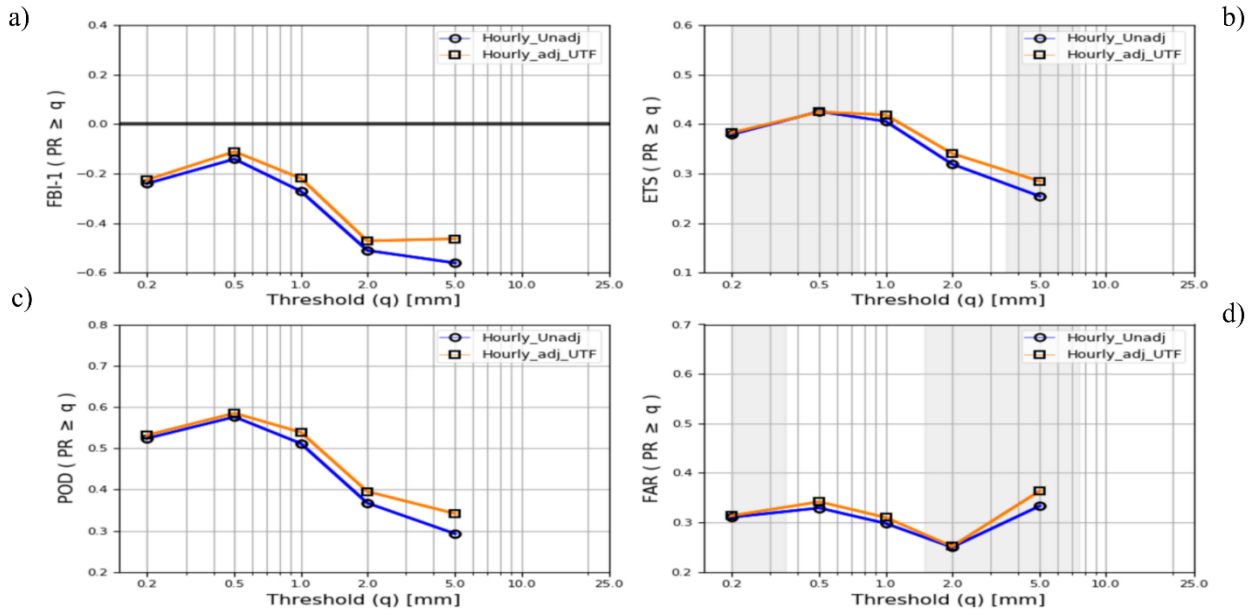


Figure 3: Objective evaluation metrics for CaPA’s analyses with the assimilation of unadjusted data (blue lines) and of data adjusted with UTF (orange lines). The evaluation is performed for winter 2019, from 1 December 2018 to 31 March 2019, and is valid over the entire study area shown in Figure 1: a) is for FBI-1 with a black line indicating no bias, b) is for ETS, c) is for POD, and d) is for FAR. The letter  $q$  provides the 6-hourly precipitation thresholds used for the evaluation (mm). White areas indicate that the differences between the two experiments are statistically significant at the 95 % confidence level, based on the bootstrap method; grey areas indicates that the differences are not statistically significant.

Comparison of Hourly\_adj\_UTF against the control run reveal that the UTF adjustment is not sufficient to compensate for the decrease of precipitation associated with the inclusion of observations from the hourly dataset (Figure 4). When compared with the control run, FBI-1 values are slightly lower than what is obtained with Control, suggesting a deterioration of the simulated precipitation amounts. These differences are statistically significant for the 0.2 mm and 0.5 mm

thresholds. The detection is also slightly decreased, suggested by a lower POD, while FAR remains unchanged. The overall effect on the accuracy of the analysis is a minor reduction of the ETS for the majority of precipitation thresholds, with the difference being statistically significant for the 0.2 mm threshold.

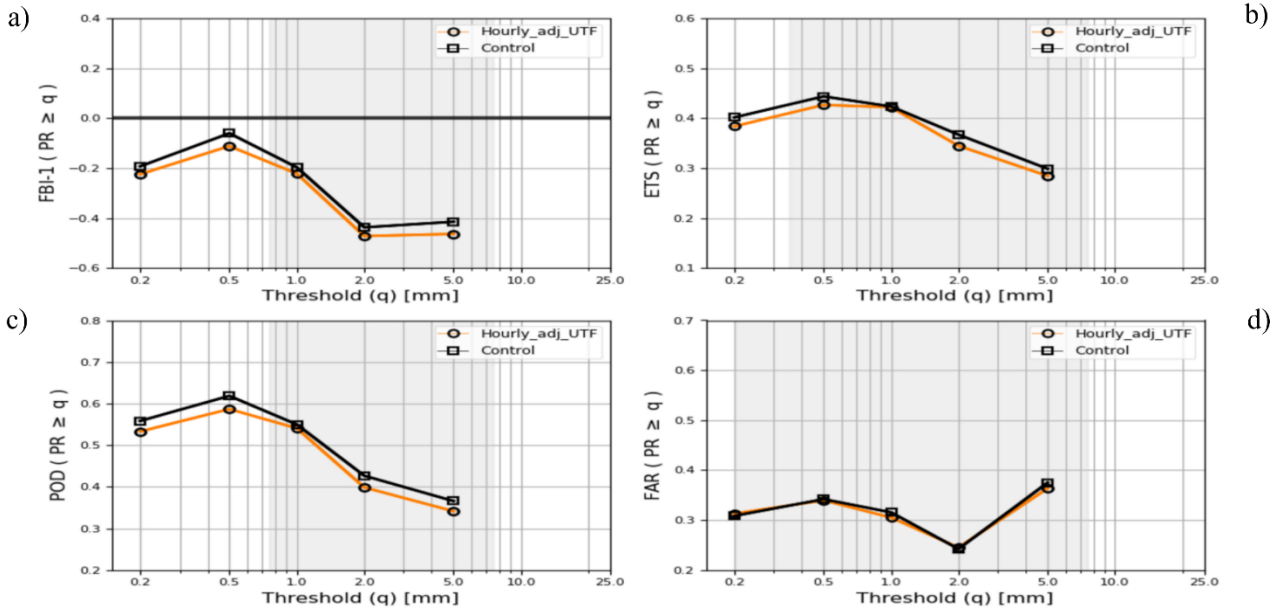


Figure 4: Same as Figure 3 but for the hourly adjusted data with the universal transfer function (orange) and the control run (black).

### 2.3.2 Impact of hourly data adjusted with climate-specific transfer functions

A comparison between the FBI and ETS scores of the UTF and the more climate specific transfer functions (at Marshall, Bratt's Lake, and Haukeliseter sites) was conducted. As all transfer functions led to highly comparable results, Table 3 displays the differences between the scores of the UTF and of the climate-specific transfer functions. Across all experiments, the differences in scores are in the range of two to three decimal. The most significant differences are seen between

the UTF and the specific transfer function developed at Haukeliseter (HAUKTF), particularly for the FBI and higher precipitation thresholds. These small discrepancies reveal that the quality of the analyses is not significantly influenced by the choice of transfer functions, whether it is the universal or climate-specific one.

Table 3: Absolute difference between universal transfer function (UTF) and more climate-specific transfer function (MARTF, BLTF HAUKTF) scores for FBI and ETS for winter 2019. White areas mean that the differences are statistically significant at the 95% confidence level, based on the bootstrap method; grey areas mean that the differences are not statistically significant. Numbers in bold represent differences that are statistically significant in favor of the more climate-specific transfer function.

Differences with UTF	SCORES	Thresholds				
		0.2	0.5	1.0	2.0	5.0
UTF - MARTF	FBI	0.000	0.000	0.002	0.000	0.048
UTF - BLTF	FBI	0.002	0.005	<b>0.002</b>	<b>0.007</b>	0.024
UTF - HAUKTF	FBI	<b>0.007</b>	<b>0.012</b>	<b>0.009</b>	<b>0.021</b>	0.024
UTF - MARTF	ETS	0.003	0.002	0.001	0.004	<b>0.012</b>
UTF - BLTF	ETS	0.002	0.000	<b>0.002</b>	0.002	<b>0.006</b>
UTF - HAUKTF	ETS	0.002	0.002	0.002	0.002	<b>0.006</b>

### 2.3.3 Impact of hourly data with adjustment depending on snowfall intensity

Another approach, based on snow intensity rather than air temperature, is used here to adjust the precipitation observations assimilated in CaPA. Since the Marshall and Haukeliseter sites have been chosen as climate-specific transfer functions in CaPA, conducting tests on these exact sites would offer valuable insights. Additionally, only three transfer functions using the snowfall intensity are available in the scientific literature, and among them, these two functions have been tested at the same sites. As a result, Marshall and Haukeliseter transfer functions were tested.

Using precipitation intensity in the transfer function rather than air temperature, the impact of the adjustment is found to be more substantial. As an example, the impact of using snow intensity instead of air temperature in the TF is shown in Figures 5 and 6 for TF for the Marshall site. With the snow intensity TF for Marshall (Figure 5), FBI as well as POD are substantially increased, which improve the precipitation amount simulated for all precipitation thresholds. The false alarms (FAR) are also increased, which deteriorated the precipitation amount simulated. The overall impact on accuracy is a slight improvement for ETS for larger precipitation threshold, although these differences are not statistically significant.

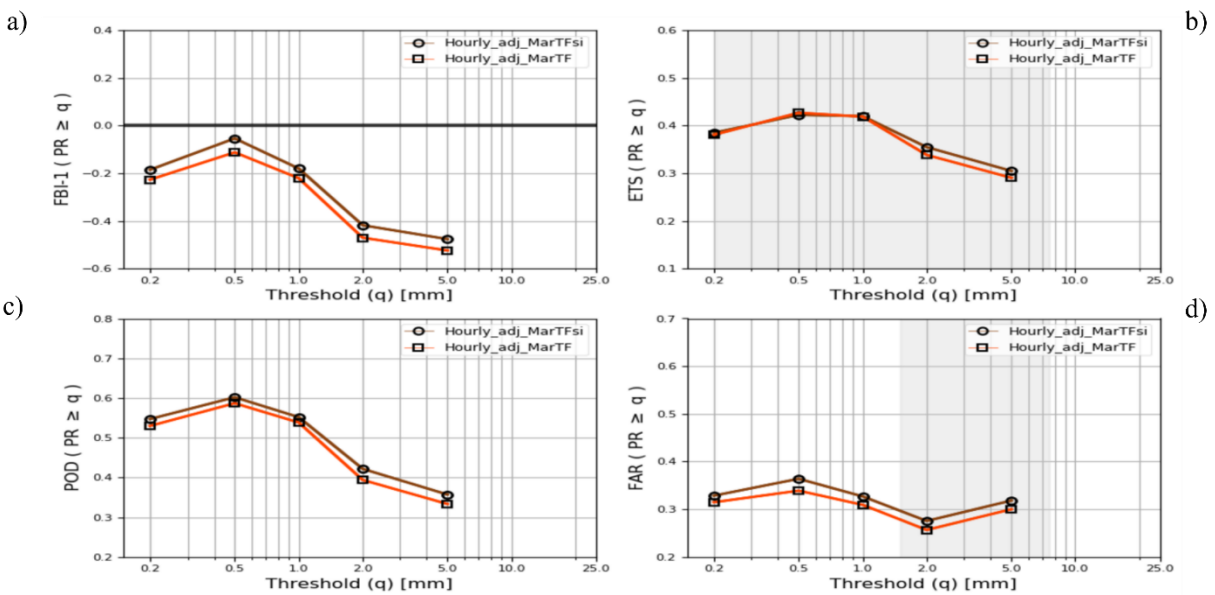


Figure 5: Same as Figure 3 but for the hourly adjusted data with the Marshall transfer function depending on the air temperature (red) and the hourly adjusted data with the Marshall transfer function depending on the snowfall intensity (brown).

In Figure 6, comparison of Hourly\_adj\_MarTFsi with the Control run indicates that results from Hourly\_adj\_MarTFsi are closer to Control than what was previously described for UTF (i.e., in Figure 4). In Figure 6, the FBI-1 and POD are quite similar. The main difference is for false alarms (FAR), which are increased with Hourly\_adj\_MarTFsi compared with Control. The accuracy (ETS) is slightly decreased for the lower thresholds (0.2 mm and 0.5 mm). In contrast to Figure 3 for UTF, ETS is similar to Control for larger precipitation thresholds.

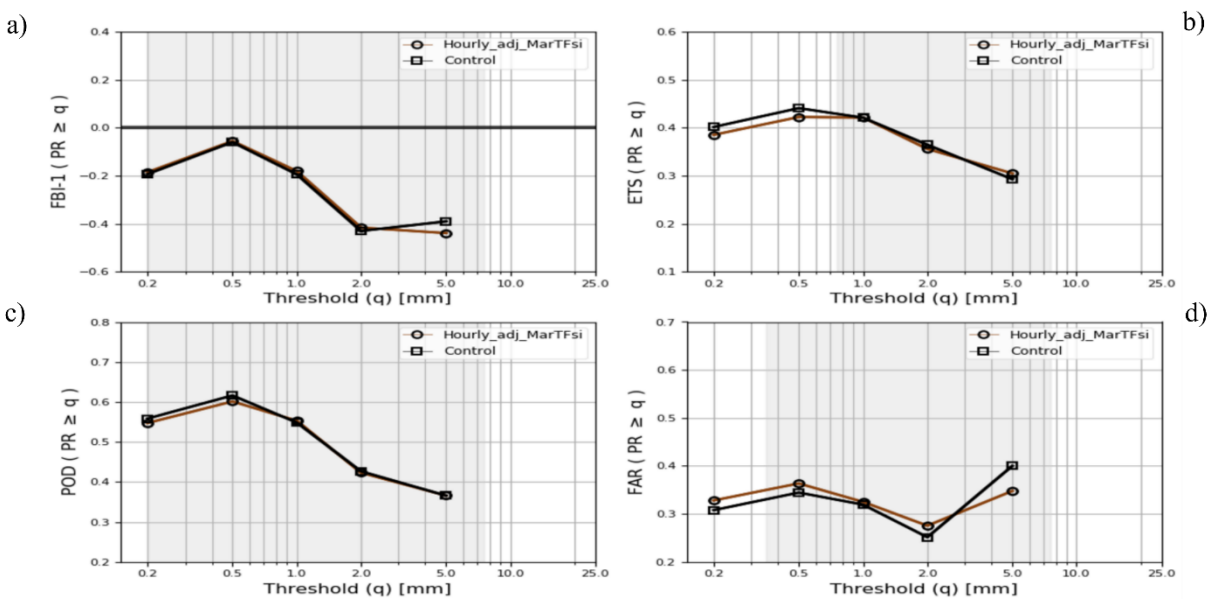


Figure 6: Same as Figure 3 but for the hourly adjusted data with the Marshall transfer function depending on snowfall intensity (brown) and the control run (black).

Another climate specific transfer function that depends on snowfall intensity has been developed in Haukeliseter, Norway. Nevertheless, when compared to either the transfer function based on air temperature developed at Haukeliseter or the control run, the results (not shown) are essentially identical to those obtained from previous experiments using the transfer functions developed at Marshall.



#### 2.3.4 Evaluation against AdjDlyRS

The impact of adding the hourly adjusted data is also determined with an objective evaluation versus daily precipitation observations from the AdjDlyRS dataset. The purpose of this second evaluation is to complement the findings from the LOOCV approach with evaluation versus a different type of reference dataset. This evaluation is exclusively conducted using the MarTFsi and HaukTFsi transfer functions, as they have shown the best results (sections 1.3.1-1.3.3).

The evaluation results against AdjDlyRS for Hourly\_adj\_MarTFsi are shown in Figure 7. When compared with the Control experiment, the FBI is relatively unchanged, although the differences are larger and more in favor of the Hourly\_adj\_MarTFsi experiment compared to the LOOCV (Figure 6). For the evaluation versus AdjDlyRS, the FBI-1 is slightly decreased for lower precipitation thresholds and slightly increased for larger thresholds, indicating that the precipitation area is generally smaller with MarTFsi but analyzed amounts are greater. This effect is seen in the POD, with an increase for precipitation thresholds between 2 and 6 mm. Combined with a substantial decrease in FAR for all thresholds below 6 mm, this leads to a substantial enhancement of the ETS for all precipitation thresholds below 6 mm.

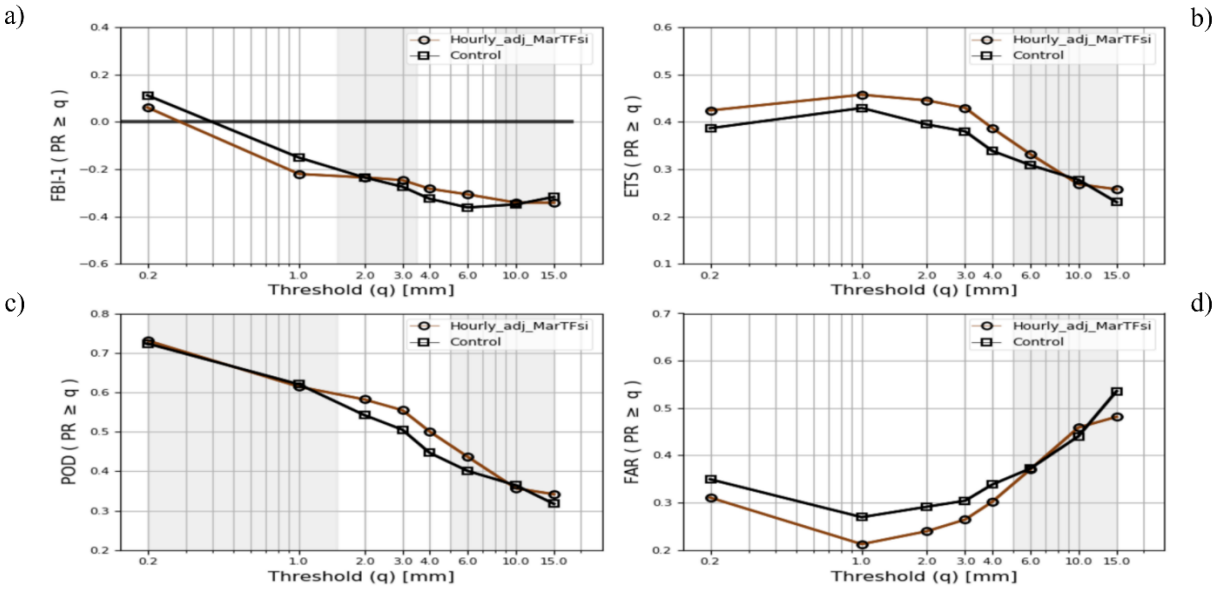


Figure 7: Objective evaluation metrics for CaPA's analyses for the Control experiment (black lines) and with the assimilation of observations adjusted with MarTFsi (brown lines). The evaluation is performed against the AdjDlyRS dataset for winter 2019, from 1 December 2018 to 31 March 2019, and is valid over the entire study area shown in Figure 1: a) is for FBI-1 with a black line indicating no bias, b) is for ETS, c) is for POD, and d) is for FAR. The letter  $q$  provides the daily precipitation thresholds used for the evaluation (mm). Because the evaluation is for daily accumulations, the thresholds are different from previous figures. White areas indicate that the differences between the two experiments are statistically significant at the 95 % confidence level, based on the bootstrap method; grey areas indicate that the differences are not statistically significant.

A similar evaluation, but for HaukTFsi, is presented in Figure 8. The results are qualitatively similar to MarTFsi (Figure 7), but with a greater improvement of CaPA. With HaukTFsi, the FBI for precipitation thresholds greater than 2 mm are substantially larger (and better) than for the Control experiment. Similarly for POD, which is larger than both the Control and MarTFsi (Figure 7). The FAR is slightly increased compared with Figure 7, but it remains lower, which suggest an improvement compared to Control for precipitation thresholds lower than 4 mm. CaPA is mainly improved when conducting the evaluation with the AdjDlyRS database because of the large increase of ETS, for all thresholds except 10 mm, which is neutral.

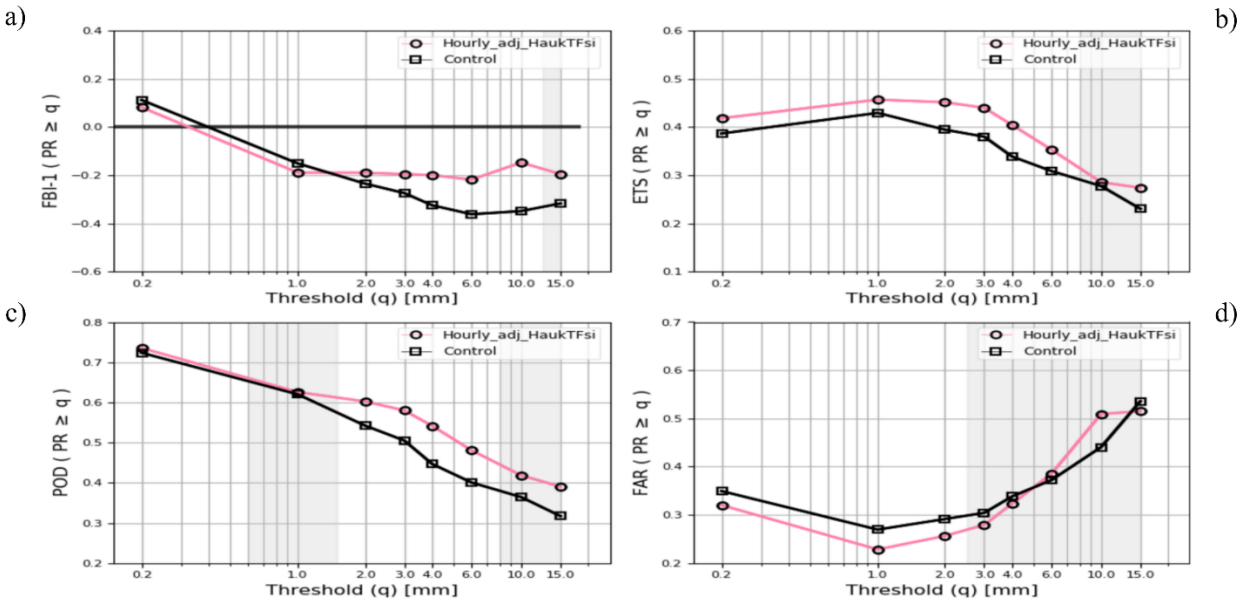


Figure 8: Same as Figure 7 but for Hourly\_adj\_HaukTFsi.

## 2.4 Discussion

Several aspects of the results are further examined below. These issues are related to the sensitivity (or lack thereof) of the quality of CaPA's precipitation analyses to the various TFs tested in this study, to the interannual variability of the results, to the more substantial impact of TFs using snow intensity rather than air temperature in their formulation, and to the role of verification dataset and approach.

### 2.4.1 Sensitivity of CaPA's results to various TFs based on air temperature

The results presented in the sections 1.3.1 and 1.3.2 indicate that the adjustment with UTF has a positive impact on the quality of the precipitation analyses when compared with a version of CaPA in which unadjusted observations are assimilated. This adjustment is, however, not sufficient to compensate for the impact of assimilating observations from the hourly dataset into CaPA, which

generally decrease precipitation amounts (see Feng et al. 2023). The LOOCV evaluation indicates that even with adjustment from various transfer functions based on near-surface air temperature, the inclusion of the hourly dataset does not seem to improve the analyses compared with the Control experiment. All four metrics examined (FBI, ETS, POD, and FAR) indicate better performance for Control.

Another key outcome is the lack of sensitivity of the results to the various transfer functions based on near-surface air temperature tested in this study, such as those developed for sites at Bratt's Lake, Marshall, and Haukeliseter. When examining the differences between the FBI and ETS metrics for CaPA's analyses including these transfer functions, there does not seem to be substantial impact with any of them during the three winter seasons examined. Only the results from the winter 2019 has been shown on figures. In this study, the universal transfer function, which only considers wind speed and air temperature, has almost no impact on the CaPA precipitation estimates. This conclusion is different from what was found in Feng et al. (2023), in which the UTF was shown to have a positive impact when evaluated over the same region as in the present study, with the same CaPA configuration. It should be mentioned the impact in their study was found to be nearly neutral for winter 2019, in contrast with the following years (2020 to 2022) for which the effect of the UTF was notably positive. A potential explanation for this inconsistency might be that the winters examined in Feng et al.'s (2023) study are more recent and involve adjusting observations from stations already included into CaPA. In contrast, the approach in the present study relies on a new data source. Differences in the quantity and location of observations could account for these variations.

## 2.4.2 Interannual variability

Comparing the adjustments over an extended time period and contrasting them with unadjusted data provides valuable insights into their impact. As mentioned above in the results section, the impact of assimilating the new hourly adjusted and unadjusted datasets is small for the first two winter seasons examined in this study, i.e., 2017 and 2018. Reasons for this lack of sensitivity could be due to the hourly data themselves, or to the assimilation process in CaPA.

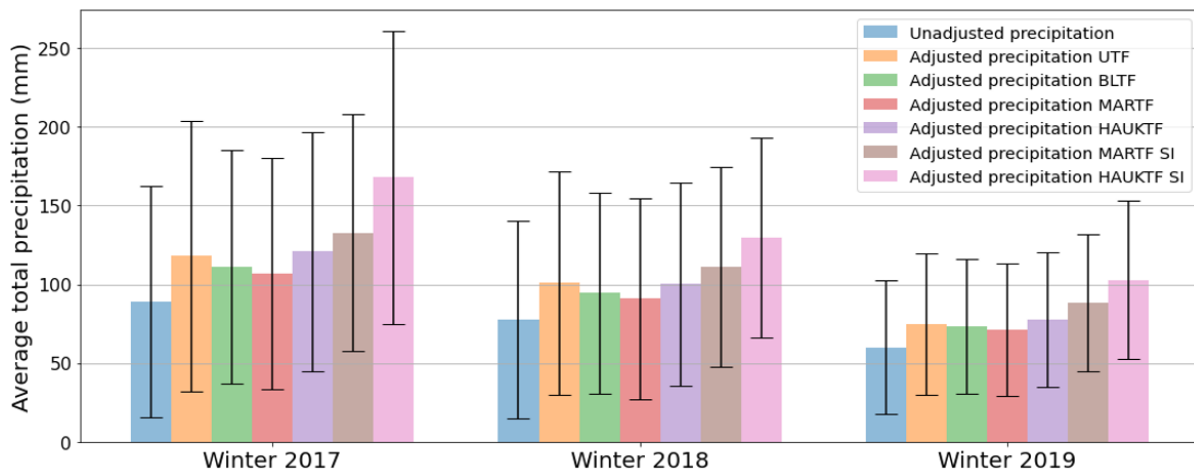


Figure 9: Average total precipitation for the 138 stations in the domain using different transfer functions for the 2017, 2018, and 2019 winter seasons. The error bar shows the standard deviation of the average total precipitation.

Figure 9 provides some insights on how data from the hourly dataset could explain this interannual variability in CaPA's analyses. In addition to showing the variability associated with the adjustment from the various transfer functions tested in this study, Figure 9 also reveals that precipitation amount and variability is less in 2019 compared with the two previous winter seasons. The decrease in adjusted precipitation for the last two winters (2018 and 2019) can be explained by the fact that some stations have made the change from single-Altet to double-Altet and are therefore not

adjusted (section 2), but only up to 14 stations were changed. Still, this variability in the values of the observations added to CaPA might at least partly explain the larger impact of the hourly datasets for winter 2019.

Regarding the assimilation process in CaPA, it remains the same for the winter seasons under investigation in this study. But it should be reminded that the first guess from short-range NWP forecasts can play a substantial role in CaPA, and that the production of this first guess depends on ECCO's NWP systems operational at the time. The first guess for each winter was compared with hourly data adjusted using the universal transfer function (Figure 10). For the first two winters (2017 and 2018), the bias for the first guess tended to have positive values for small precipitation thresholds but, somewhat negative values for larger thresholds (as measured by FBI). However, for the winter of 2019, the FBI-1 for the first guess is mostly below zero, with lower values for larger amounts of precipitation.

In March 2018, a change in the CaPA configuration introduced a new background field, which affected the last winter's first guess (Fortin et al, 2018). This change had a significant impact on the analyses because it affects how much weight is given to the observations versus the background. When the background is less accurate, the analysis relies more on the observations to correct it, while a more accurate background requires less correction through observations. Regardless of the transfer function adjustments made, if the observations play a smaller role in correcting the background, the impact of the adjustment will be less noticeable in CaPA, as seems to be the case in the present study for winter 2017 and 2018. Since the effects of the transfer functions are not apparent during the initial two winters because the background is more accurate, only the data for the most recent winter is presented.

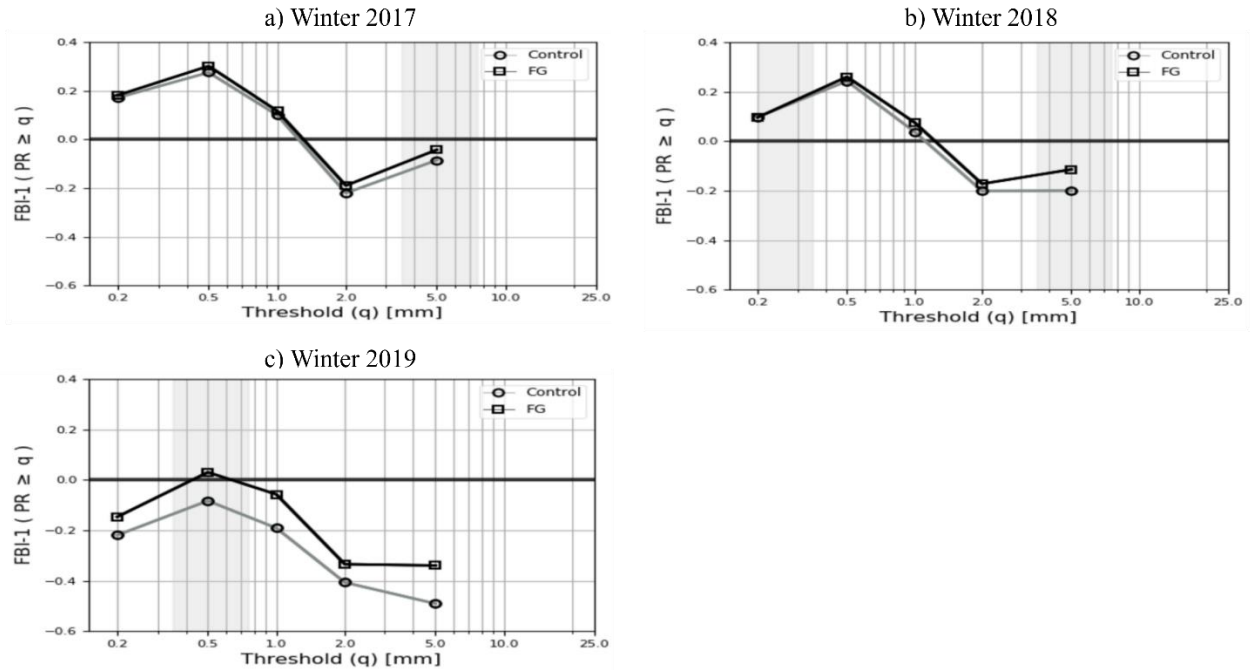


Figure 10: Evaluation with the LOOCV approach of CaPA for the Control run (black) and for the first guess (grey) for the frequency bias index FBI-1 with a black straight line indicating no bias valid for the study domain: a) is for winter 2017, b) is winter 2018 and c) is winter 2019. The letter q is the 6-hourly precipitation accumulation (mm). White areas mean that the differences between CTRL and FG are statistically significant at the 95 % confidence level, based on the bootstrap method; grey areas mean that the differences are not statistically significant.

### 2.4.3 Enhancement of the TF impact using snow intensity

In section 2.3 it was suggested that the use of snow intensity in the transfer function is likely to improve the quality of CaPA's winter precipitation analyses. The comparisons between the experiments with the Marshall and Haukeliseter transfer functions using air temperature and snow intensity are revealing. CaPA's analyses are improved when using the transfer function based on snowfall intensity, in contrast to the one based on air temperature. For both the Marshall and Haukeliseter sites, three out of the four evaluation metrics (FBI, ETS, and POD) have improved

values with the adjustment based on snowfall intensity. These includes a reduction in forecast bias, enhanced accuracy, and improved detection of precipitation events.

This could be explained by the fact that while air temperature is effective in determining the type of precipitation, it does not inform much on the large variety of crystal types and the degree of riming (Sims and Liu, 2015; Rasmussen et al., 1999; Thériault et al., 2012). The size distribution of precipitation is linked to snowfall intensity. With an increase in precipitation rates, the slope of the size distribution decreases, resulting in an elevated concentration of larger particles that are prone to fall into the gauge. This contrasts with slower-falling particles that are likely to be deviated by the updraft upstream of the gauge (Nespor and Sevruk 1999; Colli et al., 2020). Additionally, Thériault et al. (2012, 2015) reported that the catch efficiency of a shielded gauge is more related to the particle's fall speed. The differences for the magnitude of the adjustment for both approaches shown in Figure 9, in which the total precipitation for the three winter seasons from the Marshall and Haukeliseter transfer functions have been substantially increased by using snow intensity instead of air temperature.

#### 2.4.4 Role of verification dataset and approach

To complement the results obtained through the LOOCV approach, an additional evaluation was conducted using data from the AdjDlyRS dataset. This evaluation displays a significantly improved outcome when employing snowfall intensity-dependent transfer function adjustments in comparison to the control experiment. All four-evaluation metrics (FBI, ETS, POD, and FAR) exhibit improvement, with a slightly more notable enhancement observed for the transfer function developed at Haukeliseter.



Possible reasons for this disparity between the two types of evaluation are introduced using a case study. This case, for 24-h precipitation accumulations valid at 1200 UTC 7 January 2019, is presented with Figure 11. On that day, a large-scale meteorological system produced precipitation for much of the analysis domain, with daily accumulations of more than 10 mm water equivalent in central Saskatchewan and southern Manitoba.

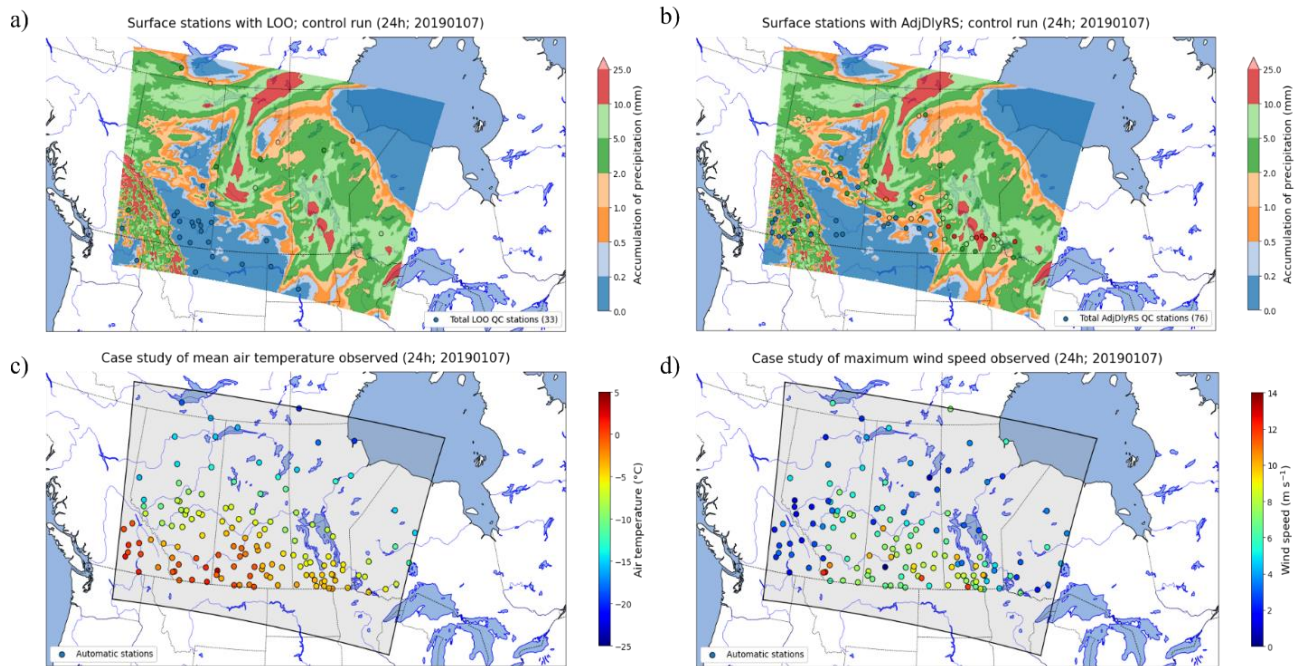


Figure 11: Case study of a precipitation event from 6 January 2019 at 1200 UTC to 7 January 2019 at 1200 UTC. Panel a) represents the precipitation accumulation (mm) with CaPA’s first guess superimposed with the location of the synoptic manual stations used for the LOOCV evaluation for that specific day. Panel b) is the same but with the location of the AdjDlyRS stations used for the evaluation. Panel c) represents observations from the hourly adjusted database that show the mean air temperature ( $^{\circ}\text{C}$ ) of the event. Panel d) represents observations from the hourly adjusted database that show the maximum wind speed ( $\text{m s}^{-1}$ ) of the event plotted at the stations.

A key aspect to consider in Figure 11 is that a much smaller number of manual synoptic stations are used for the evaluation of that specific case compared with what is used with the AdjDlyRS dataset. The LOOCV evaluation reveals that merely 33 stations are assimilated within this 24-hour analysis period, predominantly located in places devoid of recorded precipitation. Conversely, the

AdjDlyRS evaluation reveals a higher count of assimilated stations, specifically 76, in areas where precipitation is indeed observed.

For the same event, the mean air temperature and wind speed data from observations in the hourly adjusted database (Smith et al. 2022) are presented in the lower panels of Figure 11. In Figure 11c, some stations show temperature near zero in the mountain region and in southern Alberta and Saskatchewan, where not much precipitation is analyzed by CaPA. The surface stations elsewhere report mean temperature below 0°C for this event. In Figure 11d, the maximum wind speed for the 24-hour period indicate that several stations recorded winds greater than 4 m s<sup>-1</sup>, particularly in southern and central Alberta, Saskatchewan, and Manitoba.

The case study analysis sheds light on the reasons that could explain the contrasting results obtained with LOOCV based on CaPA-assimilated synoptic manual observations and with direct comparison against daily estimates provided by AdjDlyRS. Because LOOCV only uses a limited number of stations resulting from CaPA's quality control, stations located in precipitation areas can be systematically excluded from the evaluation process over areas with sub-zero temperatures and wind speeds above 3 m s<sup>-1</sup>, such as what is observed for the case presented here. In addition, the assimilated stations used for the evaluation are possibly more representative of precipitation-free zones, which could have an influence on the objective evaluation results.

This challenging problem is avoided with the other approach when directly comparing CaPA's precipitation analyses with data from AdjDlyRS, which are not assimilated in CaPA and not subject to its QC process. In that case, the evaluation considers a broader range of meteorological situations compared to the LOOCV approach.

## 2.5 Summary and conclusions

In this study, the impact of using adjusted solid precipitation amounts to correct wind-induced undercatch on CaPA's performance is investigated. Various transfer functions were tested, and the precipitation analysis was evaluated using two methods.

The findings indicate that the adjustment using the universal transfer function improves CaPA's precipitation product, but not sufficiently to compensate for problems associated with the inclusion of this solid precipitation adjustment database (Smith et al. 2022). There are also no notable disparities in CaPA when comparing the performance of the UTF with that of several climate-specific transfer functions based on air temperature. In contrast, climate-specific transfer functions that depend on snowfall intensity improved the precipitation analysis, compared to the same transfer function developed at specific sites using only air temperature. Notably, the use of these snowfall intensity-dependent transfer functions leads to an improvement over the Control experiment.

CaPA is improved further when the objective evaluation is performed with direct comparison with the AdjDlyRS dataset (Mekis et Vincent., 2011; Wang et al. 2017). With CaPA's traditional evaluation method based on LOOCV, a smaller number of surface observations are used for the evaluation, and several of them are removed from the evaluation process because of CaPA's QC process. In that context, the LOOCV evaluation may not be as representative of events characterized by strong wind and cold conditions.

These key findings have potential implications for future research and development related to applications of CaPA during the cold season. While this project has provided valuable insights into

the impact of different transfer functions in CaPA, there are some limitations that may have influenced the results and interpretations. The first limitation of this project relates to the availability of published transfer functions. The project aimed to use transfer functions that are documented in the existing literature. However, not all published transfer functions include coefficients specific to the site under study. Consequently, the choice of transfer functions for this study was somewhat restricted. A second limitation of the project pertains to the duration of the study period. Due to the constraints of data availability and consistency, only one of the three winters examined shared the same model configuration to produce CaPA's first guess. As a result, the findings obtained from this project may be representative of that winter, but may not be fully applicable to other years. Future research endeavors should aim to address these limitations by expanding the range of available transfer functions and incorporating multiple years of data to confirm the results presented in this study.

Overall, identifying these limitations is crucial in understanding the scope and potential impact of the improvement of solid precipitation in CaPA. Given the promising outcomes demonstrated by the transfer functions that depend on snowfall intensity in this study, there is merit in considering its operational testing within CaPA. This step could potentially lead to valuable advancements in precipitation analysis.

### CHAPITRE 3 - CONCLUSION

Avoir une idée de la distribution spatio-temporelle des précipitations en temps quasi-réel est pertinent pour de nombreuses applications dans le domaine de la météorologie et de l'hydrologie. Avec les observations seulement, soit les stations météorologiques, les radars et les données de télédétection satellites, il est plus difficile d'avoir une bonne estimation de la précipitation reçue qui couvre l'ensemble du Canada. C'est pour cela que le Système Canadien d'Analyse de Précipitations (CaPA) a été créé. C'est un système d'assimilation de données qui prend en compte non seulement les observations, mais aussi un champ de fond obtenu par une prévision météorologique numérique à court terme qui s'appuie sur le modèle GEM (Global Environmental Multiscale). Cela permet donc d'avoir quand même un estimé de précipitations pour les endroits non couverts par les observations.

Malgré l'intérêt de la communauté scientifique envers CaPA, certaines difficultés demeurent. Durant l'hiver, beaucoup d'observations de précipitation solides sont rejetés par le contrôle de qualité, ce qui réduit la qualité des analyses produite par CaPA. Dans des conditions froides et venteuses, la mesure de la neige comprend d'énormes incertitudes et biais parce que de la turbulence est créée autour de la jauge, ce qui empêche le flocon de tomber dans l'orifice et d'être mesuré. Pour contrer les effets du vent, des paravents ont été installés autour de la jauge, mais les études ont démontré que malgré leurs installations, le biais du vent persistait. C'est pour cela que les fonctions de transfert ont été introduites.

Les fonctions de transfert sont des équations mathématiques qui permettent de calculer une précipitation ajustée en fonctions de la vitesse du vent et de d'autres facteurs comme la température de l'air et de l'intensité des précipitations solides. Le but de ce projet était donc d'évaluer

l'efficacité de plusieurs fonctions de transfert, y compris la fonction de transfert universelle, des fonctions plus spécifiques au climat (développées au site de Bratt's Lake, Marshall et Haukeliseter) et des fonctions de transfert basées sur l'intensité des précipitations solides dans CaPA. Le choix des fonctions de transfert s'est basé sur leur publication dans la littérature, leur localisation, le type de climat et leur efficacité de collecte. Une nouvelle base de données horaire d'ECCC (Smith et al., 2022) a d'ailleurs été ajustée avec ces fonctions de transfert et ensuite introduite dans CaPA.

Le domaine de cette étude couvre principalement le centre du Canada et plus particulièrement les Prairies canadiennes, pour la période hivernale (1<sup>er</sup> décembre au 31 mars) des années 2016-2017, 2017-2018 ainsi que 2018-2019. En mars 2018, un changement dans la configuration du CaPA a affecté la prévision initiale du dernier hiver. Ce changement a eu un impact significatif sur les analyses, car il a affecté le poids accordé aux observations par rapport à la prévision. À la suite de nombreux tests pour les deux premiers hivers (2016-2017 et 2017-2018), l'impact de l'ajustement était mineur, car la prévision avait un plus petit biais que celui du dernier hiver (2018-2019). Il a donc été judicieux de présenter seulement les résultats de l'hiver 2018-2019, comme les impacts des différents ajustements étaient plus visibles dans CaPA.

Deux méthodes ont été utilisées pour évaluer les analyses de CaPA, dont l'une qui est couramment utilisée du côté d'ECCC, la méthode du 'Leave-One-Out cross validation' (LOOCV). Comme cette approche assimile déjà les stations présente dans CaPA et qui sont sujettes au contrôle de qualité, il a été convenu de faire une seconde évaluation contre un jeu de données indépendant les données Adjusted Daily Rainfall and Snowfall (AdjDlyRS) afin de contrer cette limitation. Les quatre scores métriques utilisé dans le cadre de ce projet pour les évaluations sont : l'indice de fréquence

de biais (FBI-1), le score de menace équitable (ETS), la probabilité de détection (POD) et les fausses alarmes (FAR).

Dans cette étude, l'impact de l'utilisation de quantités de précipitations solides ajustées pour corriger la sous-capture par le vent sur les performances de CaPA est étudié. Les résultats indiquent que l'ajustement à l'aide de la fonction de transfert universelle (UTF) a un impact positif sur l'analyse des précipitations, mais pas nécessairement suffisant pour compenser les problèmes associés à l'inclusion de ces nouvelles données. L'inclusion du jeu de données horaires ajustées ne semble pas améliorer les analyses par rapport à l'expérience de contrôle où les quatre scores métriques (FBI, ETS, POD et FAR) indiquent une meilleure performance pour l'expérience de contrôle. En examinant ensuite les différences entre les scores FBI et ETS, les résultats suggèrent qu'il n'y a pas de disparités notables dans CaPA lorsque l'on compare la performance de l'UTF avec celle de plusieurs fonctions de transfert spécifiques au climat (développées à Marshall, Bratt's Lake et Haukeliseter) basées sur la température de l'air, du moins pour les trois saisons d'hiver examinées dans cette étude.

Cependant, lorsque l'on considère des fonctions de transfert spécifiques au climat qui dépendent de l'intensité des précipitations solides, un meilleur résultat sur CaPA devient évident par rapport à la même fonction de transfert développée sur des sites spécifiques en utilisant uniquement la température de l'air. Pour les sites de Marshall et de Haukeliseter, trois des quatre scores (FBI, ETS et POD) ont été améliorés grâce à l'ajustement basé sur l'intensité des précipitations solides. Il s'agit notamment d'une réduction du biais de prévision, d'une amélioration de la précision et d'une meilleure détection des précipitations. De plus, l'utilisation de ces fonctions de transfert dépendant

de l'intensité des précipitations solides conduit à une amélioration par rapport à l'expérience de contrôle.

L'amélioration de CaPA avec la fonction de transfert qui dépend du taux de précipitation est plus évidente lorsque l'évaluation objective est réalisée par comparaison directe avec le jeu de données AdjDlyRS. Avec la méthode d'évaluation traditionnelle de CaPA basée sur LOOCV, un plus petit nombre d'observations de surface est utilisé pour l'évaluation, et plusieurs d'entre elles sont retirées du processus d'évaluation en raison du contrôle qualité de CaPA. Dans ce contexte, l'évaluation LOOCV peut ne pas être aussi représentative des événements caractérisés par des vents forts et des conditions froides. Ces résultats clés ont des implications potentielles pour la recherche et le développement futurs dans le domaine de CaPA, en contribuant à une meilleure compréhension des impacts des différentes fonctions de transfert.

Bien que ce projet ait fourni des informations clés sur l'impact des différentes fonctions de transfert dans la CaPA, il est important de reconnaître certaines limitations qui ont pu influencer les résultats et les interprétations. Une limitation importante de ce projet concerne la disponibilité des fonctions de transfert publiées. Le projet visait à utiliser des fonctions de transfert documentées dans la littérature existante. Toutefois, il convient de noter que toutes les fonctions de transfert publiées n'incluent pas les coefficients spécifiques des sites étudiés. Par conséquent, le choix des fonctions de transfert pour cette étude a été quelque peu restreint. Une autre limitation du projet concerne la durée de la période d'étude. En raison des contraintes de disponibilité et de cohérence des données, un seul des trois hivers étudiés avait la même version de prévision de champ de fond. Par conséquent, les résultats obtenus dans le cadre de ce projet peuvent être représentatifs de cet hiver, mais ne peuvent pas s'appliquer à tous les cas.



Pour conclure, la reconnaissance de ces limitations revêt une importance capitale pour saisir l'étendue et l'impact potentiel de l'amélioration de l'analyse des précipitations solides dans le cadre de CaPA. Les futurs efforts de recherche pourraient élargir la gamme des fonctions de transfert disponibles et incorporer plusieurs années de données afin d'améliorer la généralisation des résultats. À la lumière des résultats prometteurs démontrés par les fonctions de transfert dépendant de l'intensité des chutes de neige dans cette étude, il serait pertinent de considérer des tests opérationnels au sein de CaPA. Cette démarche pourrait éventuellement ouvrir la voie à des progrès significatifs dans l'analyse des précipitations. Il serait également pertinent d'explorer l'apprentissage automatique, susceptible d'améliorer les fonctions de transfert en modélisant les relations complexes entre les mesures des instruments et les quantités réelles de précipitations solides. L'intégration de variables météorologiques supplémentaires pourrait favoriser une adaptation dynamique aux conditions atmosphériques et du terrain, contribuant ainsi à des fonctions de transfert plus précises et adaptatives.

## RÉFÉRENCES

- Alavi, N., Bélair, S., Fortin, V., Zhang, S., Husain, S., Carrera, M., & Abrahamowicz, M. (2016). Warm season evaluation of soil moisture prediction in the Soil, Vegetation, and Snow (SVS) scheme. *Journal of Hydrometeorology*, 17(8), 2315–2332. <https://doi.org/10.1175/JHM-D-15-0189.1>.
- Asong, Z. E., Razavi, S., Wheeler, H. S., & Wong, J. S. (2017). Evaluation of Integrated Multisatellite Retrievals for GPM (IMERG) over Southern Canada against Ground Precipitation Observations: A Preliminary Assessment, *Journal of Hydrometeorology*, 18(4), 1033-1050. <https://doi.org/10.1175/JHM-D-16-0187.1>
- Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature*, 438(7066), 303-309.
- Boluwade, A., Stadnyk, T., Fortin, V., & Roy, G. (2017). Assimilation of precipitation estimates from the integrated multisatellite retrievals for GPM (IMERG, early run) in the Canadian Precipitation Analysis (CaPA). *Journal of Hydrology: Regional Studies*, 14, 10-22. <https://doi.org/10.1016/j.ejrh.2017.10.005>
- Brimelow, J., Stewart, R., Hanesiak, J., Kochtubajda, B., Szeto, K., & Bonsal, B. R. (2014). Characterization and assessment of the devastating natural hazards across the Canadian Prairie Provinces from 2009 to 2011. *Natural Hazards*, 73(2), 761–785.
- Brimelow, J., Szeto, K., Bonsal, B. R., Hanesiak, J., Kochtubajda, B., Evans, F., & Stewart, R. (2015). Hydroclimatic aspects of the 2011 Assiniboine river basin flood. *Journal of Hydrometeorology*, 16(3), 1250–1272. <https://doi.org/10.1175/JHM-D-14-0033.1>.
- Carrera, M., Bélair, S., & Bilodeau, B. (2015). The Canadian Land Data Assimilation System (CaLDAS): Description and synthetic evaluation study. *Journal of Hydrometeorology*, 16(3), 1293–1314. <https://doi.org/10.1175/JHM-D-14-0089.1>.

Colli, M., Stagnaro, M., Lanza, L. G., Rasmussen, R., & Thériault, J. M. (2020). Adjustments for wind-induced undercatch in snowfall measurements based on precipitation intensity. *Journal of Hydrometeorology*, 21(5), 1039-1050. <https://doi.org/10.1175/JHM-D-19-0222.1>

Cookson-Hills, P., Kirshbaum, D., Surcel, M., Doyle, J., Fillion, L., Jacques, D., & Baek, S.-J. (2017). Verification of 24-h quantitative precipitation forecasts over the Pacific Northwest from a high-resolution ensemble Kalman filter system. *Weather and Forecasting*, 32(3), 1185–1208. <https://doi.org/10.1175/WAF-D-16-0180.1>.

Côté, J., Gravel, S., Méthot, A., Patoine, A., Roch, M., & Staniforth, A. (1998). The Operational CMC–MRB Global Environmental Multiscale (GEM) Model. Part I: Design Considerations and Formulation. *Mon. Wea. Rev.*, **126**, 1373–1395. [https://doi.org/10.1175/1520-0493\(1998\)126<1373:TOCMGE>2.0.CO;2](https://doi.org/10.1175/1520-0493(1998)126<1373:TOCMGE>2.0.CO;2)

Deacu, D., Fortin, V., Klyszejko, E., Spence, C., & Blanken, P. (2012). Predicting the net basin supply to the Great Lakes with a hydrometeorological model. *Journal of Hydrometeorology*, 13(6), 1739–1759. <https://doi.org/10.1175/JHM-D-11-0151.1>.

Devine, K. A., & Mekis, É. (2008). Field accuracy of Canadian rain measurements. *Atmosphere-Ocean*, 46, 213–227. <https://doi.org/10.3137/ao.460202>.

Ebert, E. E., Janowiak, J. E., & Kidd, C. (2007). Comparison of near-real-time precipitation estimates from satellite observations and numerical models. *Bulletin of the American Meteorological Society*, 88(1), 47-64. <https://doi.org/10.1175/BAMS-88-1-47>

Evans, A. (2013). Investigation of enhancements to two fundamental components of the statistical interpolation method used by the Canadian Precipitation Analysis (CaPA) University of Manitoba]. <http://hdl.handle.net/1993/22276>

Feng, P.-N., Bélair, S., Khedhaouria, D., Lespinas, F., Mekis, E., & Thériault, J. M. (2023). Impact of adjusted and non-adjusted surface observations on the cold season performance of the Canadian Precipitation Analysis (CaPA) system. *Journal of Hydrometeorology*.

Fortin, V., Roy, G., Donaldson, N., & Mahidjiba, A. (2015). Assimilation of radar quantitative precipitation estimations in the Canadian Precipitation Analysis (CaPA). *Journal of Hydrology*, 531, 296-307. <https://doi.org/10.1016/j.jhydrol.2015.08.003>

Fortin, V., Roy, G., Stadnyk, T., Koenig, K., Gasset, N., & Mahidjiba, A. (2018). Ten years of science based on the Canadian precipitation analysis: A CaPA system overview and literature review. *Atmosphere-Ocean*, 56(3), 178-196. <https://doi.org/10.1080/07055900.2018.1474728>

Fry, L. M., Gronewold, A. D., Fortin, V., Buan, S., Clites, A., Luukkonen, C., ... Restrepo, P. (2014). The Great Lakes Runoff Intercomparison Project phase 1: Lake Michigan (GRIP-M). *Journal of Hydrology*, 519(PD), 3448–3465. <https://doi.org/10.1016/j.jhydrol.2014.07.021>.

Garnaud, C., Bélair, S., Berg, A., & Rowlandson, T. (2016). Hyperresolution land surface modeling in the context of SMAP Cal-Val. *Journal of Hydrometeorology*, 17(1), 345–352. <https://doi.org/10.1175/JHM-D-15-0070.1>.

Garnaud, C., Bélair, S., Carrera, M., McNairn, H., & Pacheco, A. (2017). Field-scale spatial variability of soil moisture and L-band brightness temperature from land surface modeling. *Journal of Hydrometeorology*, 18(3), 573–589. <https://doi.org/10.1175/JHM-D-16-0131.1>.

Goodison, B. E. (1978). Accuracy of Canadian snow gage measurements. *Journal of Applied Meteorology and Climatology*, 17(10), 1542-1548. [https://doi.org/10.1175/1520-0450\(1978\)0172.0.co;2](https://doi.org/10.1175/1520-0450(1978)0172.0.co;2)

Goodison, B. E., P. Y. T. Louie, and D. Yang., (1998). WMO solid precipitation measurement intercomparison. WMO Instruments and Observing Methods Final Rep. 67, 318 pp., <http://www.wmo.int/pages/prog/www/reports/WMOtd872.pdf>.

Haghnegahdar, A., Tolson, B., Davison, B., Seglenieks, F., Klyszejko, E., Soulis, E., ... Matott, L. (2014). Calibrating Environment Canada's MESH modelling system over the Great Lakes Basin. *AtmosphereOcean*, 52(4), 281–293. <https://doi.org/10.1080/07055900.2014.939131>.

Halliwell, D. (2014). Precipitation Measurements from Automatic Stations: Sensor Characteristics, Logger Processing/Filtering, and Post-Collection Evaluation. Meteorological Service of Canada. <https://doi.org/10.1080/07011784.2018.1530611>.

Husain, S., Alavi, N., Bélair, S., Carrera, M., Zhang, S., Fortin, V., ... Gauthier, N. (2016). The multibudget Soil, Vegetation, and Snow (SVS) scheme for land surface parameterization: Offline warm season evaluation. *Journal of Hydrometeorology*, 17(8), 2293–2313. <https://doi.org/10.1175/JHM-D-15-0228.1>.

Hutchinson, M. F., McKenney, D. W., Lawrence, K., Pedlar, J. H., Hopkinson, R. F., Milewska, E., & Papadopol, P. (2009). Development and testing of Canada-wide interpolated spatial models of daily minimum-maximum temperature and precipitation for 1961–2003. <https://doi.org/10.1175/2008JAMC1979.1>.

Jameson, A. R., & Kostinski, A. B. (2002). Spurious power-law relations among rainfall and radar parameters. *Quarterly Journal of the Royal Meteorological Society: A journal of the atmospheric sciences, applied meteorology and physical oceanography*, 128(584), 2045–2058. <https://doi.org/10.1256/003590002320603520>.

Khedhaouiria, D., Bélair, S., Fortin, V., Roy, G., & Lespinas, F. (2020). High-Resolution (2.5 km) Ensemble Precipitation Analysis across Canada. *Journal of Hydrometeorology*, 21(9), 2023–2039. DOI: 10.1175/JHM-D-19-0282.1

Kochendorfer, J., Earle, M., Rasmussen, R., Smith, C., Yang, D., Morin, S., ... & Meyers, T. (2022). How well are we measuring snow post-SPICE?. *Bulletin of the American Meteorological Society*, 103(2), E370–E388. <https://doi.org/10.1175/BAMS-D-20-0228.1>

Kochendorfer, J., Nitu, R., Wolff, M., Mekis, E., Rasmussen, R., Baker, B., ... & Jachcik, A. (2018). Testing and development of transfer functions for weighing precipitation gauges in WMO-SPICE. *Hydrology and Earth System Sciences*, 22(2), 1437-1452. <https://doi.org/10.5194/hess-22-1437-2018>

Kochendorfer, J., Nitu, R., Wolff, M., Mekis, E., Rasmussen, R., Baker, B., ... & Poikonen, A. (2017). Analysis of single-Alter-shielded and unshielded measurements of mixed and solid precipitation from WMO-SPICE. *Hydrology and Earth System Sciences*, 21(7), 3525-3542. <https://doi.org/10.5194/hess-21-3525-2017>

Køltzow, M., B. Casati, T. Haiden, and T. Valkonen, 2020: Verification of Solid Precipitation Forecasts from Numerical Weather Prediction Models in Norway. *Wea. Forecasting*, 35, 2279–2292, <https://doi.org/10.1175/WAF-D-20-0060.1>

Kornelsen, K., Davison, B., & Coulibaly, P. (2016). Application of SMOS soil moisture and brightness temperature at high resolution with a bias correction operator. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(4), 1590–1605. **DOI:** [10.1109/JSTARS.2015.2474266](https://doi.org/10.1109/JSTARS.2015.2474266)

Leroux, N. R., Thériault, J. M., & Rasmussen, R. (2021). Improvement of snow gauge collection efficiency through a knowledge of solid precipitation fall speed. *Journal of Hydrometeorology*, 22(4), 997-1006. <https://doi.org/10.1175/JHM-D-20-0147.1>.

Lespinas, F., Fortin, V., Roy, G., Rasmussen, P., & Stadnyk, T. (2015). Performance evaluation of the Canadian precipitation analysis (CaPA). *Journal of Hydrometeorology*, 16(5), 2045-2064. <https://doi.org/10.1175/JHM-D-14-0191.1>

Ma, Y., Zhang, Y., Yang, D., & Farhan, S. B. (2015). Precipitation bias variability versus various gauges under different climatic conditions over the Third Pole Environment (TPE) region. *International Journal of Climatology*, 35(7), 1201-1211. <https://doi.org/10.1002/joc.4045>

Mahfouf, J. F., Brasnett, B., & Gagnon, S. (2007). A Canadian precipitation analysis (CaPA) project: Description and preliminary results. *Atmosphere-ocean*, 45(1), 1-17. <https://doi.org/10.3137/ao.v450101>

Mailhot, J., Bélair, S., Lefaivre, L., Bilodeau, B., Desgagné, M., Girard, C., ... & Qaddouri, A. (2006). The 15-km version of the Canadian regional forecast system. *Atmosphere-Ocean*, 44(2), 133-149. : <https://doi.org/10.3137/ao.440202>

Mekis, E., & Brown, R. (2010). Derivation of an adjustment factor map for the estimation of the water equivalent of snowfall from ruler measurements in Canada. *Atmosphere-Ocean*, 48, 284–293. <https://doi.org/10.3137/AO1104.2010>.

Mekis, É., Donaldson, N., Reid, J., Zucconi, A., Hoover, J., Li, Q., Nitu, R., Melo, S. (2018). An Overview of Surface Based Precipitation Observations at Environment and Climate Change Canada, *Atmosphere-Ocean*, 56(2), 71-95, 10. <https://doi.org/10.1080/07055900.2018.1433627>.

Mekis, E., & Hogg, W. D. (1999). Rehabilitation and analysis of Canadian daily precipitation time series. *Atmosphere-Ocean*, 37, 53–85. <https://doi.org/10.1080/07055900.1999.9649621>.

Mekis, E. v., & Vincent, L. A. (2011). An Overview of the Second Generation Adjusted Daily Precipitation Dataset for Trend Analysis in Canada. *Atmosphere-Ocean*, 49(2), 163-177. <https://doi.org/10.1080/07055900.2011.583910>

Milbrandt, J. A., Bélair, S., Faucher, M., Vallée, M., Carrera, M. L., & Glazer, A. (2016). The Pan-Canadian High Resolution (2.5 km) Deterministic Prediction System. *Wea. Forecasting*, 31, 1791–1816. <https://doi.org/10.1175/WAF-D-16-0035.1>

Milewska, E. J., Vincent, L. A., Hartwell, M. M., Charlesworth, K., & Mekis, É. (2019). Adjusting precipitation amounts from Geonor and Pluvio automated weighing gauges to preserve continuity

of observations in Canada. *Canadian Water Resources Journal/Revue canadienne des ressources hydriques*, 44(2), 127-145. <https://doi.org/10.1080/07011784.2018.1530611>.

Milrad, S., Atallah, E., & Gyakum, J. (2013). Precipitation modulation by the Saint Lawrence River valley in association with transitioning tropical cyclones. *Weather and Forecasting*, 28(2), 331–352. <https://doi.org/10.1175/WAF-D-12-00071.1>.

Milrad, S., Gyakum, J., & Atallah, E. (2015). A meteorological analysis of the 2013 Alberta flood: Antecedent large-scale flow pattern and synopticdynamic characteristics. *Monthly Weather Review*, 143(7), 2817–2841. <https://doi.org/10.1175/MWR-D-14-00236.1>.

Milrad, S., Lombardo, K., Atallah, E., & Gyakum, J. (2017). Numerical simulations of the 2013 Alberta flood: Dynamics, thermodynamics, and the role of orography. *Monthly Weather Review*, 145(8), 3049–3072. <https://doi.org/10.1175/MWR-D-16-0336.1>.

Nešpor, V., & Sevruk, B. (1999). Estimation of wind-induced error of rainfall gauge measurements using a numerical simulation. *Journal of atmospheric and oceanic technology*, 16(4), 450-464, [https://doi.org/10.1175/1520-0426\(1999\)016<0450:EOWIEO>2.0.CO;2](https://doi.org/10.1175/1520-0426(1999)016<0450:EOWIEO>2.0.CO;2)

Nitu, R., Roulet, Y. A., Wolff, M., Earle, M. E., Reverdin, A., Smith, C. D., ... & Yamashita, K. (2019). WMO Solid Precipitation Intercomparison Experiment (SPICE) (2012-2015).

Pan, X., Yang, D., Li, Y., Barr, A., Helgason, W., Hayashi, M., ... & Janowicz, R. J. (2016). Bias corrections of precipitation measurements across experimental sites in different ecoclimatic regions of western Canada. *The Cryosphere*, 10(5), 2347-2360. doi:10.5194/tc-10-2347-2016

Pierre, A., Jutras, S., Smith, C., Kochendorfer, J., Fortin, V., and Anctil, F. (2019). Evaluation of Catch Efficiency Transfer Functions for Unshielded and Single-Alter-Shielded Solid Precipitation Measurements. *Journal of Atmospheric and Oceanic Technology* 36, 5, 865-881, available from: <https://doi.org/10.1175/JTECH-D-18-0112.1>



Pomeroy, J. W., Gray, D. M., Brown, T., Hedstrom, N. R., Quinton, W. L., Granger, R. J., & Carey, S. K. (2007). The cold regions hydrological model: a platform for basing process representation and model structure on physical evidence. *Hydrological Processes: An International Journal*, 21(19), 2650-2667. <https://doi.org/10.1002/hyp.6787>.

Rasmussen, R. M., J. Vivekanandan, J. Cole, B. Myers, and C. Masters. (1999). The estimation of snowfall rate using visibility. *J. Appl. Meteor.*, 38, 1542–1563, [https://doi.org/10.1175/1520-0450\(1999\)038<1542:TEOSRU>2.0.CO;2](https://doi.org/10.1175/1520-0450(1999)038<1542:TEOSRU>2.0.CO;2)

Rasmussen, R., Baker, B., Kochendorfer, J., Meyers, T., Landolt, S., Fischer, A. P., ... & Gutmann, E. (2012). How well are we measuring snow: The NOAA/FAA/NCAR winter precipitation test bed. *Bulletin of the American Meteorological Society*, 93(6), 811-829. <https://doi.org/10.1175/BAMS-D-11-00052.1>

Sevruk, B., Hertig, J.-A., & Spiess, R. (1989). Wind Field Deformation above Precipitation Gauge Orifices. *Internal Association of Hydrological Sciences*, 179, 65-70

Sevruk B., J.-A. Hertig, and R. Spiess. (1991). The effect of precipitation gauge orifice rim on the wind field deformation as investigated in a wind tunnel. *Atmosphere Environment* 25A: 1173-1179.

Sims, E. M., and G. Liu. (2015). A parameterization of the probability of snow–rain transition. *J. Hydrometeor.*, 16, 1466–1477, <https://doi.org/10.1175/JHM-D-14-0211.1>.

Smith, C. D. (2009). The relationship between snowfall catch efficiency and wind speed for the geonor T-200B precipitation gauge utilizing various wind shield configurations. *Western Snow Conference*.

Smith, C. D., Ross, A., Kochendorfer, J., Earle, M. E., Wolff, M., Buisán, S., ... & Laine, T. (2020). Evaluation of the WMO Solid Precipitation Intercomparison Experiment (SPICE) transfer functions for adjusting the wind bias in solid precipitation measurements. *Hydrology and Earth System Sciences*, 24(8), 4025-4043. <https://doi.org/10.5194/hess-24-4025-2020>

Smith, C.D., Mekis, E., Earle, M. & Yang, D. (s. d.). Summary of the Results and Recommendation from WMO-SPICE.

Smith, C. D., Mekis, E., Hartwell, M., and Ross, A. (2022). The hourly wind-bias-adjusted precipitation data set from the Environment and Climate Change Canada automated surface observation network (2001–2019), *Earth Syst. Sci. Data*, 14, 5253–5265, <https://doi.org/10.5194/essd-14-5253-2022>

Teufel, B., Diro, G. T., Whan, K., Milrad, S. M., Jeong, D. I., Ganji, A., & Sushama, L. (2016). Investigation of the 2013 Alberta flood from weather and climate perspectives. *Climate Dynamics*, 48(9–10), 1–19. <https://doi.org/10.1007/s00382-016-3239-8>.

Thériault, J. M., Rasmussen, R., Ikeda, K., & Landolt, S. (2012). Dependence of snow gauge collection efficiency on snowflake characteristics. *Journal of applied meteorology and climatology*, 51(4), 745-762. <https://doi.org/10.1175/JAMC-D-11-0116.1>

———, ——, E. Petro, J. Trépanier, M. Colli, and L. G. Lanza. (2015). Impact of wind direction, wind speed, and particle characteristics on the collection efficiency of the double fence intercomparison reference. *J. Appl. Meteor. Climatol.*, 54, 1918–1930, <https://doi.org/10.1175/JAMC-D-15-0034.1>.

Wang, X. L., Xu, H., Qian, B., Feng, Y., & Mekis, E. (2017). Adjusted Daily Rainfall and Snowfall Data for Canada. *Atmosphere-Ocean*, 55(3), 155-168. <https://doi.org/10.1080/07055900.2017.1342163>

Wolff, M. A., Isaksen, K., Petersen-Øverleir, A., Ødemark, K., Reitan, T., & Brækkan, R. (2015). Derivation of a new continuous adjustment function for correcting wind-induced loss of solid precipitation: results of a Norwegian field study. *Hydrology and Earth System Sciences*, 19(2), 951-967, <https://doi.org/10.5194/hess-19-951-2015>.

Xu, X., Tolson, B., Li, J., Staebler, R., Seglenieks, F., Haghnegahdar, A., & Davison, B. (2015). Assimilation of SMOS soil moisture over the Great Lakes basin. *Remote Sensing of Environment*, 169, 163–175. <https://doi.org/10.1016/j.rse.2015.08.017>.

Yang, D., Kane, D., Zhang, Z., Legates, D., & Goodison, B. (2005). Bias corrections of long-term (1973–2004) daily precipitation data over the northern regions. *Geophysical Research Letters*, 32(19). <https://doi.org/10.1029/2005gl024057>.

Yang, D., & Ohata, T. (2001). A bias-corrected Siberian regional precipitation climatology. *Journal of Hydrometeorology*, 2(2), 122-139. [https://doi.org/10.1175/1525-7541\(2001\)002<0122:ABCSRP>2.0.CO;2](https://doi.org/10.1175/1525-7541(2001)002<0122:ABCSRP>2.0.CO;2)