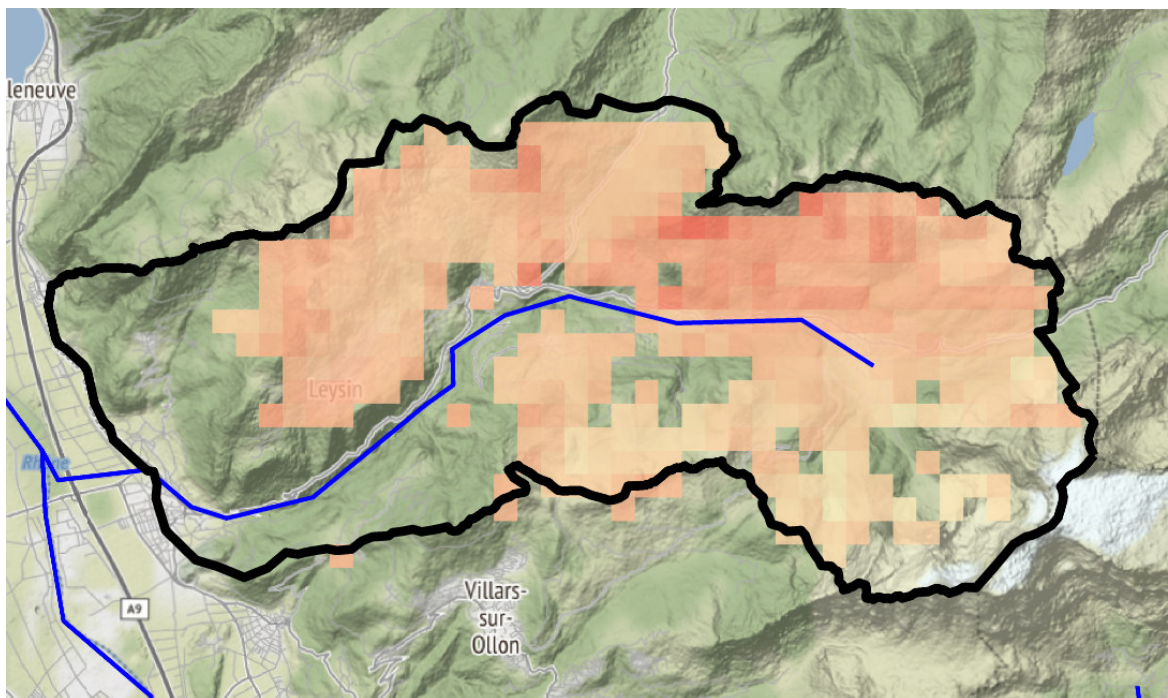




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Radar-rain gauge merging and discharge data assimilation for flood forecasting in Alpine catchments



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Résumé

Les crues génèrent un tiers des coûts liés aux dommages naturels au niveau mondial. Afin de protéger la population et les infrastructures, des systèmes de prévisions de crues utilisent les prévisions météorologiques pour anticiper avec plusieurs jours les crues, offrant plus de temps pour se préparer. Dans le canton du Valais, un système de prévision et de gestion des crues est opérationnel depuis 2013, résultat du projet MINERVE initié en 1999. Le présent projet avait pour objectif de répondre à certains défis posés par ce système.

Une nouvelle méthode de spatialisation des précipitations basée sur un co-krigeage avec régression de données de pluviomètres et de radar météorologique est présentée. Deux réseaux de mesure équipés de pluviomètres de qualité différente sont considérés. En comparant les précipitations estimées avec d'autres méthodes d'interpolation, l'évaluation quantitative des précipitations (EQP) obtenue avec le co-krigeage avec régression fournit la meilleure performance sur le bassin d'étude. L'analyse suggère le besoin de plus de prétraitement de la donnée radar, notamment en lien avec les zones d'ombre dû à la topographie complexe.

L'intégration du nouveau produit d'EQP dans un modèle de neige a révélé une claire sous-estimation des précipitations. Une méthodologie est proposée afin de corriger la sous-estimation des précipitations solides dans le calcul de produits d'EQP. Quatre produits différents sont considérés : le produit d'EQP opérationnel CombiPrecip de MétéoSuisse, le co-krigeage avec régression et deux variantes de ce dernier incluant un facteur correcteur de 1.2 et 1.3 pour la sous-estimation des précipitations solides. Le modèle de neige est calé avec des données satellitaires du spectroradiomètre MODIS et validé avec l'équivalent en eau de la neige à 11 stations de mesure. La meilleure performance est obtenue avec le produit d'EQP incluant un facteur correcteur de 1.2.

Pour évaluer d'un point de vue hydrologique la performance de ces produits d'EQP, trois sous-bassins du système MINERVE sont calés avec 5 jeux de données de précipitation différents en entrée. Les modèles hydrologiques GSM et SOCONT sont utilisés pour les parties glaciaires et non-glaciaires. Un calage du modèle en deux phases est exploré, en appliquant la méthode de calage des facteurs degré-jour de fonte nivale basée sur MODIS, avant de caler les autres paramètres à l'aide des données de débit. Les résultats suggèrent qu'en présence d'une bonne visibilité du radar, le produit d'EQP intégrant un facteur correcteur de 1.2 fournit les meilleurs résultats. Pour les deux bassins avec une moins bonne visibilité, l'utilisation de données de pluviomètres mène à des résultats équivalents ou meilleurs. Avec l'implémentation actuelle, le calage en deux phases n'a pas permis de surpasser le calage conventionnel.

Finalement, un filtre de Kalman d'ensemble (EnKF) est implémenté pour améliorer les conditions initiales utilisées pour les prévisions hydrologiques. Les résultats sont comparés, pour deux événements de fortes précipitations, au scénario sans mise à jour et à l'assimilation de données actuelle du système MINERVE, mettant à jour la saturation du sol sur la base d'une comparaison des volumes de débit sur les 24 dernières heures. Le filtre de Kalman d'ensemble (EnKF) montre de bonnes performances sur les 2 événements mais également des difficultés lors des faibles débits, notamment en présence de perturbations hydroélectriques.

Lien vers le rapport de thèse : <https://infoscience.epfl.ch/record/273163?ln=fr>



Zusammenfassung

Überschwemmungen verursachen ein Drittel der weltweiten Naturschadenskosten. Zum Schutz der Bevölkerung und der Infrastruktur nutzen Hochwasservorhersagesysteme Wettervorhersagen, um Überschwemmungen mehrere Tage vorauszusehen und deshalb mehr Vorlaufzeit für Schutzmassnahmen zu haben. Im Kanton Wallis ist seit 2013 ein Hochwasservorhersage- und Managementsystem in Betrieb, das aus dem 1999 gestarteten MINERVE Projekt resultiert. Das Ziel dieser Arbeit ist es, einige der Herausforderungen, die sich aus diesem System ergeben, anzugehen.

Eine neue Methode der Bestimmung der räumlichen Verteilung von Niederschlag basierend auf Co-Kriging mit Regression von Regenmessungen und meteorologischen Radardaten wird vorgestellt. Zwei Messnetze, die mit Regenmessern unterschiedlicher Qualität ausgestattet sind, werden berücksichtigt. Der Vergleich der geschätzten Niederschlagsmengen mit anderen Interpolationsmethoden zeigt auf, dass die quantitative Niederschlagsschätzung (*Quantitative precipitation estimates* auf English (QPE)), die mit Co-Kriging mit Regression erhalten wurde, das beste Resultat über das untersuchte Einzugsgebiet ergibt. Die Analyse zeigt, dass eine gute Aufbereitung der Radardaten erforderlich ist, insbesondere in Bezug auf Schattenbereiche aufgrund der komplexen Topographie.

Die Integration des neuen QPE-Produkts in ein Schneemodell ergab eine deutliche Unterschätzung der Niederschlagsmengen. Es wird eine Methodik zur Korrektur der Unterschätzung des festen Niederschlags bei der Berechnung von QPE-Produkten vorgeschlagen. Vier verschiedene Produkte werden betrachtet: das operationelle QPE-Produkt von MeteoSchweiz CombiPrecip, das Co-Kriging mit Regression und zwei Varianten davon mit einem Korrekturfaktor von 1.2 und 1.3 für die Unterschätzung der festen Niederschläge. Das Schneemodell wird mit Satellitendaten aus dem MODIS-Spektroradiometer kalibriert und an 11 Messstationen mit dem Schneewasseräquivalent validiert. Die beste Leistung wird mit dem QPE-Produkt mit dem Korrekturfaktor 1.2 erzielt.

Um die hydrologische Leistung dieser QPE-Produkte zu beurteilen, werden drei Teilbecken des MINERVE-Systems mit 5 verschiedenen Niederschlagsdatensätzen als Input kalibriert. Die hydrologischen Modelle GSM und SOCONT werden für glaziale und nicht-glaziale Flächen verwendet. Eine zweiphasige Modellkalibrierung wurde untersucht, in der die Schneeschmelzfaktoren mit der MODIS-basierten Kalibrieremethode geschätzt werden, bevor die anderen Parameter mit Hilfe von Abflussdaten kalibriert werden. Die Ergebnisse deuten darauf hin, dass bei guter Radarsicht das QPE-Produkt mit einem Korrekturfaktor von 1.2 die besten Ergebnisse liefert. Für die beiden Einzugsgebiete mit geringerer Radarsichtbarkeit führt die Verwendung von Regenmessdaten zu gleichwertigen oder besseren Ergebnissen. Bei der aktuellen Implementierung hat die zweiphasige Kalibrierung die konventionelle Kalibrierung nicht verbessert.

Schliesslich wird ein Ensemble Kalman-Filter (EnKF) implementiert, um die Ausgangsbedingungen für hydrologische Vorhersagen zu verbessern. Die Ergebnisse werden für zwei Starkniederschlagsereignisse mit dem Szenario ohne Aktualisierung und mit der aktuellen MINERVE-Systemdatenassimilation, in der die Bodensättigung mit der Abflussmengen über die letzten 24 Stunden aktualisiert wird, verglichen. Der Ensemble Kalman-Filter zeigt bei beiden Ereignissen eine gute Leistung, aber auch Schwierigkeiten bei niedrigen Durchflüssen, insbesondere bei Einfluss durch die Wasserkraft.

Link zu der Dissertation : <https://infoscience.epfl.ch/record/273163?ln=fr>



Summary

Floods are responsible for one third of the economic losses induced by natural hazards throughout the world. To better protect the population and infrastructures, flood forecasting systems make use of weather forecasts to foresee floods several days in advance, providing more lead time for preventive measures. In the canton of Valais, an operational flood forecasting and management system is operational since 2013, as a result of the MINERVE project initiated in 1999. The present project aims at answering some of the challenges faced by this system.

First, a new methodology for spatial interpolation of precipitation is implemented based on regression co-kriging using rain gauge and weather radar data. Two rain gauge networks equipped with instruments of different quality are considered. Compared to other precipitation interpolation methods, the quantitative precipitation estimates (QPE) obtained from the regression co-kriging provides the best performance over the studied area using cross-validation. The analysis highlights the need for further pre-processing of radar data, in particular to account for beam shielding by the complex topography.

Integration of the above-mentioned QPE product in a snow model revealed a clear precipitation underestimation. A methodology to account for solid precipitation undercatch in QPE computation is therefore proposed. Four different QPE products are compared: the operational QPE product CombiPrecip of MeteoSwiss, the regression co-kriging QPE and two variants of it considering a correction factor of 1.2 and 1.3 for solid precipitation undercatch, applied before the interpolation. The snow model is calibrated using satellite-based data from the MODIS spectroradiometer and validated using snow water equivalent measurements from 11 snow monitoring sites. The best performance is obtained using the QPE product including a correction factor of 1.2.

To evaluate the performance of the developed QPE products from a hydrological perspective, three sub-catchments of the MINERVE system were calibrated considering 5 different inputs. The GSM and SOCONT hydrological models are used to model respectively the glacial and non-glacial parts. A two-phase calibration of the model is explored, applying the MODIS based calibration of snow-melt degree-day factors, before calibrating the other parameters using discharge data. Results suggest that the developed QPE product accounting for solid precipitation undercatch (factor 1.2) leads to the best performance over the catchment with a good radar visibility. In case of lower radar visibility, using station data provides equal or better performances. With the current implementation, the two-phase calibration did not allow to outperform the conventional calibration.

Finally, an ensemble Kalman filter (EnKF) is implemented to improve initial conditions used for hydrological forecasts. Results are compared, for two high flow events, to the scenario without assimilation and to the simple assimilation scheme currently implemented in the MINERVE system, updating the soil saturation based on a discharge volume comparison over the preceding 24 hours. The Ensemble Kalman filter (EnKF) shows good performance during these events but also highlights difficulties over base flow, strengthened in presence of hydropower perturbations.

Link to the thesis report: <https://infoscience.epfl.ch/record/273163?ln=en>



Take-home messages

- L'intégration de réseaux secondaires de pluviomètres dans l'interpolation spatiale des précipitations peut apporter une plus-value mais cela nécessite une méthode d'interpolation adaptée, permettant notamment de tenir compte du possible problème de biais entre les réseaux.
- La correction des précipitations solides aux pluviomètres avec un facteur correcteur fixe de 1.2 a permis une meilleure reproduction avec un modèle de neige des quantités de neige observées au sol. Cela représente une première étape vers une considération de la sous-estimation des précipitations solides par les pluviomètres, l'étape suivante étant l'utilisation de fonction de transfert tenant compte de la vitesse du vent à la station au moment de la mesure. Ces corrections ont pour objectif une meilleure quantification de la ressource en eau, que cela soit pour la prévision des crues ou pour l'apport en eau dans les barrages.
- L'utilisation de produits spatialisés de précipitation intégrant la donnée radar pour la modélisation hydrologique a permis une amélioration des performances par rapport à l'utilisation uniquement des valeurs aux stations pour le bassin avec la meilleure visibilité radar. Dans les deux autres cas, les performances étaient égales ou meilleures avec les valeurs des stations.
- L'implémentation d'un filtre de Kalman d'ensemble pour un système de prévision de crues nécessite l'existence d'un modèle permettant une bonne reproduction des débits autant pour les débits faibles qu'élevés, ainsi que l'accès à toutes les données des restitutions hydroélectriques.



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Liste des abréviations

CREALP	Centre de recherche sur l'environnement alpin
EnKF	Ensemble Kalman Filter
EPFL	Ecole Polytechnique Fédérale de Lausanne
EQP	Estimation quantitative des précipitations
GSM	Glacier and SnowMelt model
MG	MeteoGroup
MINERVE	Modélisation des Intempéries de Nature Extrême du Rhône Valaisan et de leurs Effets
MODIS	Moderate Resolution Imaging Spectroradiometer
NDSI	Normalized Difference Snow Index
OFEN	Office fédéral de l'énergie
OMM	Organisation Météorologique Mondiale
PPM	(Radar of) Pointe de la Plaine Morte
QPE	Quantitative precipitation estimates
RCK	Regression Co-Kriging
RMSE	Root Mean Square Error
SLF	Institut Suisse pour l'étude de la neige et des avalanches
SMN	SwissMetNet
SOCNT	SOil CONTRibution model
SWE	Snow Water Equivalent (équivalent en eau de la neige)
VBU	Volume Based Update



1 Introduction

En Suisse, les crues sont responsables de la majorité des coûts liés aux dangers naturels, avec un coût moyen estimé sur les quatre dernières décennies à CHF 306 millions par année (Andres and Badoux 2019). Le Canton du Valais est particulièrement exposé de par sa topographie et sa météorologie. En octobre 2000, d'importantes précipitations ont généré des crues ayant mené à la mort de 16 personnes et des dégâts estimés à CHF 470 millions. Le projet MINERVE (Modélisation des Intempéries de Nature Extrême du Rhône Valaisan et de leurs effets) a été initié en 1999 avec pour objectif la mise en place d'un système de prévision et de gestion des crues pour le Rhône à l'amont du Lac Léman (Jordan 2007; García Hernández 2011; Tobin 2012). Il est basé sur un modèle hydrologique-hydraulique qui permet de modéliser l'écoulement dans les rivières du bassin avec pour données d'entrée la précipitation et la température. L'implémentation et la maintenance du système ainsi que le suivi de la situation hydro-météorologique sont réalisés depuis 2011 sur mandat du Canton du Valais par le Centre de recherche sur l'environnement alpin (CREALP) à Sion. Le système est opérationnel pour l'ensemble du Canton depuis 2013.

En 2015, une thèse de doctorat a débuté à l'EPFL avec pour objectif d'améliorer certaines composantes du système opérationnel MINERVE, notamment l'estimation des précipitations, le calage du modèle de neige ainsi que l'élaboration d'une méthodologie d'assimilation de données de débit en temps réel pour l'amélioration de la qualité des prévisions hydrologiques. Le présent article présente les principaux résultats de ce travail (Foehn et al. 2019a).

2 Interpolation spatiale des précipitations

Les précipitations constituent un facteur clé dans la génération des crues. Il est important de pouvoir les estimer le plus correctement possible sur l'ensemble du territoire. Cependant, en présence de topographie complexe comme en Valais, cela n'est pas simple. Heureusement, un nouveau radar météorologique a été installé à l'intérieur du bassin en juin 2014 au sud du glacier de la Plaine Morte (voir Figure 1), améliorant considérablement la qualité du produit radar en Valais. De plus, le réseau de mesure automatique SwissMetNet (SMN) de l'Office Fédéral de Météorologie et Climatologie (MétéoSuisse) y est particulièrement dense comparativement aux autres cantons (58 stations à fin 2017). Malgré cela, reproduire fidèlement l'importante variabilité spatiale des précipitations dans les régions alpines reste un défi important. Ainsi, afin de reproduire au mieux cette variabilité spatiale, la considération d'un second réseau de mesure, celui de la société privée Meteogroup Switzerland AG (MG), a été explorée pour l'analyse (23 stations supplémentaires). La considération de ce second réseau pour l'interpolation spatiale représente l'une des principales différences de cette étude (Foehn et al. 2018) avec le produit raster opérationnel de précipitations horaires *CombiPrecip* de MétéoSuisse, combinant également les données radar avec les valeurs aux pluviomètres du réseau SMN (Sideris et al. 2014). La seconde différence majeure réside dans l'étendue spatiale de l'analyse, qui ne concerne ici que le Valais, alors que *CombiPrecip* est calculé à l'échelle nationale.

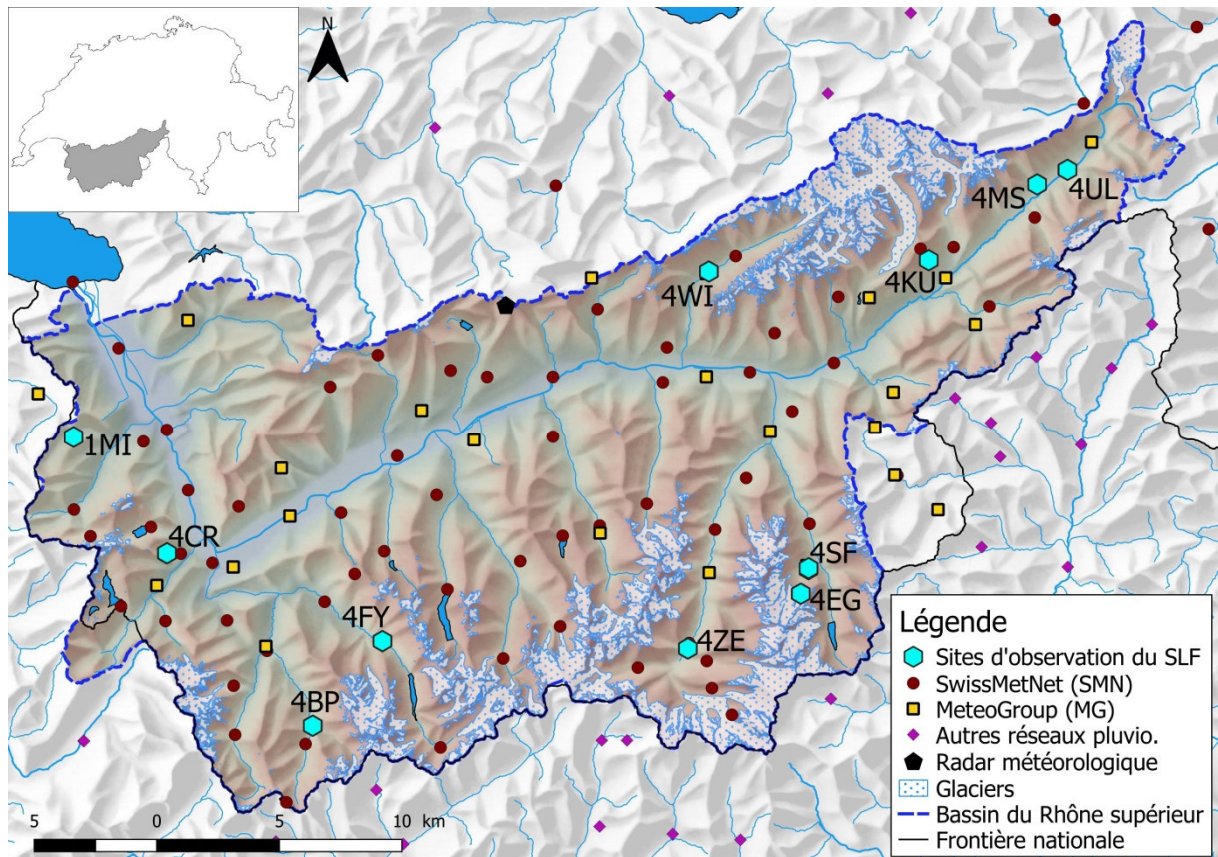


Figure 1 Carte du bassin du Rhône à l'amont du Lac Léman. L'emplacement des stations météorologiques (SwissMetNet et MeteoGroup) ainsi que les sites d'observation du SLF utilisés pour l'étude sont indiqués.

Les réseaux SMN et MG sont équipés avec des pluviomètres différents, ce qui implique une disparité dans la qualité de la mesure. Ainsi, lors de l'analyse préliminaire des données, l'écart entre précipitations moyennes entre les deux réseaux pouvaient dépasser 20%, les pluviomètres du réseau MG reportant moins de précipitation. Cela est en accord avec les résultats d'une étude de l'Organisation Météorologique Mondiale (OMM) publié en 2009 (Vuerich et al. 2009), qui conclut à une qualité « très bonne » et « satisfaisante » pour les équipements utilisés par MétéoSuisse (respectivement de la marque OTT et Lambrecht) et « insuffisante » pour ceux utilisés par MeteoGroup (de la marque Davis). Dans le but d'analyser la possibilité de considérer également les données du réseau MG pour l'interpolation spatiale des précipitations au pas de temps horaire, un co-krigeage avec régression est explorés parmi les différentes méthodes étudiées. L'application d'un co-krigeage permet de considérer deux variables en évaluant leur corrélation pour chaque pas de temps, et ainsi compenser d'éventuels biais de mesures entre les réseaux.

2.1 Méthodes d'interpolation

Cinq différentes méthodes sont comparées. La première consiste à utiliser le produit radar de MétéoSuisse sans correction (résolution spatiale de 1 km). Cela permet d'évaluer la qualité du produit sans modification. La seconde méthode considère uniquement les valeurs des stations en y appliquant une interpolation en fonction de l'inverse de la distance (« inverse distance weighting» (IDW), en anglais).



Les trois autres méthodes considèrent une combinaison de la donnée radar avec les pluviomètres. La donnée radar (Figure 2i)) est dans un premier temps multipliée par un coefficient spatialement constant déterminé de manière horaire sur la base d'une régression linéaire entre les valeurs des pixels du radar contenant les stations SMN et les valeurs aux stations. Une tendance (grille) basée sur la donnée radar (Figure 2ii)) est ainsi calculé. La différence entre les valeurs aux stations et la valeur du pixel de tendance contenant chaque station est ensuite calculée, fournissant les résidus aux stations. Ces résidus sont alors interpolés pour donner une grille de correction (Figure 2iii)), ensuite additionnée à la tendance pour obtenir l'estimation finale des précipitations (Figure 2iv)). La manière d'interpoler les résidus différencie les 3 méthodes. Dans la première, une interpolation en fonction de l'inverse de la distance est appliquée, donnant à cette méthode le nom de *Regression Inverse distance weighting* (RIDW). Les deux autres méthodes appliquent un krigeage sur les résidus pour la spatialisation. Dans un cas, il s'agit d'un krigeage simple considérant uniquement les données SMN, méthode nommée *Regression kriging* (RK). Dans l'autre cas, un co-krigeage considère les données SMN comme variable principale et les données MG comme variable secondaire, donnant à cette méthode le nom de *Regression co-kriging* (RCK).

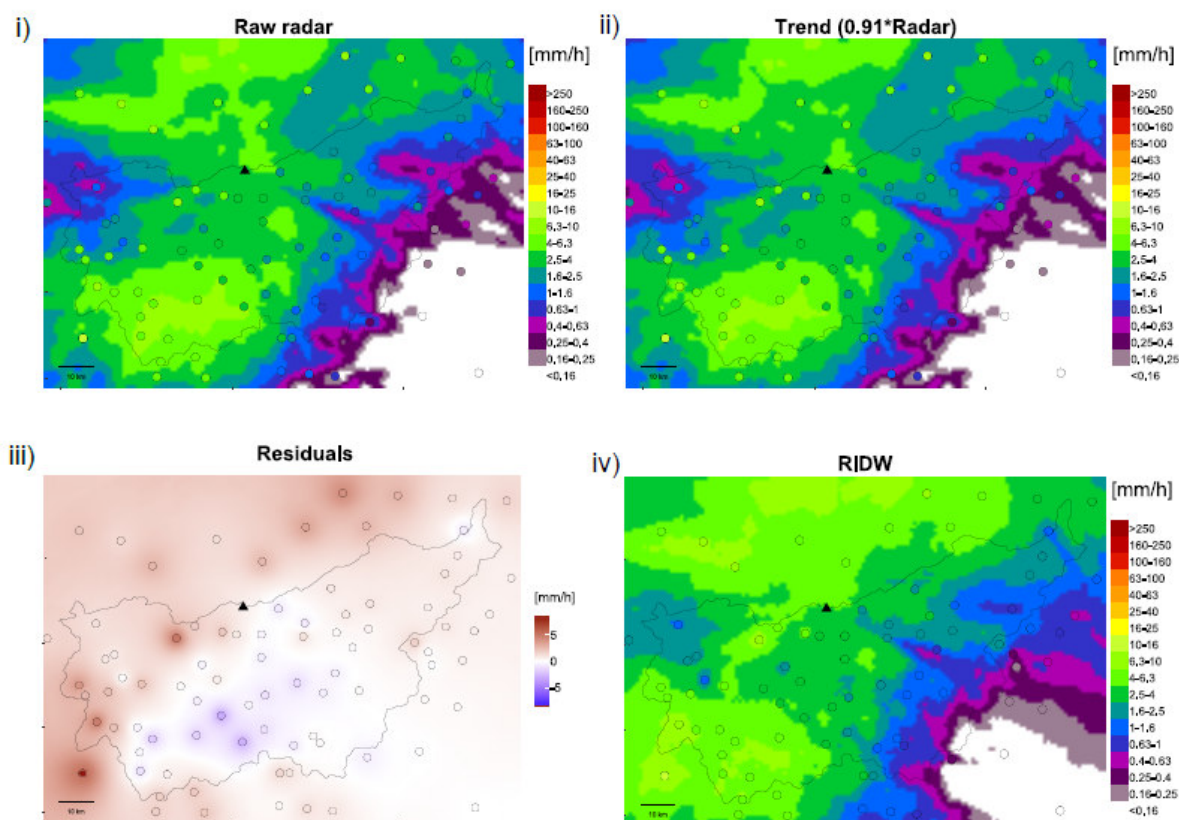


Figure 2 Différentes étapes dans l'interpolation spatiale des précipitations pour la méthode RIDW : la données radar (i) est dans un premier temps multipliée par un coefficient multiplicateur pour obtenir une tendance (ii) ; les résidus aux stations (valeur à la station - valeur du pixel) sont ensuite calculés et interpolés spatialement pour obtenir une carte de correction (iii) ; cette carte est additionnée à la tendance pour obtenir le résultat final (iv). Le triangle noir indique l'emplacement du radar de la Pointe de la Plaine Morte (PPM).

Pour les deux méthodes appliquant un krigeage pour l'interpolation des résidus, un variogramme (respectivement un modèle linéaire de co-régionalisation constitué de trois variogrammes pour la



méthode RCK) doivent être calculé automatiquement chaque heure (voir Foehn et al. 2018 pour les détails). De plus, une pré-transformation des données en amont de l'interpolation est explorée en considérant la racine carrée des valeurs (du radar et des pluviomètres). Cela permet de rapprocher la distribution des résidus d'une distribution Gaussienne, ce qui constitue l'une des hypothèses classiques pour l'application du krigeage (Erdin et al. 2012; Sideris et al. 2014). Les résultats avec et sans transformation sont évaluées pour estimer le gain d'une telle transformation.

Afin de comparer les méthodes entre elles, différents indicateurs de performance sont calculés avec une validation croisée, c'est-à-dire que les valeurs en chaque point de mesure sont estimées à partir de toutes les autres données (en excluant celle de l'emplacement calculé). Ainsi, le *Bias* permet d'identifier des erreurs systématiques. Le *Median absolute deviation* (MAD), le *Root Mean Square Error* (RMSE) et le *Mean-Root-Transformed Error* (MRTE) quantifient quant à eux l'erreur entre observations et estimations. Finalement, le *Scatter* fournit une mesure de la dispersion du ratio entre valeurs observées et estimées.

Ces indicateurs ont été calculés pour 4 événements de précipitation intense répartis entre 2014 et 2017. Trois événements supplémentaires, survenus entre 2012 et 2014, ont été également étudiés pour analyser le scénario avant l'installation du nouveau radar de la Pointe de la Plaine Morte (PPM).

2.2 Résultats

Les résultats suggèrent que l'utilisation du radar sans correction présente les moins bonnes performances (Figure 3), avec notamment des problèmes de biais importants. Les différences de performance entre les 4 autres méthodes sont moins élevées, avec cependant une tendance de la méthode RCK à présenter les meilleurs résultats. La méthode RCK permet d'ailleurs également d'obtenir de meilleures performances sur les 3 événements sans le nouveau radar (PPM), la rendant intéressante également pour le calcul de séries historiques, nécessaires pour une application hydrologique (résultats non présentés ici, voir Foehn et al. 2018 pour tous les résultats).

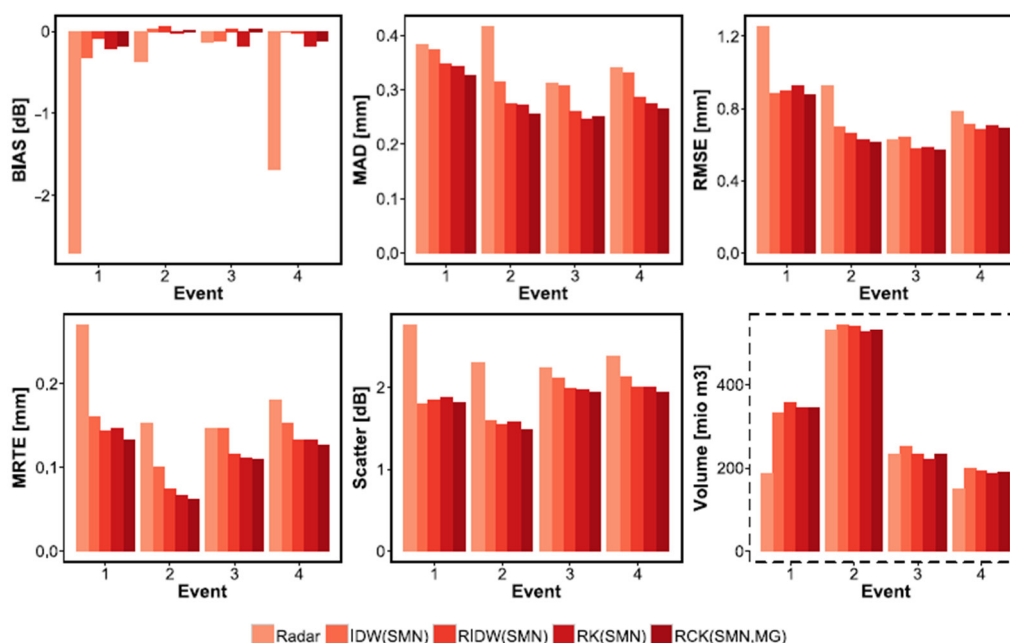


Figure 3 Indicateurs de performances pour les différentes méthodes d'interpolations obtenus pour les 4 événements analysés.

L'application d'une transformation des données avant l'interpolation permet de réduire le *Bias* sur les 4 événements étudiés. Pour les autres indicateurs, les différences étaient faibles voir quasi inexistantes.

L'analyse des résultats a également permis de mettre en évidence des zones de faible visibilité du radar. La plus évidente, en direction du sud-est, est bien visible sur la Figure 2. Cette zone d'ombre résulte de la présence du Mont Bonvin, culminant à une altitude de 2'994 m s.m., soit 68 m plus haut que l'altitude du radar. Avec un tel obstacle, la visibilité du radar dans cette direction ne peut être que limitée.

3 Correction de la sous-capture des précipitations solides et modélisation nivale

La méthodologie présentée au Chapitre 2 considère la mesure aux pluviomètres comme valeur de référence. Or, cette mesure souffre d'imprécision, même lorsqu'il s'agit de pluviomètres de haute qualité. Cela est particulièrement vrai lorsque les précipitations tombent sous forme solide. En effet, lorsqu'il neige, les particules sont beaucoup plus sujettes au transport par le vent, ce qui affecte la mesure. Une étude de l'OMM (Kochendorfer et al. 2017) a évalué à 34% la sous-capture des pluviomètres (« gauge undercatch », en anglais) sur 8 sites à travers le monde en comparaison avec des pluviomètres protégés par un bouclier contre les effets du vent. Ainsi, ce chapitre explore la correction des valeurs aux pluviomètres avant le calcul d'interpolation spatiale pour ensuite utiliser ces valeurs dans un modèle de neige. L'application de la correction au niveau de la mesure de la station permet de modifier uniquement les valeurs des stations auxquelles la précipitation est supposée solide (température inférieure à 2°C). Cela permet une correction plus ciblée qu'une application d'un facteur correcteur à l'ensemble d'une grille après interpolation. Dans la présente étude, des valeurs de



facteur correcteur de 1.2 et 1.3 ont été explorées. Ainsi, en plus des deux produits d'estimation quantitative des précipitations (QPE) *CombiPrecip* de MétéoSuisse, ci-après nommé QPE1, et le produit *RCK*, présentée au chapitre 2 et ci-après nommé QPE2, deux autres produits ont été calculé, avec respectivement les valeurs de 1.2 (QPE2-120) et 1.3 (QPE2-130). L'analyse se porte sur la période du 1^{er} octobre 2012 au 30 septembre 2018.

Afin de disposer de valeurs de température pour la modélisation, un produit spatialisé de température a également été calculé pour l'ensemble du territoire. Une surface 2D de température est calculée (chaque heure) à partir d'un modèle numérique de terrain transformé en température à l'aide d'une relation non-linéaire température-altitude. Un krigeage avec dérive externe utilisant cette surface 2D est ensuite appliqué pour considérer les particularités locales.

3.1 Modélisation de la neige

La modélisation de la quantité de neige est réalisée avec le modèle Snow-SD (version modifiée du modèle de neige proposé par Schaepli et al. 2005), disponible dans le logiciel RS MINERVE (Foehn et al. 2019b; García Hernández et al. 2019). Le modèle permet de simuler l'accumulation de neige ainsi que la fonte au travers d'un coefficient de fonte basé sur la température. Le modèle est calé en utilisant des données satellitaires de couverture neigeuse, le Normalized Difference Snow Index (NDSI) du radiospectromètre MODIS (Hall et al. 2002). La donnée satellitaire et la quantité de neige modélisée sont converties en séries binaires de présence/absence de neige en appliquant des seuils spécifiques. Ainsi, le coefficient de fonte de neige est calé pour reproduire au mieux avec le modèle la présence de neige définie par la donnée MODIS. L'indicateur *d'Overall Accuracy*, optimisant le nombre de cas correct de présence et absence de neige, est utilisé à cette fin (Parajka and Blöschl 2008). Le calage est réalisé pour 11 sites de mesures de l'Institut Suisse pour l'étude de la neige et des avalanches SLF, permettant une validation de l'équivalent en eau de la neige simulé par le modèle avec des valeurs in situ.

3.2 Pré-traitement des données

L'équivalent en eau de la neige simulé avec le modèle après calage permet une bonne reproduction des valeurs observées pour la plupart des sites étudiés. Cela n'est cependant pas le cas par exemple pour le site de mesure d'Egginer (4EG), et dans une moindre mesure de Saas-Fee (4SF), tous deux dans la vallée de Saas. L'analyse des résultats à démontrer qu'à partir de l'hiver 2014-2015, le modèle y sous-estimait fortement les valeurs observées. Cela correspond au premier hiver après à la mise en service du nouveau radar (PPM). Les séries de précipitation du produit radar pour ces deux emplacements ainsi que pour l'emplacement de la station SMN la plus proche (Saas-Balen) ont ainsi été extraites pour analyse. La Figure 4 présente la différence en termes de pluie cumulée entre les deux pixels contenant les sites SLF et le pixel contenant la station SMN. Un point de rupture y est évident en juin 2014. Avant cette date, le pixel contenant la station Saas-Balen reporte moins de précipitation que les 2 pixels contenant les sites 4EG et 4SF. Cette tendance est inversée après juin 2014. Une analyse des données du produit radar pour le pixel contenant la station SMN a révélé un gain important en visibilité du produit radar pour le pixel contenant la station SMN. Cela n'est pas le cas au-dessus des deux sites du SLF. Lors de la combinaison radar-stations, la meilleure visibilité au-dessus de Saas-Balen se traduit localement par une moins forte correction positive, alors que les deux pixels contenant les sites 4EG et 4SF nécessiteraient encore une telle correction. Cet exemple illustre bien les possibles difficultés liées à l'intégration de données radar dans l'interpolation des précipitations, cette donnée apportant une information essentielle sur la variabilité spatiale des précipitations, mais présentant également une variabilité spatiale en termes de qualité de l'information.



Ces deux emplacements ont été écartés de l'analyse au-delà de juin 2014, tout comme la station Morgins (sur toute la période d'analyse) en lien avec un problème de températures lié à la présence une partie de l'hiver d'un lac d'air froid dans la partie amont du bassin.

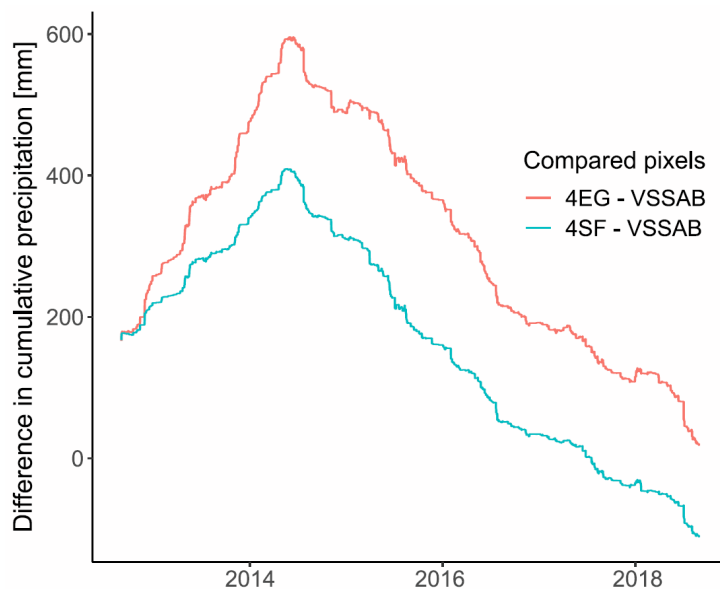


Figure 4 Différence de pluie cumulée (produit radar) entre les pixels contenant les deux sites de mesure du SLF avec les valeurs du pixel contenant la station SMN Saas-Balen. La rupture nette en juin 2014 correspond à la mise en service du radar de la Pointe de la Plaine Morte (PPM).

3.3 Résultats

Le modèle a été calé pour les 10 emplacements de mesure du SLF retenus et pour chacun des 4 produits de précipitation. Les valeurs du modèle sont comparées aux observations in situ (Figure 5). Les résultats suggèrent que les valeurs obtenues avec les deux produits QPE1 et QPE2 sous-estiment les valeurs observées (biais négatif), avec des valeurs de régressions linéaires de 0.71 et 0.85. Ces valeurs sont de 1.00 et 1.06 en utilisant respectivement les produits QPE2-120 et QPE2-130, suggérant une forte réduction du problème de biais.

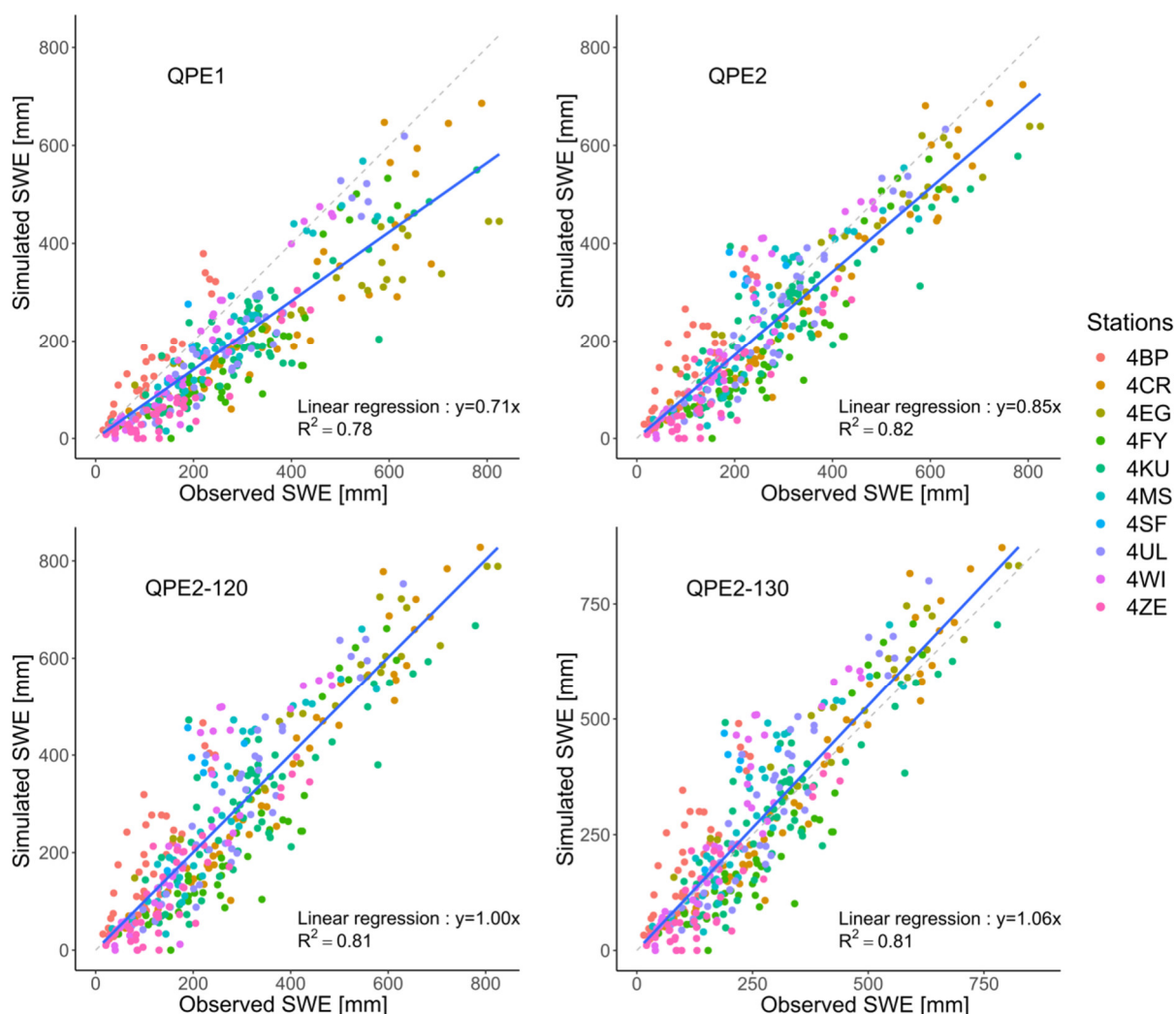


Figure 5 Valeurs d'équivalent en eau de la neige simulé par le modèle vs. valeurs observées in situ ; Chaque sous-graphique correspond à un produit de précipitation.

Il est intéressant de noter la différence entre les valeurs obtenues avec les produits QPE1 et QPE2, alors que localement la données d'entrée est identiques dans les deux cas et que la méthode de calcul est à priori également relativement semblable. La Figure 6 présente le même nuage de points que la partie QPE1 de la Figure 5, avec un code de couleur permettant de regrouper les valeurs en fonction de l'existence ou non du radar PPM au moment de la mesure. Cette distinction permet d'illustrer une nette sous-estimation, notamment des valeurs élevées d'équivalent en eau de la neige, avant l'installation du nouveau radar. Une telle différence n'existe pas avec le produit QPE2. Cela s'explique par le fait que le produit QPE1 est calculé pour l'ensemble du territoire national, alors que le produit QPE2 ne l'est qu'au niveau du bassin étudié. Avant l'installation du nouveau radar, le produit radar tendait globalement à fortement sous-estimer la précipitation en Valais. Avec une correction appliquée au niveau Suisse, cette sous-estimation n'est pas véritablement compensée. Avec le produit cantonal QPE2, la correction peut tenir compte du biais négatif sur l'ensemble du domaine étudié, éliminant ce problème de sous-estimation. Cet exemple illustre bien comment un produit non-biaisé sur l'ensemble du territoire, car issu d'un krigeage qui est un estimateur non-biaisé, peut présenter localement des biais non négligeables.

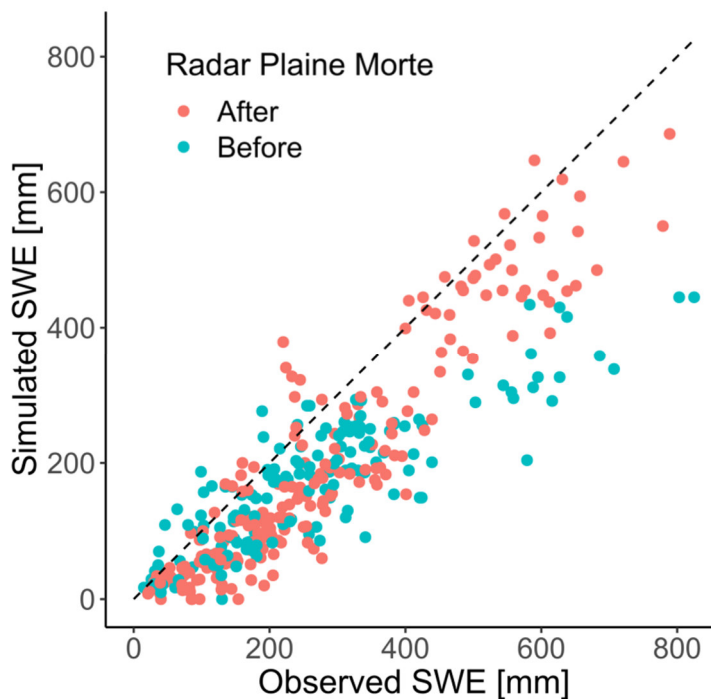


Figure 6 Valeurs d'équivalent en eau de la neige observées et simulées avec le produit QPE1 (CombiPrecip). Le code de couleur distingue les points en fonction du moment de la mesure par rapport à l'installation du radar de la Pointe de la Plaine Morte (PPM).

Finalement, l'erreur moyenne absolue a été calculée pour chacun des quatre produits de précipitation. L'erreur moyenne la plus faible ayant été obtenue avec le produit QPE2-120, ce produit a été retenu pour la suite de l'étude comme variante avec correction des précipitations solides.

3.4 Conclusions

L'intégration de coefficients correcteurs a permis de réduire la sous-estimation par un modèle de neige des valeurs mesurées in situ. Cependant, l'approche proposée considère des coefficients fixes et uniques pour toutes les stations. De futurs développements de la méthodologie devront considérer la vitesse du vent au moment de la mesure au travers de « fonctions de transfert » (Kochendorfer et al. 2017) pour obtenir une correction plus adéquate.



4 Modélisation hydrologique

Dans une perspective de prévision de crues à l'ensemble du bassin, l'approche du calage basé sur MODIS a été appliquée sur trois bassins équipés de stations hydrométriques de l'Office Fédéral de l'Environnement (la Grande-Eau à l'amont d'Aigle, la Lonza à l'amont de Ferden et la Saltina à l'amont de Brig). Les modèles hydrologiques SOCONT et GSM (Schaeffli et al. 2005 ; Hamdi et al. 2005) sont utilisés respectivement pour la modélisation des parties non-glaciaires et glaciaires. Le calage est réalisé en deux phases : dans un premier temps, les coefficients degré-jour de fonte nivale sont déterminés pour tous les pixels avant d'être agrégés sur les entités spatiales du modèle semi-distribué (bandes d'altitude d'environ 400 mètres d'altitude) ; dans un second temps, les autres paramètres du modèle hydrologique sont calés sur la base de données de débit. En parallèle, le modèle est également calé avec une approche conventionnelle basée uniquement sur les données de débit.

De plus, les performances hydrologiques sont comparées en calant le modèle avec différents produits de précipitation. D'une part, deux jeux de données sont constitués de valeurs aux pluviomètres : (i) le réseau SMN et (ii) le réseau SMN couplé au réseau MG (sans distinction). D'autre part, trois produits spatialisés sont considérés : (i) le produit CombiPrecip de MétéoSuisse (QPE1) ; (ii) le produit QPE2 calculé avec la méthode RCK présentée au Chapitre 2 ; (iii) le produit QPE2-120 présenté dans le Chapitre 3.

Le calage est réalisé sur la période 2014 - 2018 et la validation sur la période 2012-2014 (dans les deux cas de début septembre à fin août). Cette division tient compte de l'installation du radar PPM en juin 2014. Le calage hydrologique est réalisé avec l'indicateur de performance Kling-Gupta Efficiency (Kling et al. 2012).

4.1 Différence de cumul de précipitation

Avant intégration dans le modèle hydrologique des différents produits de précipitation, les cumuls par produit sur chaque bassin ont été comparés. Considérant le jeu de données avec le réseau SMN comme référence (100%), l'intégration des stations Meteogroup (jeu de données SMN+MG) confirme l'introduction d'un biais négatif avec des valeurs de cumuls variant entre 92.1% et 97.1% de SMN (en considérant indépendamment les 3 bassins et les périodes de calage et de validation). Pour les produits spatialisés, il est à nouveau intéressant de comparer les valeurs entre QPE1 et QPE2. Sur la période de calage (correspondant à la période après l'installation du radar PPM), les cumuls diffèrent peu entre les deux produits avec 103 et 107% respectivement pour QPE1 et QPE2 sur le bassin de Saltina, 92 et 90% pour Lonza et 89 et 89% pour Grande-Eau. Il en est autrement sur la période de validation, avec respectivement 100 et 126% pour Saltina, 97 et 120% pour Lonza et 84 et 105% pour Grande-Eau. Les valeurs bien supérieures de QPE2 par rapport à QPE1 s'expliquent de la même manière que pour l'observation réalisée sur la Figure 6, avec une correction de la sous-estimation du radar sur le bassin plus importante lors d'une correction locale (QPE2) par rapport à une correction réalisée sur l'ensemble de la Suisse (QPE1).

4.2 Résultats

Le modèle hydrologique des trois bassins a été calé considérant les différents jeux de données d'entrée et les deux approches de calage (conventionnelle et en 2 phases).



Du point de vue du calage du modèle de neige, la Figure 7 illustre les valeurs obtenues par pixel sur le bassin de la Grande-Eau. Il est facilement observable que les pentes orientées sud tendent à présenter des valeurs légèrement supérieures aux pentes orientées nord. Les valeurs aux pixels sont ensuite agrégées par bande d'altitude pour fournir les valeurs utilisées dans le modèle.

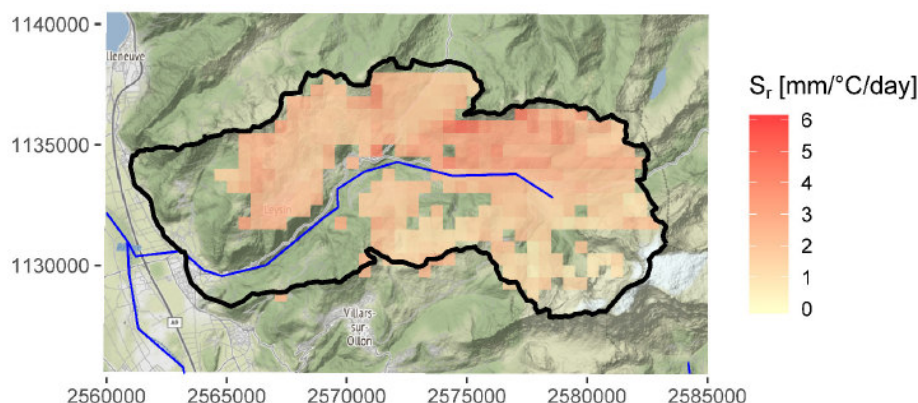


Figure 7 Valeurs du coefficient degré-jour obtenues pour le bassin de la Grande-Eau. Seules les valeurs de pixels ayant obtenu une valeur d'Overall Accuracy supérieure à un seuil dépendant de l'enneigement annuel du pixel sont affichées. Image d'arrière-plan: map tiles by Stamen Design, under CC BY 3.0. Data by OpenStreetMap, under ODbL.

D'un point de vue hydrologique, le calage en deux phases n'a pas permis de véritable amélioration des performances par rapport au calage conventionnel, du moins pour la période de calage. Sur la période de validation, certains des indicateurs de performance ont obtenu leur meilleure valeur pour des configurations considérant le calage en deux phases. Pour le bassin de la Saltina, avec la meilleure visibilité radar parmi les trois bassins étudiés, les meilleures performances sont obtenues avec le produit QPE2-120. Dans le cas de la Lonza, avec une visibilité légèrement moins bonne, le produit QPE2-120 est égalé par le jeu de données des valeurs SMN. Pour le moins bon scénario de visibilité étudié (Grande-Eau), les meilleures performances sont obtenues avec le jeu de données des valeurs SMN. On observe donc que l'intérêt d'un produit spatialisé basé sur l'image radar semble dépendre de la qualité du produit radar avant correction. De futures améliorations du produit radar semblent donc encore nécessaires avant de pouvoir obtenir un produit spatialisé de précipitation de haute qualité pour l'ensemble du territoire.

4.3 Conclusions

L'analyse réalisée dans ce chapitre n'a pas permis d'identifier un produit de précipitation menant aux meilleures performances pour l'ensemble des trois bassins étudiés, celle-ci dépendant de la qualité du produit radar sur chaque bassin. En outre, le calage en deux phases n'a pas permis de surpasser en performance un calage conventionnel. L'utilisation d'un indicateur de performance plus complexe ainsi qu'un meilleur filtrage selon la performance des pixels retenus pour l'agrégation ont été identifiés comme développement futurs.



5 Assimilation de données

La dernière partie du projet avait pour objectif d'élaborer et implémenter une méthodologie d'assimilation de données de débit afin d'améliorer la qualité des prévisions hydrologiques. Le but est d'améliorer les conditions initiales utilisées pour la prévision afin qu'elles soient le plus adéquates possibles. Le système MINERVE dispose déjà d'une routine adaptant la saturation en eau du sol du modèle sur la base d'une comparaison entre volume simulé et volume observé sur les 24 heures précédant la prévision (Jordan 2007). L'objectif est de proposer une méthode plus élaborée en adaptant non seulement la saturation du sol mais plus largement les variables d'état pertinentes.

Pour ce faire, le choix s'est porté sur l'implémentation d'un filtre de Kalman d'ensemble (Evensen 1994). La méthode est basée sur une approche ensembliste, c'est-à-dire qu'un certain nombre d'itérations du modèle sont simulées en parallèle, ce qui permet d'obtenir un échantillon des valeurs possibles des variables d'état. Une analyse de covariance permet ensuite de corriger les membres sur la base d'une pondération des erreurs du modèle et des erreurs associées aux observations. Pour assurer une certaine divergence entre les membres, les données d'entrée sont aussi perturbées. Pour les précipitations, cette perturbation est multiplicative et suit une distribution log-normale avec une médiane à 1, alors que pour les températures, elle est additive et suit une distribution normale centrée en 0. En outre, les observations de débit sont également perturbées, ce qui permet de considérer l'incertitude dans la donnée d'observation. Finalement, les conditions initiales lors de la première itération sont distribuées selon une distribution normale, afin de générer une distribution initiale des membres.

La méthodologie a été implémentée dans le langage et environnement R (R Core team 2018) pour interagir avec le logiciel RS MINERVE (Foehn et al. 2019b ; García Hernández et al. 2019). La méthodologie a été appliquée sur deux événements récents de fortes précipitations, l'un en juin 2019 sur le bassin du Rhône à l'amont de la station hydrométrique de Reckingen, l'autre en mai 2015 sur le bassin de la Grande-Eau à l'amont d'Aigle.

Dans les résultats, trois scénarios sont présentés : *Control* correspond au scénario de référence sans aucune mise à jour du modèle; *VBU (Volume Based Update)* correspond à la mise à jour opérationnelle basée sur le volume des 24 dernières heures ; *EnKF (Ensemble Kalman Filter)* correspond à la nouvelle méthode implémentée.

Pour l'évaluation de l'erreur, le Root Mean Square Error (RMSE) pour chaque heure de prévision moyenné sur toutes les prévisions est calculé.

5.1 Résultats

La Figure 8 présente un exemple de prévision hydrologique pour 72 heures selon les différentes approches de mise à jour. La correction par la méthode EnKF y est relativement importante, avec un décrochement marqué de la courbe entre la phase d'assimilation et celle de prévision.

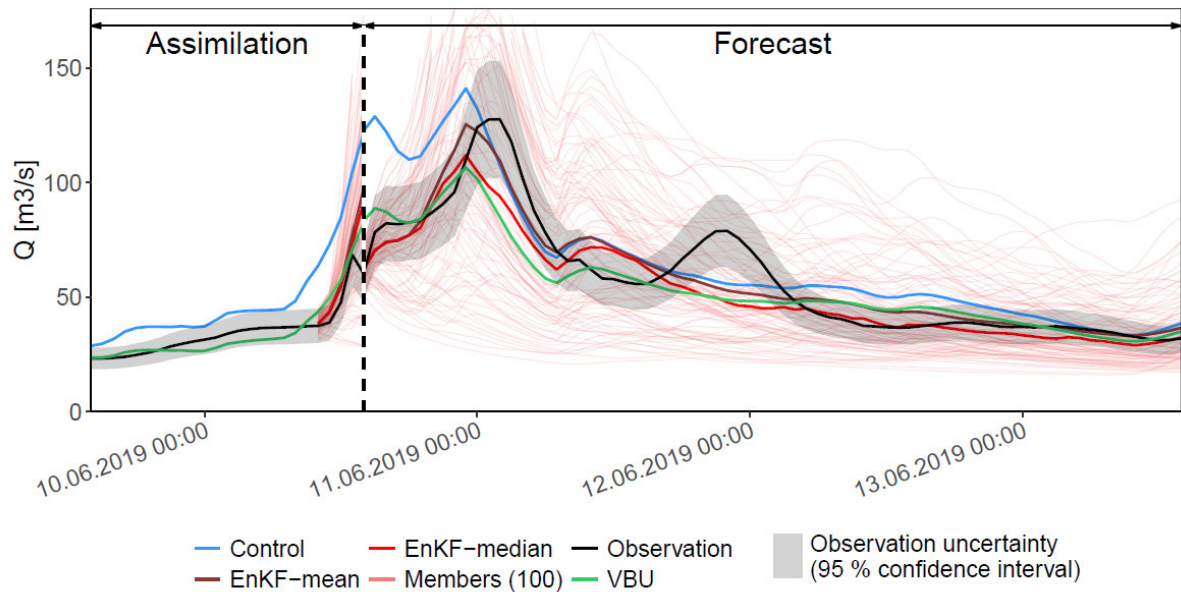


Figure 8 Prévisions hydrologiques pour le Rhône à la station de Reckingen selon les trois différentes approches. Le traitillé vertical correspond au 10-06-2019T14+01:00. Les traits roses (légers) correspondent aux 100 membres. La zone grise autour du débit observé correspond à l'intervalle de confiance de 95% selon l'incertitude attribuée aux données de débit.

Du point de vue des performances globales sur l'événement, EnKF-median fournit la valeur de RMSE la plus faible sur tout l'horizon de prévision (Figure 9). Cela est particulièrement vrai pour les premières heures de prévision, la correction étant réalisée sur la base de la dernière observation disponible et celle-ci modifiant par exemple également le débit dans les tronçons de rivières du modèle (effet limité dans le temps).

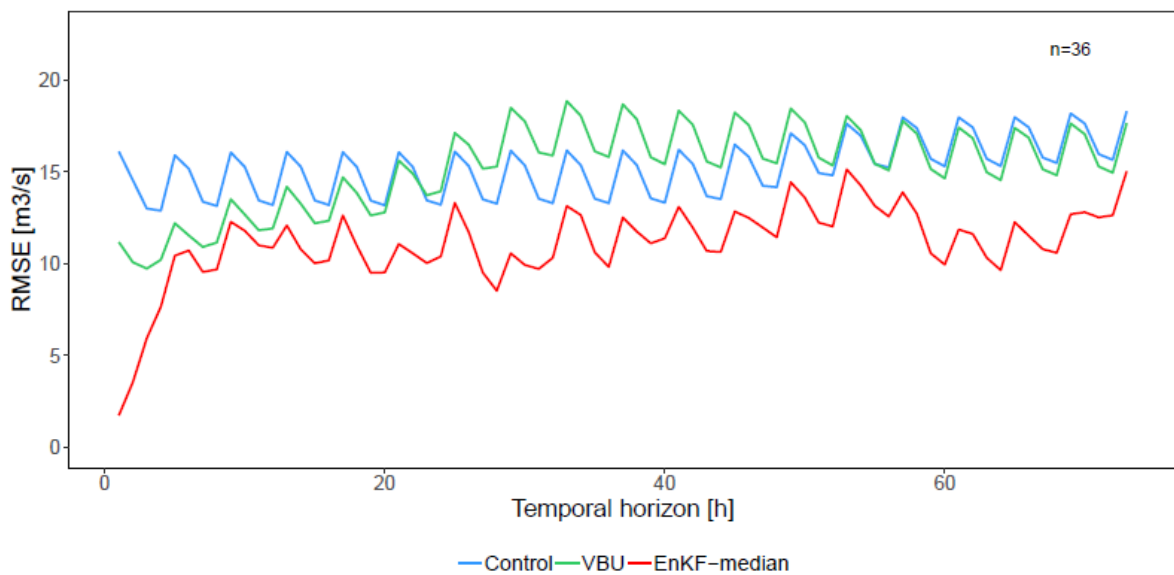


Figure 9 Valeurs de RMSE obtenues pour les trois approches sur l'ensemble de l'événement de juin 2019 sur le Rhône à Reckingen (moyenne sur 36 prévisions).



Afin d'évaluer la performance également sur le débit de base (sans crue), la même analyse a été réalisée sur les 4 jours précédant la crue. Dans ce cas, l'EnKF fournit toujours les meilleures performances sur la première journée de prévision. Pour des horizons de prévision supérieurs, l'erreur tend cependant à être plus élevée qu'avec les deux autres approches. Avec des cycles de débit journaliers marqués et une analyse de l'EnKF basé uniquement sur la dernière valeur de débit disponible, des décalages temporels même faibles du débit simulé peuvent se traduire par des adaptations des variables d'état inadaptées. Cela illustre l'importance d'un bon calage du modèle autant pour les faibles que les hauts débits pour l'application d'une méthode d'assimilation de données tel qu'un filtre de Kalman d'ensemble.

Dans le cas de la crue de mai 2015 sur la Grande-Eau, un autre problème a pu être mis en évidence. En effet, la Grande-Eau reçoit les eaux d'un réservoir situé à l'extérieur du bassin hydrologique, dont les données ne sont pas disponibles pour la modélisation. Cette contribution, qui peut dépasser 50% du débit de base naturel, impacte directement les performances des deux méthodes d'assimilation de données (VBU et EnKF) en menant à une forte surestimation de la crue à cause d'une hausse artificielle de la saturation en eau du sol. Cet exemple illustre l'importance de disposer des valeurs de débit turbiné avant de pouvoir implémenter une méthode tel qu'un filtre de Kalman d'ensemble dans des bassins perturbés par des activités hydroélectriques.

6 Conclusions

La prévision hydrologique en milieu alpin reste un défi important malgré l'amélioration continue des données à disposition. Le projet de doctorat présenté ci-dessus a notamment permis l'élaboration d'une méthodologie de spatialisation des précipitations incluant une correction pour les précipitations solides avant interpolation. Cela constitue une première étape vers un développement futur intégrant également des vitesses du vent pour une correction plus fines des précipitations solides.

Les résultats présentés suggèrent que d'un point de vue hydrologique, l'intégration de données radar dans la donnée de précipitation n'apporte une plus-value que si la visibilité du radar sur le bassin étudié est suffisamment bonne. Les estimations radar devront donc à l'avenir encore être améliorées avant que les produits spatialisés de précipitation combinant radar et valeurs de stations ne puissent être considérés comme une alternative évidente à l'interpolation des valeurs aux stations. De plus, avec un nombre croissant de source de données disponibles, le choix de la meilleure combinaison implique une analyse comparative approfondie.

L'implémentation d'un filtre de Kalman d'ensemble fournissant des résultats prometteurs a également montré l'importance d'un bon calage pour les débits à la fois faibles et élevés, ainsi que celle de l'accès aux données de turbinage pour un système de prévision des crues, sans quoi des méthodes avancées tel que filtre de Kalman d'ensemble ne semblent pas être des solutions adaptées.

Les différents axes de recherches développés dans le cadre de ce travail constituent des outils essentiels pour une meilleure gestion des crues et permettront également à l'avenir, au travers d'une meilleure quantification de la ressource en eau, une meilleure gestion de l'approvisionnement, que cela soit pour la force hydraulique ou pour d'autres utilisations de l'eau.



7 Publications

A. **Foehn**, J. García Hernández, B. Schaefli, G. De Cesare, and A. J. Schleiss. Spatialization of precipitation data for flood forecasting applied to the Upper Rhone River basin. International Conference Hydro 2016, Montreux, Switzerland, 10-12 October **2016**.

A. **Foehn**, J. García Hernández, S. Alesina, A. J. Schleiss, and J. Fluixá Sanmartín. Los desafíos de la modelización hidrológica y la previsión de crecidas en tiempo real en alta montaña. XXVII Congreso Latinoamericano de Hidráulica -LADHI. International Association of Hydraulic Engineering and Research, IAHR, 28-30 September **2016**, Lima, Peru. ID113, 3421-3430.

A. **Foehn**, J. García Hernández, B. Schaefli, and G. De Cesare. Spatial interpolation of precipitation from multiple rain gauge networks and weather radar data for operational applications in Alpine catchments. *Journal of Hydrology*, 563:1092–1110, **2018**. ISSN 00221694. doi:10.1016/j.jhydrol.2018.05.027.

J. García Hernández, A. **Foehn**, J. Fluixá-Sanmartín, B. Roquier. El sistema MINERVE para la modelización de crecidas en el Canton de Valais en Suiza: análisis de la cuenca de Grande-Eau. Presented at the XX Congreso Nacional de ingeniería civil, 23-27 April **2018**, Lima, Peru.

A. **Foehn**, J. García Hernández, G. De Cesare, and J. Fluixá Sanmartín. Amélioration du calage du modèle hydrologique du bassin de la grande-eau en suisse avec des produits spatialisés de précipitation, température et couverture de neige. International Conference De la prévision des crues à la gestion de crise, Avignon, 14-16 Novembre **2018**, Société hydrotechnique de France.

A. **Foehn**, A. Schwob, D. Pasetto, J. García Hernández, and G. De Cesare. Application of an Ensemble Kalman filter to a semi-distributed hydrological flood forecasting system in alpine catchments. SimHydro 2019 Conference. Sophia Antipolis, France, 12-14 June **2019**.

A. **Foehn**, J. García Hernández, B. Schaefli, G. De Cesare and A. Rinaldo. Accounting for solid precipitation gauge undercatch in quantitative precipitation estimates for snow modelling in Alpine catchments. *Journal of Hydrometeorology*, [**under review**].



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9 Annexes – Principales publications



Spatial interpolation of precipitation from multiple rain gauge networks and weather radar data for operational applications in Alpine catchments

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ABSTRACT

Increasing meteorological data availability and quality implies an adaptation of the interpolation methods for data combination. In this paper, we propose a new method to efficiently combine weather radar data with data from two heated rain gauge networks of different quality. The two networks being non-collocated (no common location between the two networks), pseudo cross-variograms are used to compute the linear model of coregionalization for kriging computation. This allows considering the two networks independently in a co-kriging approach. The methodology is applied to the Upper Rhône River basin, an Alpine catchment in Switzerland with a complex topography and an area of about 5300 km². The analysis explores the newly proposed Regression co-kriging approach, in which two independent rain gauge networks are considered as primary and secondary kriging variables. Regression co-kriging is compared to four other methods, including the commonly applied Inverse distance weighting method used as baseline scenario. Incorporation of additional networks located within and around the target region in the interpolation computation is also explored. The results firstly demonstrate the added value of the radar information as compared to using only ground stations. As compared to Regression kriging using only the network of highest quality, the Regression co-kriging method using both networks slightly increases the performance. A key outcome of the study is that Regression co-kriging performs better than Inverse distance weighting even for the data availability scenario when the radar network was providing lower quality radar data over the studied basin. The results and discussion underline that combining meteorological information from different rain gauge networks with different equipments remains challenging for operational purposes. Future research in this field should in particular focus on additional pre-processing of the radar data to account for example for areas of low visibility of the weather radars due to the topography.

1. Introduction

In Switzerland, severe flooding events in recent decades have increased the need for reliable forecasting systems to mitigate flood effects. In 1999, the research project MINERVE (Jordan, 2007a,b; Jordan et al., 2010; Jordan et al., 2012; García Hernández et al., 2007, 2009; García Hernández, 2011a,b; Bérod, 2013) was initiated with the objective of developing a flood forecasting and management system for the Upper Rhône River basin upstream of Lake Geneva (Hingray et al., 2010; Foehn et al., 2016). After the major flood of October 2000 in the Canton of Valais (Switzerland), the need for such a system has increased and since 2013, a forecasting system is operational for the entire basin and used as a tool for decision-making tasks (García Hernández et al., 2014).

Since the beginning of the forecasting system development, enhancing the estimation of the spatial precipitation distribution has been identified as essential (Jordan, 2007a; García Hernández, 2011a; Tobin, 2012). Indeed, to accurately predict flooding induced by heavy precipitation, it is crucial to estimate with good accuracy the causative precipitation (Sikorska and Seibert, 2018). Two main data sources are usually considered: rain gauges (point observations) and weather radars (spatial information). Combining these two data types has been shown to produce improved precipitation estimates (Foehn et al., 2016; Sideris et al., 2014a; Goudenhoofd and Delobbe, 2009; Jewell and Gausiat, 2015) for flood forecasting and hydrological modelling in general.

Rain gauges provide direct precipitation measurements which can be fairly accurate; but point observations are heterogeneously distributed over the domain and typically do not cover the entire elevation

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range of Alpine basins. They are also subject to various sources of error and uncertainty (Villarini and Krajewski, 2010; Ceginati et al., 2017a), such as wind-induced measurement errors (Nešpor and Sevruck, 1999), evaporation and wetting errors (Upton and Rahimi, 2003) or heating-related losses for heated tipping-buckets (Savina et al., 2012). In addition, rain gauge values have to be considered to be spatially representative of their surrounding area, which is a strong hypothesis, in particular for short-time scales (Ciach and Krajewski, 1999; Villarini et al., 2008).

Weather radars, alternatively, provide a better spatial coverage but require a relatively sophisticated post-treatment of the signal back-scattered by the precipitation particles and are subject to significant bias and many sources of error (Germann et al., 2006; Germann et al., 2009; Berne and Krajewski, 2013). Radar estimates are in general well correlated both in space and time with rain gauge data, particularly for long accumulation periods but this correlation tends to decrease for sub-hourly accumulation periods (Sideris et al., 2014a).

A wide range of precipitation interpolation methods has been proposed in the literature for rain gauge data interpolation or radar-gauge combination, from rather simplistic methods such as Thiessen polygons (Thiessen, 1911) or Inverse distance weighting (Shepard, 1968) to more sophisticated methods such as simple and multiple linear regressions (Di Piazza et al., 2011), copulas (Vogl et al., 2012) and the wide range of geostatistical methods (Creutin et al., 1988). Univariate geostatistical methods (e.g. simple or ordinary kriging) generally tend to smooth the interpolated variable and therefore struggle to accurately reproduce spatial variability. Multivariate geostatistical methods use additional spatial information from either static (e.g. elevation) or dynamic (e.g. weather radar) covariates to improve the interpolation performance (Wagner et al., 2012). Different approaches of multivariate geostatistics applied to precipitations have been explored in the literature, including Kriging with external drift (KED) (Cantet, 2017), Co-kriging (Goovaerts, 2000), Conditional merging (Ehret, 2003) or Bayesian kriging (Verdin et al., 2015). Ly et al. (2013) propose a methods review for spatial interpolation of daily rainfall data for hydrological modelling at the catchment scale.

Regarding possible covariates (additional information), only few studies really focused on multivariate interpolation of hourly precipitation over Alpine catchments. Schiemann et al. (2011) showed that applying KED to hourly rain gauges and radar data over entire Switzerland performs better than interpolated rain gauge data or radar data alone. For flatter areas, Haberlandt (2007) has shown over the Elbe basin, in Germany, that for hourly precipitation, the most important additional information was the radar, followed by daily precipitation observations of a denser network with lower temporal resolution, and finally the elevation, which was considered “to play only a secondary role” in the studied case. Goovaerts (2000) reported that incorporating elevation can improve spatial interpolation of monthly and yearly rainfall when applied to a basin in Southern Portugal. Ly et al. (2011) analyzed the integration of elevation in KED and Ordinary Co-kriging and concluded that it did not improve the interpolation accuracy for daily rainfall over a basin in Belgium. These observations tend to agree with Bárdossy and Pegram (2013), who found over three regions in Germany that “correlation between precipitation and topography increases with the length of time interval”. Sikorska and Seibert (2018) showed that radar-based daily precipitation estimates, adjusted to precipitation rates from ground stations, provided better flood predictions as compared to using only rain gauges observations.

Sideris et al. (2014a) proposed a methodology applied in Switzerland in which rain gauges were combined with weather radar data using data from the time step of interpolation as well as from the preceding time step (as secondary co-kriged variable) in a co-kriging with external drift (CED) approach. Comparing their spatio-temporal method with a classical KED approach, they concluded that the skill scores were similar when considering an aggregation time of 60 min. However, for shorter aggregation periods (10–30 min), CED resulted in higher

performance values than KED. This methodology is used for the computation of the *CombiPrecip* product (MeteoSwiss, 2014a), the operational hourly spatialized precipitation product of the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss).

Numerical weather forecasts can also represent an alternative covariate. Tobin et al. (2011) have applied KED for interpolation of precipitation and temperature in Switzerland using (i) elevation and (ii) the COSMO7 weather forecast product of MeteoSwiss (MeteoSwiss, 2017). Whereas temperature measurements were found to be “strongly correlated with the closest COSMO7 grid point” at an hourly time step, good correlation between measurements and COSMO7 estimates was observed for precipitation only for “cumulative data over the event”. Tobin et al. (2011) thus proposed to use an event averaged linear drift for precipitation interpolation. Compared to Inverse distance weighting (IDW) and Ordinary kriging (OK), KED with elevation tended to produce the least biased estimation in their study. In terms of error, OK and both KED methods using elevation and the COSMO7 data had similar scores and outperformed IDW. However, when looking only at stations above 1500 m asl., KED with COSMO7 showed the highest error for their case study in Switzerland.

Covariates can also be processed before being used in combination with rain gauge data. Berndt et al. (2014) showed that smoothing radar data both spatially with the adjacent cells or/and temporally over several time steps improved the performance of merging rain gauges and radar data. Instead of always using the radar pixel containing a rain gauge, Sideris et al. (2014b) incorporated in the *CombiPrecip* product a convection control routine, in which the coefficient of dispersion over the 25 pixels around the rain gauge pixel is computed. When a certain threshold is exceeded, the value of the pixel with the closest value to the rain gauge within the 25 pixels is used for the merging.

Commercial microwave link networks have also been explored over the last decade as a supplementary source of precipitation data (Messner et al., 2006). Hydrological applications show a great potential of this approach, in particular in poorly equipped areas (Smiatek et al., 2017).

Besides providing a reliable radar-rain gauge combination for the target region, the objective of this paper is to assess in detail what gain can be expected from combining the most recent radar data for precipitation interpolation with rain gauge data from two ground-based networks of different data quality. This includes a comparison to the commonly used deterministic Inverse distance weighting method applied to rain gauge data as baseline scenario. Another key question is the quality of the radar-gauge combination methodology if applied to the data situation prevailing before the installation of a new weather radar covering the studied basin in 2014. Using the data from the already existing other Swiss weather radars, such an application allows computing series over a longer time period which is required for hydrological modelling purposes. Finally, the paper also aims at analyzing the effect of incorporating additional station networks located within and around the target region in the interpolation computation.

2. Study region and data

2.1. Hydrological basin

The studied area corresponds to the Upper Rhône river basin, defined as the hydrological basin between the Rhône Glacier (on the east) and Lake Geneva (on the west). The area is 5351 km² (Fig. 1) and the elevation varies from 372 m asl. at the outlet to 4634 m asl. on the top of the Dufourspitze, with a mean elevation of 2158 m asl. (Fig. S.1 in Supplementary material). The area above 3000 m asl. represents 13.0% of the area, whereas the part above 4000 m asl. only covers 0.3% of the total area. The glacierized area has been estimated to 569.2 km² in 2010 (Fischer et al., 2015), which corresponds to about 10.6% of the total area.

Yearly precipitation intensities are spatially variable over the basin. The yearly average over the period 1981–2010 is of 603 mm for the

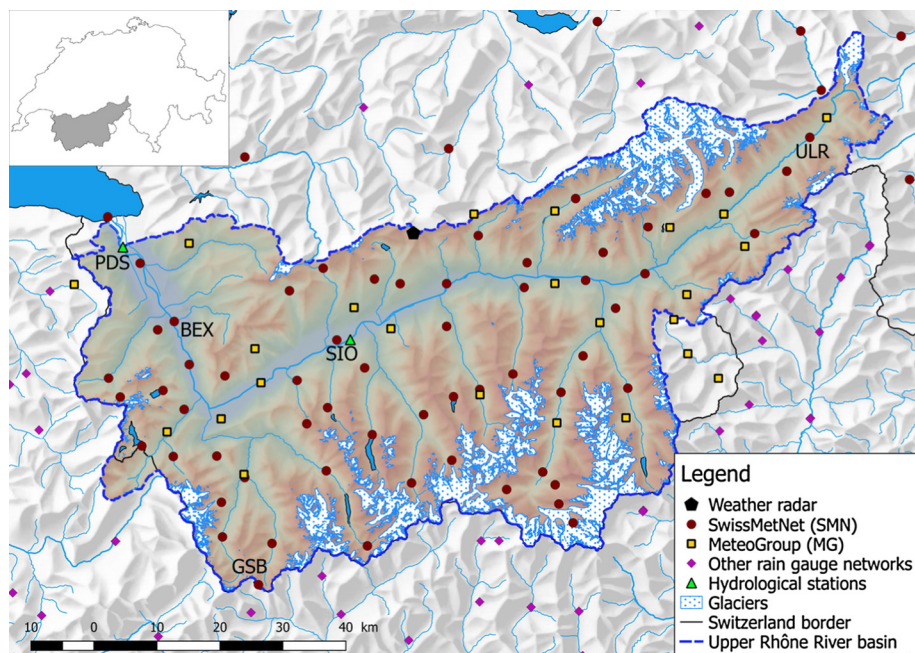


Fig. 1. Location of the MeteoSwiss, MeteoGroup and surrounding meteorological networks, as well as the Pointe de la Plaine Morte weather radar and a selection of hydrological stations. Abbreviations indicate the MeteoSwiss stations Sion (SIO), Col du Grand St-Bernard (GSB), Bex (BEX) and Ulrichen (ULR) as well as the hydrological stations Sion (SIO) and Porte du Scex (PDS). Glaciers and principal rivers are also shown. (Topographic data source: Swisstopo (2017a) for rivers and lakes, Swisstopo (2013) for the glaciers (with modifications), Swisstopo (2005) for the DEM, Swisstopo (2012) for the relief and Swisstopo (2017b) for the national boundary line).

station Sion (SIO), at 482 m asl. and located near the center of the basin (Fig. 1), whereas the station at Col du Grand St-Bernard (GSB), on the south-western border and situated at 2472 m asl., reported an average of 2368 mm per year over the same period (MeteoSwiss, 2014b). Precipitation is observed all year long, with a monthly average minimum and maximum of 35 mm (April) to 64 mm (December) for SIO and 135 mm (July) to 248 mm (November) for GSB. Depending on the elevation, the solid precipitation fraction can represent a significant proportion of the annual precipitation.

2.2. Rain gauges data within the basin

Several networks of rain gauges are available within the basin, but only the two networks with heated rain gauges have been considered for this study, in order to make the methodology applicable all year round. The first one is the SwissMetNet (MeteoSwiss, 2016a) network of MeteoSwiss, hereafter referred as SMN. The SMN data are based on reliable equipment and subject to a serious quality control (Musa et al., 2003). On July 1st, 2013, 40 SMN stations were operational within the basin. This number had increased to 58 on March 1st, 2017, which represents an average area per station of 92 km², which makes it a particularly dense network. As a comparison, on the same date, the Swiss average was 168 km² per station and values reported by other authors tend to be higher: about 571 km² per station in Germany (Berndt et al., 2014) or 135 km² in the Wallon region, where Goudenhoofd and Delobbe (2009) described the network as “dense”. A complete list of used SMN stations is given in Tables S.1 and S.2 (Supp. Mat.).

For the analysis, all available stations have been considered in each event, regardless whether the station was available or not for the other events. This implies that the number of stations considered for the computation increases over the events between 2012 and 2017. Table 1 lists the equipment used in the different networks (MeteoSwiss, 2015) and the number of stations.

The second network is composed of 23 stations of the private company MeteoGroup Switzerland AG, hereafter referred as MG. More stations of this network are available within the basin, but data from only 23 stations were available for the present study, which have been selected to supplement SMN stations over uncovered areas. A complete list of used MG stations is given in Table S.3 (Supp. Mat.).

Combined with the SMN stations, the average area per station over the basin drops to 66 km². The elevation range is 381–2472 m asl. for the SMN stations and 460–2347 m. asl for the MG stations, with median elevations of respectively 1537 and 1365 m. asl.

The analysis of the data has shown a tendency of MG stations to report less precipitation than the SMN stations, with differences largely exceeding 20% for some hourly time steps. Similar observations had been made by MeteoSwiss when comparing their manual daily precipitation measurements with automatic observations from MeteoGroup stations (J. Fislser, MeteoSwiss, personal communication, January 9, 2017). In the field intercomparison of rain intensity gauges realized by Vuerich et al. (2009) for the account of the World Meteorological Organization (WMO), all three concerned station types, or their predecessor (for the OTT equipment), had been tested (Lanza and Vuerich, 2009). The stations used by MeteoSwiss were evaluated as “satisfactory” (Lambrecht) and “very good” (OTT), whereas the stations installed by MeteoGroup (Davis) were evaluated as “insufficient”. Based on these conclusions, the SMN stations have been defined for this study as being the “primary” network and the MG stations as the “secondary” network. This distinction will be considered when using data from both networks. It is worth mentioning here that neither the MeteoSwiss nor the MeteoGroup station data are corrected for undercatch of solid precipitation, which is known to have an effect on solid precipitation intensity estimation in mountainous regions (Egli et al., 2009).

2.3. Rain gauges data around the basin

In addition to the presented two networks located within the basin (81 stations) and their 12 stations located around the basin (Table 1), 62 stations of networks located around the basin and equipped with heated rain gauges have been considered (Table 1). This additional information allows a better estimation at the border of the basin as well as a more correct estimation of the precipitation fields for example in the southern neighbouring area. This is important as more than half of the meteorological situations having produced more than 110 mm/d of precipitation over 3 days in the Upper Valais since 1975 have originated from souths according to Attinger and Fallot (2003), as cited in Tobin et al. (2011).

Table 1List of considered rain gauge networks and respective characteristics. Number of stations for MeteoSwiss refers to March 1st, 2017.

Network	Number of stations	Location	Sensor model	Period
SwissMetNet (SMN)	17 (+9)	Basin (+ neighbouring cantons)	1518 H3 and 15188 by Lambrecht (tipping bucket)	2012–2017
SwissMetNet (SMN)	41 (+2)	Basin (+ neighbouring cantons)	Pluvio ² by Ott (weighing principle)	2012–2017
MeteoGroup (MG)	23 (+1)	Basin (+ France)	Rain Collector II by Davis (tipping bucket)	2012–2017
Kanton Bern	11	Bern (Switzerland)	Unknown (heated)	2012–2017
MeteoFrance	5	France	Unknown (heated)	2012–2017
EDF	10	France	Unknown (heated)	2012–2016
Regione Autonoma Valle d'Aosta	25	Italy	Unknown (heated)	2012–2017
ARPA Piemonte	11	Italy	Unknown (heated)	2012–2015

2.4. Weather radar data

MeteoSwiss has operated since 1995 three weather radars covering the entire national territory of Switzerland (MeteoSwiss, 2016b), modernized in 2011 and 2012 with new technologies (MeteoSwiss, 2012). In May 2014, a fourth installation has been inaugurated at the Pointe de la Plaine Morte (see Fig. 1), within the basin studied in here (MeteoSwiss, 2014c), followed two years later by a fifth radar in the Eastern part of Switzerland (MeteoSwiss, 2016c) (Fig. S.2, Supp. Mat.). The radar of Pointe de la Plaine Morte is officially operational since June 2014. The two additional radars contributed to a better radar coverage of Alpine regions (Germann et al., 2015). The back-scattered signal measured by the five dual-polarization Doppler C-band radars (Gabella, 2017) is transformed into rain rate estimates through several procedures, described in Germann et al. (2006). Radar precipitation estimates are generated every 5 min over a 1-km resolution raster based on a combination of the data of the available radars over Switzerland. For the present study, the hourly aggregated radar precipitation estimates product of MeteoSwiss is used, classified into 256 categories. The production routine of the product had been optimized by MeteoSwiss for the configuration with 3 weather radars in Switzerland. A new radar precipitation estimates product is generated by MeteoSwiss since February 2018, but no historical data are yet available (MeteoSwiss, personal communication, March 7, 2018).

It is worth pointing out that the highly mountainous aspect of the studied basin implies an accuracy loss of the radar estimate as compared to flatlands (Erdin et al., 2012). Beam shielding by mountain ranges is certainly one of the major issues, as discussed later in Section 5. To reduce this effect, a fixed adjustment map computed based on a long-term comparison between weather radar estimation and rain gauge measurements is used by MeteoSwiss in the computation of their radar precipitation estimates product (Germann et al., 2006). However, this long-term comparison-based correction does not consider the data of the two newly installed radars. Positive effect on the basin of interest

is therefore probably lower than for some other regions of Switzerland. Ground echoes elimination also requires a proper pre-treatment of the data. In addition, radar data suffer of bias issue, by over- or under-shooting the precipitation. This is why they are combined with rain gauges to properly adjust the precipitation field. Furthermore, solid precipitation estimation is known to be more challenging than the liquid phase, resulting in better detection performance in summer than in winter (Speirs et al., 2017), whereas melting snow tends to enhance the back-scattered signal (Germann et al., 2006).

2.5. Events description

The main analysis is carried out on four events that occurred over the period of data availability for the meteorological radar of Pointe de la Plaine Morte (2014–2017). Additionally, two events in 2012 and 2013, corresponding to the highest peak flow in the basin over the 2008–2017 period, as well as an event in July 2014 during which the radar of Pointe de la Plaine Morte was temporary not operating, are also considered to discuss the performance of the methodology before the installation of the radar of Pointe de la Plaine Morte. This is important as data over several years are necessary when using the interpolated data for hydrological model calibration.

The four events considered for the main analysis cover different seasons and were chosen for their high precipitation accumulation over the events. The period for each event has been defined such as to start two hours before the first hour with at least four SMN stations reporting at least 1.5 mm/h, and to stop two hours after the last hour respecting this condition; interruptions of less than 12 h of the above mentioned condition were considered to be part of the same event.

The characteristics of the events are given in Table 2 and presented hereafter, listed in chronological order. The median and maximum accumulation values are computed from the rain gauge values. The snow line elevation has been estimated from archives of short term weather forecasts of MeteoSwiss. In fact, even if recent developments

Table 2

Characteristics of the seven analyzed events.

Event identifier	A	B	C	1	2	3	4
Year	2012	2013	2014	2014	2015	2016	2017
Start [day.month Time]	1.7 12:00	28.7 21:00	28.7 11:00	4.11 08:00	30.4 22:00	10.1 07:00	5.3 15:00
End [day.month Time]	2.7 16:00	29.7 17:00	29.7 15:00	6.11 04:00	4.5 10:00	13.1 04:00	7.3 13:00
Duration [h]	28	20	28	44	84	69	46
Season	Summer	Summer	Summer	Fall	Spring	Winter	Winter
Approx. snow line elevation [m asl.]	3200–3400	2600	2500–3100	800–2000	1800–2600	800–1400	700–1400
Plaine Morte radar data	No	No	No	Yes	Yes	Yes	Yes
Median accumulation at stations [mm]	24.3	39.3	45.5	37.5	96.2	41.2	34
Maximum accumulation at a station [mm]	65.3	69.7	62.7	179.5	375.7	158	150.7
SMN stations (number)	28	40	52	52	52	55	58
MG stations (number)	20	22	23	23	23	23	23
Qmax at Sion [m ³ /s]	703	708	394	146	231	64	53
Qmax at Porte du Seex [m ³ /s]	864	901	537	272	606	191	139

enable hydrometeor type analysis from radar data (Grazioli et al., 2015), snow line elevations cannot yet be estimated directly from the radar data. Return periods are provided by *MeteoSwiss* (2016d) from which only statistically robust results were considered. Peak discharges (Q_{max}) and corresponding return periods of the events at the hydro-metric stations of the Federal Office for the Environment (FOEN, 2017a,b) in Sion and in Porte du Scex, at the outlet of the basin (Fig. 1), are also indicated in Table 2 and discussed hereafter where relevant. All times are given in UTC + 1.

2.5.1. Events without Pointe de la Plaine Morte data

Event A: 1.7.2012 12:00 to 2.7.2012 16:00.

The event of July 2012 mostly concerned the eastern part of the basin. The overall precipitation was not particularly intense, with a median accumulation over all the stations of 24.3 mm, but with a snow line elevation reaching 3400 m asl., most of the precipitation fell as rain. This resulted in a peak discharge in the Rhône at Sion of 703 m³/s on 2 July (FOEN, 2017b), corresponding to an estimated return period of 20 years according to FOEN (2017a).

Event B: 28.7.2013 21:00 to 29.7.2013 17:00.

The event of July 2013 touched the entire basin with locally intense storms (median accumulation of 39.3 mm). The high snow line elevation, situated at about 2600 m asl., resulted in a high proportion of rainfall, which led to a peak discharges of 708 m³/s in Sion and 901 m³/s in Porte du Scex on 29 July (FOEN, 2017b). The return period of the discharge in Sion was estimated to 21 years (FOEN, 2017a).

Event C: 28.7.2014 11:00 to 29.7.2014 15:00.

A westerly depression affected the entire basin and particularly its western part. The median accumulation reached 45.5 mm over the event. The snow line elevation varied between around 2500 and 3100 m asl. Compared to the events in 2012 and 2013, the intense precipitation was less concentrated in time, probably partially explaining why the resulting flow in downstream rivers did not reach values as high as in 2012 and 2013 (see Table 2). The event has the particularity of having taken place after the entry into service of the radar of Pointe de la Plaine Morte, but with the mentioned radar not being in operation over the event (temporary interruption). This offers a station density close to the maximum density of 2017 with a radar data configuration corresponding to the one of before 2014 (without the radar of Pointe de la Plaine Morte), which is interesting for analysis purposes.

2.5.2. Events including Pointe de la Plaine Morte data

Event 1: 4.11.2014 08:00 to 6.11.2014 04:00.

An active westerly disturbance with polar air resulted in heavy precipitation mostly in the Eastern part of the basin. The median accumulation over the 44 h was 37.5 mm but station Ulrichen (Fig. 1) reported for example 96.2 mm over 16 h, corresponding to a return period of 18 years according to *MeteoSwiss* (2016d). The snow limit varied between 800 and 2000 m asl.

Event 2: 30.04.2015 22:00 to 4.5.2015 10:00.

A heavy precipitation event coming from the west with air relatively mild and very humid reached Switzerland, with successive precipitation fronts. The snow limit varied between 1800 and 2600 m asl. The median accumulation was 96.2 mm for a maximum accumulation over the 84 h of 375.7 mm (in station Clusanfe). In terms of return period, the station Bex (Fig. 1), in the western part of the basin, reported a rainfall accumulation of 100.9 mm over 3 days, corresponding to a return period of 58 years. Other stations within the basin reported accumulation with return periods exceeding 10 years.

Event 3: 10.1.2016 07:00 to 13.1.2016 04:00.

A series of disturbances reached Switzerland from the west with heavy snowfalls on the Alps, exceeding in some places 100 cm of fresh snow over the 3 days. The snow limit varied between 800 and 1400 m asl and the median liquid-equivalent precipitation was 41.2 mm.

Event 4: 5.3.2017 15:00 to 7.3.2017 13:00.

Strong westerly winds resulted in successive fronts towards the Swiss Alps, with a median precipitation of 34 mm. The snow limit varied between 700 and 1400 m asl. over the event, thus a large fraction of the precipitation fell as snow.

3. Methodology

The high spatial variability of precipitation implies the use of methods capable of analyzing and reproducing as reliably as possible the spatial pattern of the precipitation fields. On one side, the interpolation method should be efficient in combining the available rain gauge and radar data, considering different networks of ground stations. On the other side, for being used operationally, it should not imply long computational time and must work on an automatic basis.

3.1. Estimation methods

Five different estimation methods are compared within this work, ranging from commonly used methods to the newly proposed one handling with two non-collocated rain gauge networks of varying quality. The first method is the so-called Inverse distance weighting method (Shepard, 1968), hereafter referred to as IDW, currently used within the MINERVE forecasting system and therefore considered as the baseline scenario. This method only uses the rain gauge data. The second method considers directly the raw radar value over the entire basin. The three other methods combine rain gauge and radar data by applying a multiplying coefficient to the radar raster, based on a linear regression of the radar data on the rain gauge data, to obtain a trend (“corrected radar”). Residuals, defined as the difference between the value observed at a rain gauge and the value of the containing pixel of the trend, are then computed at each gauge location before being interpolated. The way this interpolation is carried out differentiates the three last methods. The first one is applying IDW to the residuals, whereas the two others are based on a kriging approach (Webster and Oliver, 2007; Delhomme, 1978). Finally, interpolated residuals are added to the trend to get the final product. Table 3 summarizes the five methods.

The implementation has been done on the R language and environment for statistical computing (R Core Team, 2016). For the three regression methods, the methodology and nomenclature is partly based on Sideris et al. (2014a).

3.1.1. Inverse distance weighting (IDW)

The Inverse distance weighting method (Shepard, 1968) is a deterministic interpolation method (Ly et al., 2013), in the sense that it does not exploits the statistical properties of the observation sample, thus not providing a prediction error assessment. In general, the aim of interpolation is to estimate the precipitation depth p at an unsampled spatial location s_0 with coordinates (x_0, y_0) using the available observation data at rain gauges (see Table 7 for variables list). IDW applies a linear combination of the observations within a research radius

Table 3
Estimation methods.

Name	Short name	Rain gauges	Radar	Remark
Inverse distance weighting	IDW	Yes	No	Reference
Radar value	Radar	No	Yes	Raw radar data
Regression inverse distance weighting	RIDW	Yes	Yes	IDW on residuals
Regression kriging	RK	Yes	Yes	Simple kriging on residuals
Regression co-kriging	RCK	Yes	Yes	Co-kriging on residuals

Table 4
Summary of the performance indicators.

Indicator	Min. value	Max. value	Optimal value
Bias	$-\infty$	∞	0
MAD	0	∞	0
RMSE	0	∞	0
M RTE	0	∞	0
Scatter	0	∞	0

ρ , with a decreasing influence with increasing distance. The rain gauge measurements vector over a period t is given by:

$$\mathbf{g}(t) = [g(s_1, t), g(s_2, t), \dots, g(s_N, t)] \tag{1}$$

where N is the number of available rain gauge measurements over the period t and $s = (x, y)$ the spatial-coordinate vector of a given point.

The estimated precipitation $\hat{p}(s_0, t)$, at a given location s_0 , is then given by:

$$\hat{p}(s_0, t) = \begin{cases} g(s_i, t) & \text{if } \exists i: d(s_0, s_i) = 0 \\ \frac{\sum_{i=1}^N \lambda_i g(s_i, t)}{\sum_{i=1}^N \lambda_i} & \text{else } \forall i: 0 > d(s_0, s_i) \leq \rho \end{cases} \forall s_0 \in D \subseteq \mathbb{R}^2 \tag{2}$$

where

$$\lambda_i = \frac{1}{d(s_0, s_i)^\beta} \tag{3}$$

with d being the distance between the location of interpolation and the location of observation i , β a power coefficient, ρ the research radius and D the spatial domain; \mathbb{R} is the set of real numbers. The normalization allows the sum of the weights to equal 1.

3.1.2. Radar value (Radar)

The Radar value method consists in using directly the raw radar data as the precipitation estimation over the basin. The quality of the raw radar product can thereby be investigated.

3.1.3. Regression inverse distance weighting (RIDW)

In the three remaining methods, from the geostatistical interpolation methods, the radar information is used to compute a trend of the precipitation field with a multiplicative coefficient. It is worth noting here that merging rain gauge and radar data implies several hypotheses (Sideris et al., 2014a). Firstly, it is assumed that for both the rain gauges and the radar estimates, the measured physical quantity is the precipitation depth over spatial blocks of a size equal to the spatial resolution of the radar (1 km²). This ignores the difference in spatial resolution. In complex topographies like in the context of this study, this can have implications due to the limited spatial representativeness of rain gauges. Secondly, the precipitation estimates of the radar over a spatial block of 1 km² is assumed to reflect the precipitation depth falling on the surface of the same block. This presumes perfect vertical precipitation fluxes and no exchange with adjacent blocks, which is not the case in reality. In addition, it must be noted that the precipitation depth estimates given by the radar can be affected by areas of invisibility due to shielding of the radar beam by mountain ranges. This obviously also impacts the performance of the interpolation.

In addition to the rain gauge measurements vector $\mathbf{g}(t)$ defined in the IDW method, the radar precipitation estimates at rain gauge locations over the period t are considered:

$$\mathbf{r}(t) = [r(s_1, t), r(s_2, t), \dots, r(s_N, t)] \tag{4}$$

During the interpolation, radar precipitation estimates at each interpolation point are also used.

In geostatistics, a random process $Z(s, t)$ can be modeled as the sum of a deterministic part $m_z(s, t)$, corresponding to the average or trend component, and a stochastic residual component $\epsilon(s, t)$, which corresponds to local fluctuations of the trend, so that:

$$Z(s, t) = m_z(s, t) + \epsilon(s, t) \quad \forall s \in D \subseteq \mathbb{R}^2; t \in T \subseteq \mathbb{R} \tag{5}$$

where s is the vector of spatial coordinates of a given point and T the temporal domain.

In the context of the present work, Eq. (5) can be rewritten for the precipitation depth p over the entire domain as:

$$p(s, t) = m_p(s, t) + \epsilon(s, t) \tag{6}$$

The trend $m_p(s, t)$ for a spatial coordinates vector s is commonly modeled as a linear function of a smoothly varying external variable (Goovaerts, 1997). In our case, this external variable is the radar $r(s, t)$:

$$m_p(s, t) = a(t)r(s, t) \tag{7}$$

where $a(t)$ is a regression coefficient and $r(s, t)$ is the radar values vector at time t . The coefficient $a(t)$ is computed as the slope of a linear regression of all pairs of points composed of the gauge values on the y-axis and the values of the containing radar pixel on the x-axis. $a(t)$ is assumed to be constant spatially in the interest of robustness.

In other methods, such as Kriging with external drift (KED), the trend is computed using two regression parameters (thereby adding also an intercept) and often evaluated within the kriging estimation process itself (e.g. in KED). The choice of a unique parameter has been motivated by the wish of maintaining zero precipitation in the trend where there was no precipitation reported by the radar estimates.

To compute the residuals $\epsilon(s, t)$, the trend $m_p(s, t)$ is subtracted from the observed value at the station locations:

$$\epsilon(s, t) = g(s, t) - m_p(s, t) = g(s, t) - a(t)r(s, t) \tag{8}$$

The residuals $\epsilon(s, t)$ are then interpolated using the inverse distance weighting method to obtain the interpolated residuals $\hat{\epsilon}_{RIDW}(s_0, t)$ at location s_0 . The final estimate is obtained by adding the trend $m_p(s_0, t)$ to the interpolated residual:

$$\hat{p}_{RIDW}(s_0, t) = m_p(s_0, t) + \hat{\epsilon}_{RIDW}(s_0, t) \quad \forall s_0 \in D \subseteq \mathbb{R}^2 \tag{9}$$

Fig. 2 illustrates the different steps of the RIDW method.

3.1.4. Regression kriging (RK)

Kriging is a family of interpolation methods in which the covariance between observations is used to define a linear combination of the observations for interpolation. Practically, kriging methods consider the increasing dissimilarity between observations to characterize the spatial structure of the data. One of the conditions to apply the elementary methods of kriging, Simple and Ordinary kriging, is to assume the random variable to be first-order stationary: the expected value is constant over the domain of interpolation. This condition is hardly satisfied when working directly with rain gauge data, as it might rain for example only in one part of the basin. This non-stationarity of the precipitation fields is here addressed by removing a trend based on the radar data so that Simple or Ordinary kriging can be applied to the computed residuals. This is however an approximation as the non-stationarity of the precipitation statistical properties cannot be fully captured by the radar data.

This approach is named Regression kriging (RK) in the present paper, according to the nomenclature in Odeh et al. (1995). Other names have been proposed for similar approaches in the literature: *kriging combined with linear regression* (Ahmed and De Marsily, 1987), *kriging detrended data* (Phillips et al., 1992), *kriging with a trend model* (Goovaerts, 1997) or *residual kriging* (Alsamamra et al., 2009). Hengl et al. (2007) discussed the characteristics of *regression-kriging* and applied the approach to three case studies. RK is somewhat similar to Kriging with external drift (KED), the difference being that the linear regression and the kriging interpolation is done in successive steps in RK and all-at-once in KED. This choice of successive steps allows us to define a subset of stations for (a) the linear regression step, (b) the variogram computation for the spatial interpolation of the residuals and

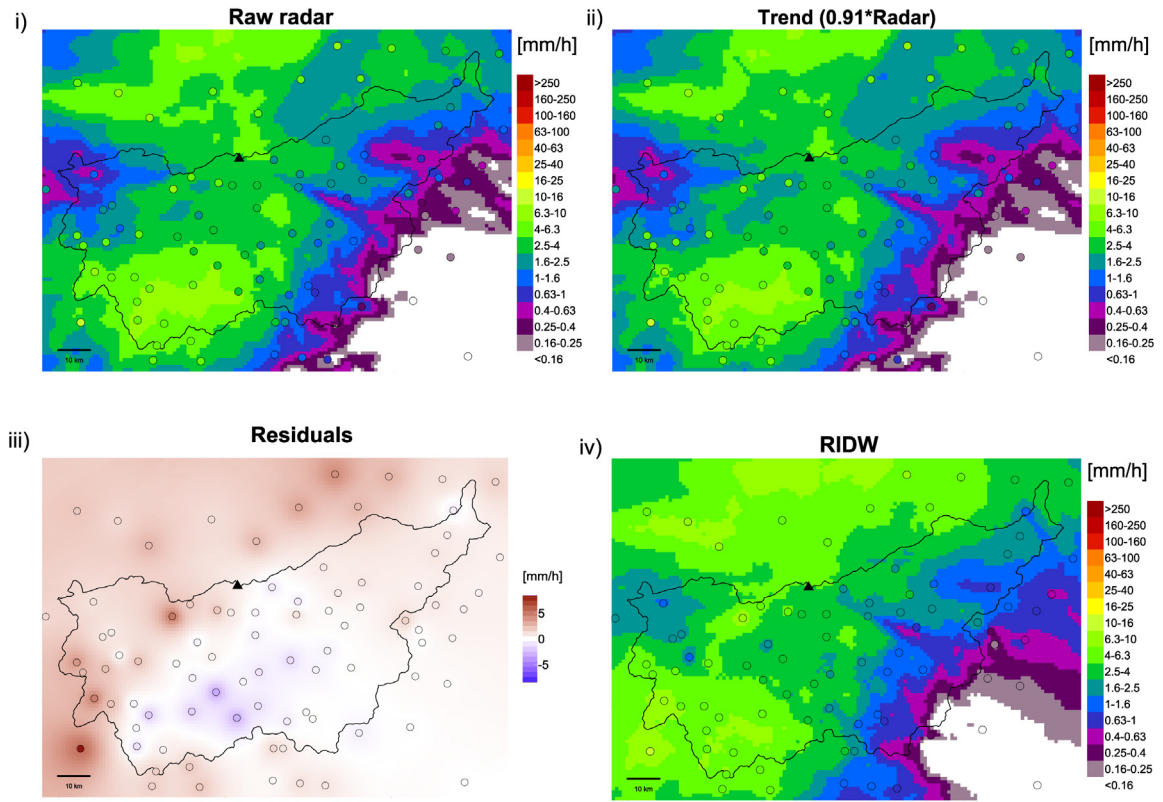


Fig. 2. Illustration of the different steps in RIDW: (i) Raw radar data; (ii) Trend obtained by multiplying the raw radar data by the regression coefficient (Eq. (7)); (iii) Residuals computed for each station and interpolated; (iv) Final product obtained by adding the trend (ii) and the interpolated residuals (iii). Circles represent rain gauge locations and filling colour the precipitation intensity observed at the station. The black triangle represents the radar of Pointe de la Plaine Morte. (Time step: 01-05-2015 2200 UTC + 1).

(c) the interpolation of the residuals, to explore for example a larger number of stations in the last step.

Eqs. (5)–(8) about trend and residuals computation remain valid for RK. The covariance of the residuals at the locations of observation is given by the $N \times N$ covariance matrix C_{aa} :

$$C_{aa} = \begin{pmatrix} \sigma_z^2 & C_{12} & \cdots & C_{1N} \\ C_{21} & \sigma_z^2 & \cdots & C_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ C_{N2} & C_{N2} & \cdots & \sigma_z^2 \end{pmatrix} \quad (10)$$

where each element C_{ij} of the matrix is given by the covariance between the observation locations i and j and σ_z^2 is the variance of the observations. Assuming a gaussian distribution of the residuals (discussed later in Section 3.3) and considering a constant zero mean and known variance, we use Simple kriging to spatialize the residuals. Considering the two conditions imposed by the kriging approach which are (i) an unbiased estimator and (ii) a minimal estimation variance, the following equation is obtained (Webster and Oliver, 2007):

$$C_{aa}\lambda = \mathbf{c}_a \quad (11)$$

where \mathbf{c}_a is the covariance vector between the locations of interpolation and the observation locations.

Resolution of the system given in Eq. (11) provides the weights for the linear kriging predictor used to compute residual values at the interpolation location s_0 , given by the linear combination of the observations:

$$\hat{\epsilon}_{RK}(s_0, t) = \sum_{i=1}^N \lambda_i \epsilon_i(\mathbf{s}, t) \quad (12)$$

which is then added to the trend $m_p(s_0, t)$ to get the expected value of the precipitation depth:

$$\hat{p}_{RK}(s_0, t) = m_p(s_0, t) + \hat{\epsilon}_{RK}(s_0, t) \quad (13)$$

$$\forall s_0 \in D \subseteq \mathbb{R}^2$$

Interpolation of the residual is done using a global neighborhood, that means all the points are used for the interpolation.

3.1.5. Regression co-kriging (RCK)

Based on the comparative analysis between the MeteoSwiss and MeteoGroup networks (see Section 2), the choice was made to explore a variant of Regression-kriging using co-kriging and hereafter referred to as Regression co-kriging (RCK). Co-kriging has the advantage of offering the possibility of considering more than one variable in the kriging interpolation.

Thus, the multivariate RCK variant allows considering different vectors of rain gauges. Instead of having only one vector of observations, vector $\mathbf{g}(t)$ of Eq. (1) is replaced by two vectors:

$$\mathbf{g}_a(t) = [g(s_{a,1}, t), g(s_{a,2}, t), \dots, g(s_{a,N_a}, t)] \quad (14)$$

$$\mathbf{g}_b(t) = [g(s_{b,1}, t), g(s_{b,2}, t), \dots, g(s_{b,N_b}, t)] \quad (15)$$

where the subscripts a and b refer to the primary (a) and secondary (b) networks and N_a and N_b are the number of available rain gauges in respectively the primary and the secondary networks over the period t .

Similarly, the radar precipitation estimates' vector of Eq. (4) is replaced by two vectors:

$$\mathbf{r}_a(t) = [r(s_{a,1}, t), r(s_{a,2}, t), \dots, r(s_{a,N_a}, t)] \quad (16)$$

$$\mathbf{r}_b(t) = [r(s_{b,1}, t), r(s_{b,2}, t), \dots, r(s_{b,N_b}, t)] \quad (17)$$

Statements about the trend and residuals computation of Eqs. (5)–(8) remain valid. The residuals are computed with the two equations:

$$\epsilon_a(\mathbf{s}_a, t) = g_a(\mathbf{s}_a, t) - a_a r_a(\mathbf{s}_a, t) \tag{18}$$

$$\epsilon_b(\mathbf{s}_b, t) = g_b(\mathbf{s}_b, t) - a_b r_b(\mathbf{s}_b, t) \tag{19}$$

where a_a and a_b are the multiplicative coefficients for the primary and secondary variables computed with a linear regression of the radar data on the rain gauge data. These two terms are the result of a linear regression computed for each of the corresponding subsets of data with respect to the corresponding radar data.

The consideration of two variables in RCK instead of one modifies Eq. (11) as follows (Myers, 1982):

$$\begin{pmatrix} \mathbf{C}_{aa} & \mathbf{C}_{ab} \\ \mathbf{C}_{ba} & \mathbf{C}_{bb} \end{pmatrix} \begin{pmatrix} \lambda_a \\ \lambda_b \end{pmatrix} = \begin{pmatrix} \mathbf{c}_a \\ \mathbf{c}_b \end{pmatrix} \tag{20}$$

where \mathbf{c}_a and \mathbf{c}_b are the covariance vectors of residuals between the unmonitored locations and the locations with observations and \mathbf{C}_{ab} (respectively \mathbf{C}_{ba}) the cross-covariance matrix between the primary and secondary variables (respectively the secondary and primary variables). Consequently, the estimator equation is given by:

$$\hat{\epsilon}_{\text{RCK}}(s_0, t) = \sum_{i=1}^{N_a} \lambda_{a,i} \epsilon_a(\mathbf{s}_a, t) + \sum_{i=1}^{N_b} \lambda_{b,i} \epsilon_b(\mathbf{s}_b, t) \tag{21}$$

before being added to the trend $m_p(s_0, t)$:

$$\hat{p}_{\text{RCK}}(s_0, t) = m_p(s_0, t) + \hat{\epsilon}_{\text{RCK}}(s_0, t) \quad \forall s_0 \in D \subseteq \mathbb{R}^2 \tag{22}$$

3.2. Variogram fitting for non-located networks

Computation of the weights vector λ of Eq. (11) as well as λ_a and λ_b of Eq. (20) requires an estimate of the covariance matrices. Instead of computing the covariance, which is sensitive to sampling effects, kriging generally uses the concept of semivariogram (Matheron, 1971), which represents how the dissimilarity between pairs of points increases with increasing separation distance. The semivariogram, or simply variogram as called from now, is defined for the univariate case and expressed in terms of precipitation residuals by:

$$\gamma_a(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (\epsilon(s_i) - \epsilon(s_i + h_i))^2 \quad \forall (s_i, s_i + h_i) \in D \subseteq \mathbb{R}^2 \mid h_i \in [h-b/2, h + b/2], \tag{23}$$

where h is the distance lag between pairs of locations, $\gamma_a(h)$ the variogram value for distance lag h , b the bin size (the width of the distance interval up to which point pairs are grouped for variogram computation), h_i the distance separating a given pair of points, $N(h)$ the number of considered pairs of observations separated by distance h , $\epsilon_a(s_i)$ the residual value at location s_i and $\epsilon(s_i + h_i)$ the residual value at location $s_i + h_i$ (Pebesma, 2014).

In the case of Regression kriging, one variogram is computed with Eq. (23) for each time step of computation. For the Regression co-kriging, two direct variograms (one for each variable) and one cross-variogram must be computed to define the so-called linear model of coregionalization (Webster and Oliver, 2007). For the computation of the cross-variogram, Eq. (23) must be generalized to two variables, identified by the subscript a and b :

$$\gamma_{ab}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (\epsilon_a(s_i) - \epsilon_a(s_i + h_i))(\epsilon_b(s_i) - \epsilon_b(s_i + h_i)) \quad \forall (s_i, s_i + h_i) \in D \subseteq \mathbb{R}^2 \mid h_i \in [h-b/2, h + b/2] \tag{24}$$

where $\epsilon_b(s_i)$ is the residual value at location s_i and $\epsilon_b(s_i + h_i)$ the residual value at location $s_i + h_i$.

However, Eq. (24) can be used only in case of collocated variables (observations for both variables are available for a sufficient number of given points). In the case of SMN and MG stations, this is not the case as

stations are situated in different locations. Accordingly, one needs to work with so-called pseudo cross-variograms in which pairs of both variables are considered, as proposed by Pebesma (2014):

$$\gamma_{ab}^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (\epsilon_a(s_i) - \epsilon_b(s_i + h_i))^2 \quad \forall (s_i, s_i + h_i) \in D \subseteq \mathbb{R}^2 \mid h_i \in [h-b/2, h + b/2] \tag{25}$$

where $\gamma_{ab}^*(h)$ is the pseudo cross-variogram value for distance lag h considering variables a and b .

The equivalence between variogram and covariance is defined for second-order stationary processes (for which the variogram is always bounded), as follows (Webster and Oliver, 2007):

$$\gamma(h) = C(0) - C(h) \tag{26}$$

where $\gamma(h)$ is the variogram value for a distance h , $C(0)$ is the covariance at $h = 0$ and $C(h)$ the covariance at distance h . If the variogram is bounded by a sill, the value of $C(0)$ is equal to the total sill value.

In the present study, the variogram models have been fitted using the package ‘gstat’ (Pebesma and Graeler, 2017), within the software R (R Core Team, 2016). The empirical variogram has been fitted with a spherical variogram model (Schuurmans et al., 2007):

$$\gamma(h) = \begin{cases} 0 & \text{if } h = 0, \\ K_0 + K \left(\frac{3h}{2\alpha} - \frac{h^3}{2\alpha^3} \right) & \text{if } 0 < h \leq \alpha, \\ K_0 + K & \text{if } h > \alpha. \end{cases} \tag{27}$$

in which K_0 is the nugget value, K the partial sill, α the range (distance within which measures are considered correlated).

The implemented code explores different values of bin size until a valid variogram model can be fitted. The routine also tries to obtain a low nugget-to-sill ratio by gradually increasing a success threshold: 100 iterations are first attempted with a threshold value of 0.1. If none of the obtained valid models has a nugget-to-sill ratio lower than the threshold, the threshold is increased by 0.1 until 0.9 with each time 100 iterations. In case of failure with the highest threshold value, the last valid variogram of previous time steps is considered.

Anisotropy of the variogram (different spatial variability in different directions) has not been explored in this work. This choice is justified by the use of the radar data, in which spatial variability of the precipitation fields is assumed to be contained and therefore considered in the interpolation process.

3.3. Transformation

Precipitation is inherently heteroscedastic (the variance is not constant over the domain) and has a skewed distribution, which is in contradiction with basic assumptions of classical geostatistics which assumes a gaussian distribution and stationarity of the mean and spatial covariance (Erдин et al., 2012). Therefore, several methods have been explored in the literature to transform the data before their interpolation (Sideris et al., 2014a; Erдин et al., 2012; Schuurmans et al., 2007) and it has been shown that quantitative improvements is dependent on temporal and spatial variability (Cecinati et al., 2017b). The process of applying kriging to data transformed into a more gaussian distribution is generally named trans-gaussian kriging.

In the case of the two methods employing kriging in this paper, namely regression kriging (RK) and regression co-kriging (RCK), interpolation is not done directly on the precipitation observations but on the residuals (see Section 3.1), to which the gaussianity issue therefore applies. A transformation is applied to both the rain gauge and the radar data to translate them into a more gaussian distribution, with the objective of getting better gaussianity in the residuals. In this paper, we use for both RK (3.1.4) and RCK (3.1.5) methods a square-root transformation of the data (Sideris et al., 2014a). Analysis of the residuals distribution has shown that this transformation tends to increase overall

the gaussianity of the residuals, even though the effect is somewhat limited and for few time steps even negative. In analysing the effect of such data transformation on precipitation interpolation, [Erdin et al. \(2012\)](#) reported “only small effects of transformation for the point estimates” but mentioned that “transformation improved the reliability of the probabilistic estimates substantially”. The corresponding gain of introducing such transformation scheme is discussed in Section 4.2.2.

The advantage of the square-root transformation is the possibility of analytical back-transformation of the mean and the variance ([Sideris et al., 2014a](#)), given by:

$$E[Y^2] = \mu_Y^2 + \sigma_Y^2 \tag{28}$$

and,

$$\text{Var}[Y^2] = 4\mu_Y^2\sigma_Y^2 + 2\sigma_Y^4 \tag{29}$$

where μ_Y is the mean and σ_Y the standard deviation of the square-root-transformed kriging prediction at a certain location, whereas $E[Y^2]$ represents the expected value of the back-transformed random variable, or, in other words, the final prediction, and $\text{Var}[Y^2]$ the related variance. However, [Eq. \(28\)](#) is composed of two positive terms (both are squared values) with the variance (σ_Y^2) being positive and reaching the sample variance of the (transformed) residuals at estimation locations situated at a distance from the nearest observation higher than the variogram model range ([Eq. 27](#)). Thereby, the back-transformed estimation would never provide zero precipitation estimates apart from rain gauge locations (where estimation variance is minimum). In the work of [Sideris et al. \(2014a\)](#), this problem is addressed by correcting the interpolated field and assigning zero precipitation to locations where the radar does not show any precipitation (I. Sideris, personal communication, May 30, 2017). The methodology proposed here overcomes this issue by weighting the variance term of [Eq. \(28\)](#) with the predicted precipitation:

$$\sigma_Y^{*2} = \frac{\mu_Y^2}{\tau} \sigma_Y^2 \tag{30}$$

where τ is a precipitation intensity threshold below which the variance is weighted and σ_Y^{*2} is the variance effectively added in [Eq. \(28\)](#) instead of σ_Y^2 , which gives:

$$E[Y^2]^* = \mu_Y^2 + \sigma_Y^{*2} \tag{31}$$

where $E[Y^2]^*$ represents the expected value of the back-transformed random variable considering the modified estimation variance. The value for τ has been fixed to 0.5 mm/h after initial tests. The impact of applying the transformation or not is discussed in Section 4.2.2.

3.4. Skill scores and cross-validation

The performance analysis is based on the leave-one-out approach: the precipitation is estimated at a rain gauge location using all observations except the one corresponding to the interpolation location. The procedure is undertaken on an hourly basis for each location and for each of the methods. The quality of the point estimates is then assessed over all locations for each time step using following skill scores:

1. Bias: Systematic errors are assessed with the bias indicator:

$$\text{Bias}(t) := 10 \log_{10} \frac{\sum_{i=1}^N \hat{g}_i(t)}{\sum_{i=1}^N g_i(t)} \tag{32}$$

where $\hat{g}_i(t)$ refers to the estimated value for a given location and a given time step, $g_i(t)$ to the observed value and N to the number of considered locations. As a result of the logarithmic scale used in [Eq. \(32\)](#), the bias is expressed in decibel (dB). For each event, the overall bias is averaged over the entire period and the entire spatial extent. The bias has been computed only for hourly time steps during which the mean precipitation over the MeteoSwiss stations

was higher than 0.5 mm/h. This avoids values at the denominator close to 0, resulting in exaggeratedly high bias values.

2. MAD: The median absolute deviation (MAD), provides the median of the absolute value of the difference between estimated and observed values ([Sideris et al., 2014a](#)):

$$\text{MAD}(t) := \text{median}(|\hat{g}_i(t) - g_i(t)|) \tag{33}$$

3. RMSE: The Root mean square error is the most common parameter used in verification ([Goudenhoofdt and Delobbe, 2009](#)). It represents the standard deviation of the differences between predicted and observed values:

$$\text{RMSE}(t) := \sqrt{\frac{\sum_{i=1}^N (\hat{g}_i(t) - g_i(t))^2}{N}} \tag{34}$$

4. MRTE: The mean-root-transformed error ([Erdin et al., 2012](#)), mitigates the dominant influence of errors at large precipitation amounts as compared to RMSE:

$$\text{MRTE}(t) := \frac{1}{N} \sum_{i=1}^N (\sqrt{\hat{g}_i(t)} - \sqrt{g_i(t)})^2 \tag{35}$$

5. Scatter: The scatter is a measure of the spread of the ratio between estimated and measured values. It is based on the cumulative error distribution function of these ratios, expressed in decibel ([Germain et al., 2006](#); [Schiemann et al., 2011](#)):

$$\text{Scatter} := \frac{1}{2} (\xi_{84} - \xi_{16}) \tag{36}$$

where ξ_{16} and ξ_{84} represent the 16% and the 84% percentiles of the cumulative error distribution function. Only pairs of points for which both estimated and observed values were higher than 0.5 mm/h were considered for the computation of the scatter.

3.5. Methodology application

For the IDW method, a value of 2 (common default value) is given to the power coefficient β ([Eq. 3](#)) and the research radius is fixed to 50 km. For the methods including a regression of the radar data, the regression has been computed only on stations located within the basin.

For the methods considering a single rain gauge network (IDW, RIDW and RK), the primary variable (SMN) data are considered. For the RCK method, both primary (SMN) and secondary (MG) variables data are used.

Variograms fitting with an insufficient number of points can lead to ill-defined variogram. For the RK method, a minimum of 5 stations with a precipitation of at least 0.5 mm/h is set as condition. For the RCK method, the condition is set to 5 stations exceeding the same precipitation threshold value for each variable. When the condition is not satisfied, the last previously computed valid variogram is used. The condition being generally not satisfied at the beginning of an event, an initial variogram must preliminarily be computed over an arbitrarily chosen time step during the event with sufficient stations exceeding the threshold.

In addition, for both the RK and RCK methods, the model fitting has been constrained to a maximum range of 50 km. This value has been defined based on visual variogram analysis and allows to constrain the model for experimental variograms that do not show a clear upper bound.

4. Results

The five methods presented in Section 3 and listed in [Table 5](#) have been applied to the four events presented in Section 2.5.2. For all the

Table 5
Analyzed methods and corresponding used data. For methods abbreviations, see Table 3.

Application	Radar	Primary variable	Secondary variable
Radar	Yes	–	–
IDW(SMN)	No	SMN	–
RIDW(SMN)	Yes	SMN	–
RK(SMN)	Yes	SMN	–
RCK(SMN, MG)	Yes	SMN	MG

five methods, the interpolation has been computed over a grid with a resolution corresponding to the one of the raw radar data (1 km² per pixel).

For the cross-validation, the computation was based on the locations of the SMN rain gauges within the basin, even if more stations such as MG stations were used for the interpolation, to ensure a constant comparison basis for all methods. It is worth noting here that no direct comparison has been possible within this study with the *CombiPrecip* product of MeteoSwiss, as no leave-one-out computation was possible on the delivered *CombiPrecip* product.

The performance of the different methods is first discussed based on the cross-validation approach, including a discussion of the performance before the installation of the new weather radar in 2014. Results of the variogram fitting and the effect of data transformation are then presented. The last section discusses the effect of additional networks.

4.1. Methods performance analysis

In order to assess the performance of the different methods, the presented performance indicators have been computed for the four events 1 to 4 (Table 2). For each performance indicator (Table 4), hourly values were averaged over each event. Results are given in Fig. 3. The cumulative volume over the events, considering all the pixels located within the basin, is also presented (dashed line border).

The estimation method considering only raw radar data (Radar)

clearly shows the weakest performance. Particularly in terms of bias, which confirms the need of bias correction of the raw radar data with a regression using rain gauges. This observation is strengthened by the total volume that differs substantially from the other methods for part of the events. Overall, the RCK method provides the best performance. This is the case for the MRTE indicator for which the RCK method provides the best value over all four events. In terms of absolute bias, RCK outperforms for all the events the RK method but for some events, other methods such as IDW perform better than RCK. Furthermore, the results are not clear for all the indicators. For example for event 1, RMSE and Scatter values are comparable for RCK and IDW. It is worth to recall here that the station density within the basin is particularly high, which allows IDW to reach already good performances. It must also be pointed out that IDW has been applied with the default value of 2 for the exponent β of Eq. (2). Adjustment of this parameter could improve the performance of the IDW method.

For a finer analysis, Fig. 4 presents hourly values for the four performance indicators computed at each time step, for the reference IDW method and the RCK method. Scatter is not shown here as it is computed directly over the events. Results for the bias show how reactive the indicator can be, with a strong negative value for the RCK method on 2 May 2015 at 16:00. However, this corresponds to the beginning of the second front and only few stations already observed precipitation, in which case one single important cross-validation error can strongly affect the hourly indicator value. It must also be noted that such single negative (respectively positive) values can compensate for an overall positive (respectively negative) bias value and lead to an improvement in the overall value. This is one of the limitation of the bias indicator.

Regarding the three other indicators, all strictly positive by definition, it is interesting to note the varying difference between the two methods over the three fronts: whereas there is only a small gain of RCK over IDW over the first front, it increases over the second and third front, in particular for the MRTE indicator. When analyzing the different fronts, it appears that over the third one, only the north-western part of the basin is covered by the precipitation (Fig. 5). The gain of integrating the radar information is here clearly visible, with the IDW

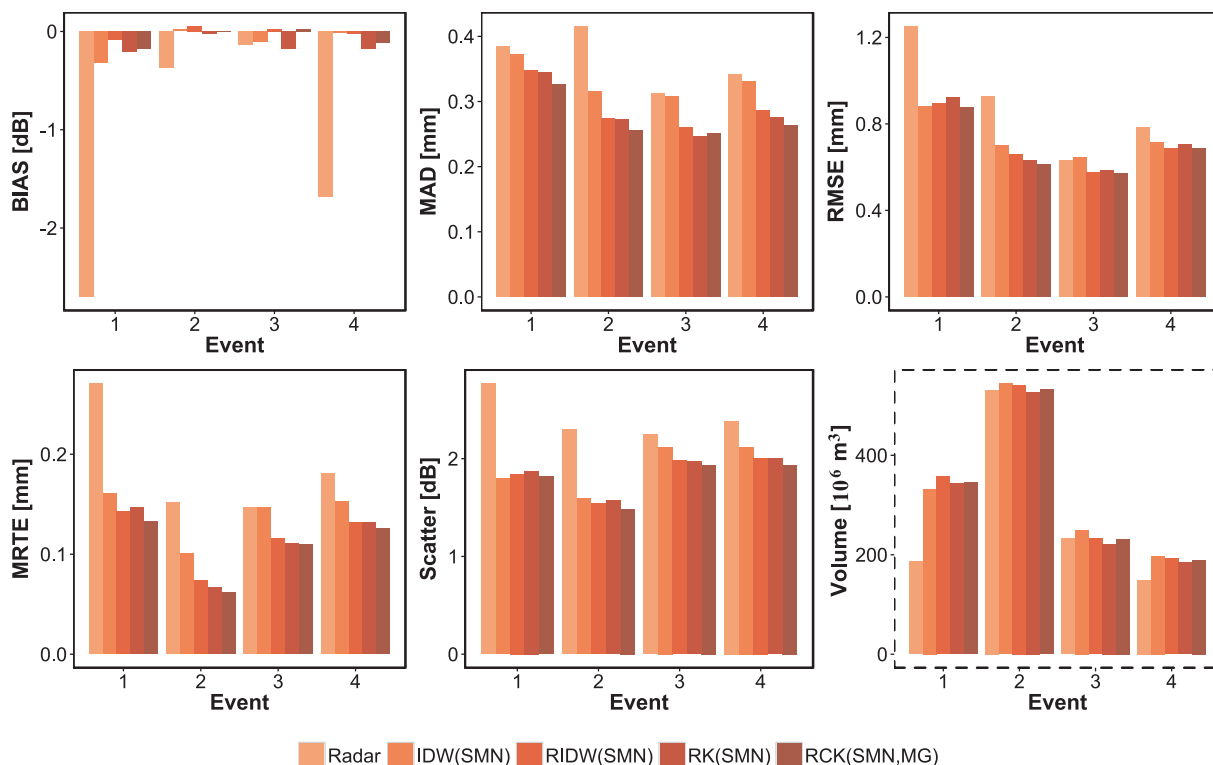


Fig. 3. Event-averaged performance indicator values and cumulative volume over the entire basin (dashed line border) over the 4 events.

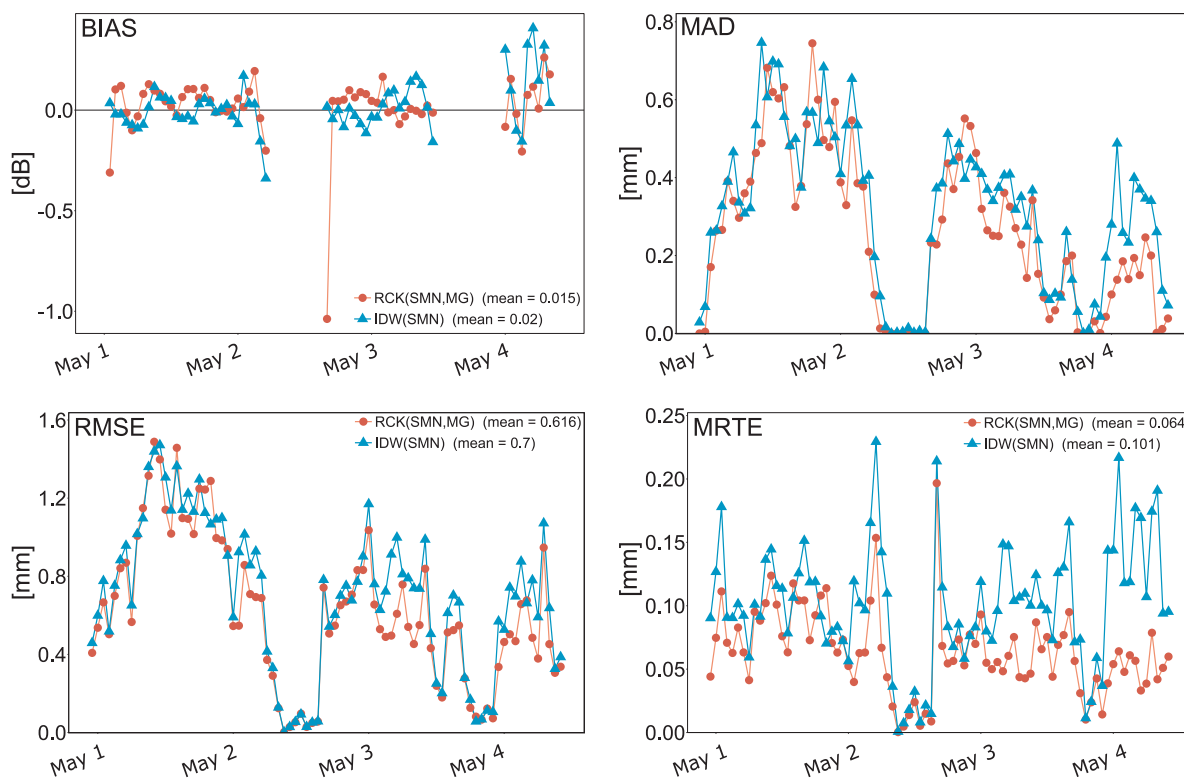


Fig. 4. Hourly values of performance indicators for IDW(SMN) and RCK(SMN, MG) over event 2 (May 2015).

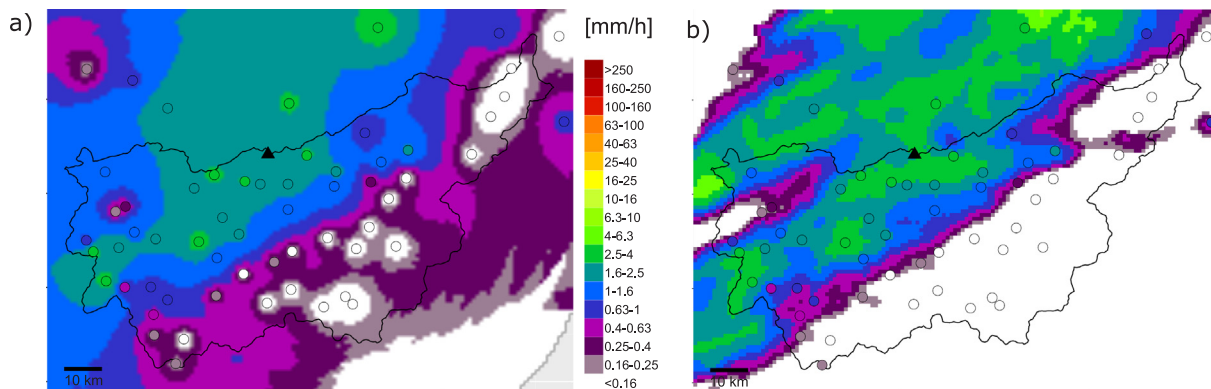


Fig. 5. Hourly interpolated precipitation using (a) IDW(SMN) and (b) RCK(SMN, MG) on 04-05-2015 0100 UTC + 1. Circles represent rain gauges' locations and filling colour the intensity observed at the station. The black triangle represents the radar of Pointe de la Plaine Morte.

method not being able to reproduce the sharp gradient cutting the basin in two parts. Figs. S.5 to S.10 (Supp. Mat.) show the same indicators for the 6 other events.

When analyzing the cross-validation errors of event 1, it appeared that the station Col du Grand St-Bernard (GSB) resulted almost systematically (over the entire event) in high cross-validation errors, with both IDW and RCK methods not being able to correctly reproduce the observed precipitation, despite using the radar information in the RCK method. When looking at the total precipitation over the event for both methods, the GSB station is also very well visible at the south-western corner of the basin (Fig. 6). The high difference between the rain gauge values and the bias-corrected radar data only at this station suggested to further investigate this particularity. Interestingly, this station, located at an elevation of 2472 m asl., had already been pointed out in a precedent analysis (Erdin et al., 2012), in which the station was reported to suffer of “several known measurement problems (shielding, wind exposure, and drifting snow)”. And with a snow limit varying between 1000 and 2000 m asl. over the event 1, the GSB station only measured

solid precipitation.

To investigate the impact of the station over the global performance over the event, the interpolation has been recomputed by totally excluding the GSB station. Fig. 7 shows the result for the two methods, both with and without considering the GSB station. Results show that all indicators are improved when removing the station. In particular for RMSE and MRTE, the difference is non-negligible. This example shows well how considering as truth the data from the rain gauges can lead to incoherence or errors in the interpolation result.

The analysis carried out over events 1 to 4 considered radar data including the new radar of Pointe de la Plaine Morte. In order to assess the quality of the Swiss-wide radar product over the studied basin before the installation of this new radar, performances over the three events A, B and C are presented in Fig. 8. The performance gain of RCK over IDW for the three events is higher than for events 1 to 4. This is probably partly explained by the number of rain gauges available over the three events: only 28 and 40 SMN stations for 2012 (event A) and 2013 (event B) whereas at least 52 stations were available for the events

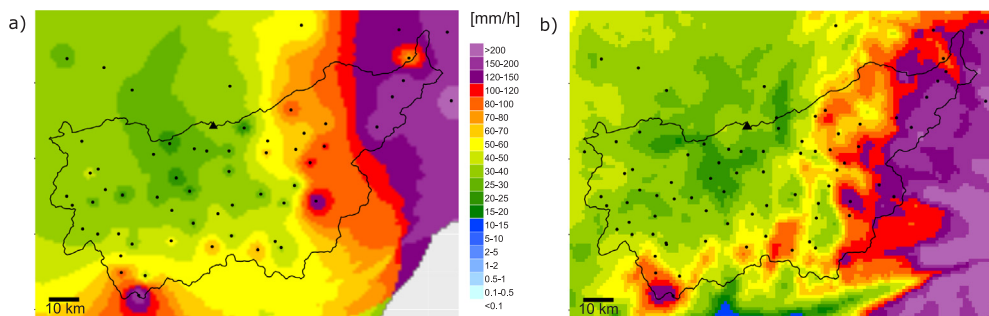


Fig. 6. Comparison of total precipitation over event 1 (04-11-2014 0800 to 06-11-2014 0400 UTC + 1) for (a) IDW(SMN) and (b) RCK(SMN, MG). The black points represent the locations of the considered rain gauges. The black triangle represents the radar of Pointe de la Plaine Morte. The gray back-ground on the bottom-right corner of (a) results from the absence of data within the research radius (50 km) of these pixels.

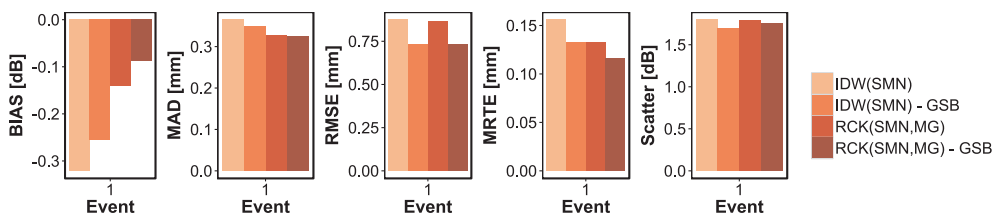


Fig. 7. Performance indicators over event 1 with exclusion of Col du Grand St-Bernard (GSB) station.

1 to 4. The lower station density reduces the performance of IDW and thereby increases the relative gain of RCK over IDW.

The performance of the RCK method over the three analyzed events excluding Pointe de la Plaine Morte radar data suggests that this method provides clearly better results than IDW for the studied basin even before the installation of the new weather radar. This is an important result in the perspective of computing precipitation fields for hydrological modelling with data requirement over relatively long time periods, as it shows that even with an Alpine topography like the one in the studied basin, radar data seem to be usable even without a weather radar located within the basin.

4.2. Variogram and data transformation analysis

Performance of the variogram model fitting for the results presented in Section 4.1 are presented hereafter, before analyzing the effect of data transformation looking at the RCK method.

4.2.1. Variogram fitting results

Good fitting of the variogram is essential to obtain a reliable interpolation. The implemented solution resulted in few time steps (0.5%) without valid variogram fitting. This considers only the time steps with enough stations reporting sufficient precipitation as defined in Section 3.5. The percentage of time steps with insufficient stations is considerably high: 7.4% for the RK method and 31.7% for the RCK method of the time steps over the four events 1 to 4. These time steps generally correspond to the lower intensity phase of the events. For all these time steps (both failure and insufficient stations), the previously computed last valid variogram was used instead.

Fig. 9 shows four direct variograms for the RK method over event 3.

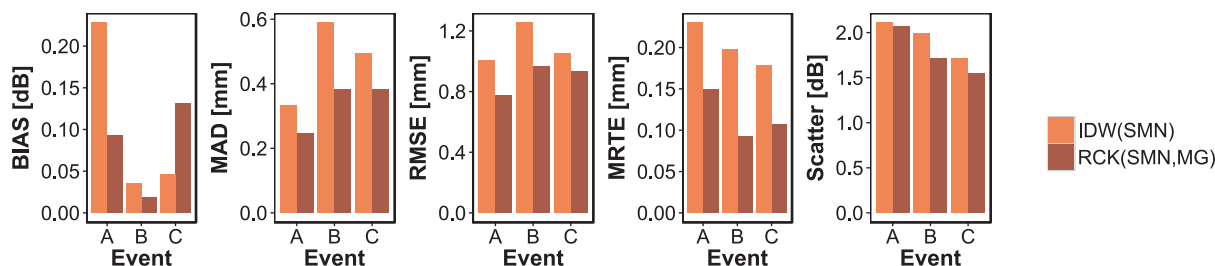


Fig. 8. Performance indicators for the method IDW using SMN data and the RCK method using SMN (primary) and MG (secondary) data over the 3 events without data for the radar of Pointe de la Plaine Morte.

The differences in bin size are well visible: the fewer points are visible on a sample variogram, the more points were grouped together and averaged to compute each point of the experimental variogram. Fig. 10 gives an example of the linear model of coregionalization, composed of two direct variograms (SMN and MG) and one pseudo cross-variogram (SMN vs. MG), all three fitted simultaneously. The higher variability observed in the MG direct variogram tends to be a common behavior within this study. This difference cannot be directly attributed to a difference in the quality of the MG sensors, as these stations are also much less numerous, with only 23 MG stations for 52 SMN stations over the chosen event, enhancing the issue of limited number of wet stations for the MG network.

In addition, if most of the fitted models describe well the experimental variogram, for some times steps, a manual fitting would probably have led to more appropriate fittings.

4.2.2. Effect of data transformation

The RCK method has been applied to events 1 to 4, both with and without transformation (Fig. 11). The bias is considerably improved for two of the four considered events when applying the discussed square-root transformation (Eq. 31). For the MRTE, a gain is observed for all events. For the other indicators, the difference is less important and more variable, for example for the MAD, for which loss and gain are observed; for the Scatter, the tendency is slightly negative, probably due to the back-transformation process.

These results are coherent with the conclusions of Erdin et al. (2012), who reported only “small effects of the transformation” on the point estimates, but reported a higher reliability of the estimates when comparing “each gauge measurement against the probability function of the corresponding cross-validation probabilistic estimate”. Further

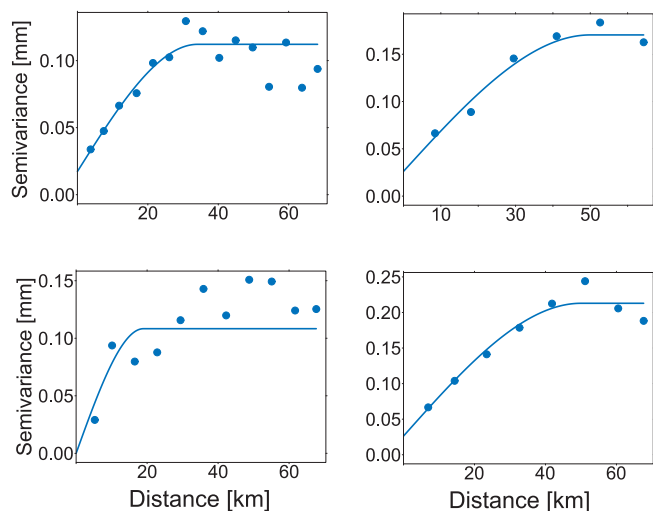


Fig. 9. Sample of the variogram and automatically fitted models for the first four hours of event 3 (January 2016).

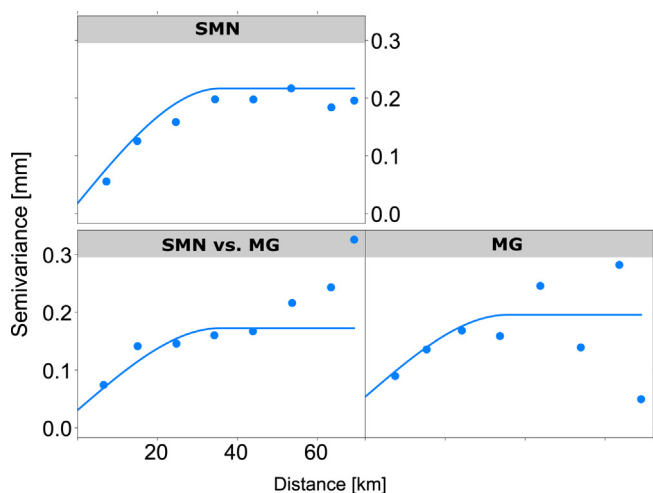


Fig. 10. Example of linear model of coregionalization composed of two direct variograms and one pseudo cross-variogram (bottom left) using SMN as primary variable and MG as secondary variable (01-05-2015 2200 UTC + 1).

improvements in the transformation could be explored, not only on the power coefficient of the transformation, but also on the back-transformation process. Based on the obtained results, applying the proposed transformation is recommended.

4.3. Effect of additional networks

In the results presented in Section 4.1, the MG data have been used only in the RCK method as secondary variable. Combination of SMN and MG data as a unique set of data is discussed hereafter. Fig. 12 presents the performance indicators for the IDW, RIDW and RK methods, each time considering first SMN data only and then combining SMN and MG data, considering them together as one single variable (Table 6). Results of RCK using SMN data as primary variable and MG as secondary variable are also presented.

For all indicators except the bias, considering MG data directly with SMN data as one single variable tended to improve the performance of the methods as compared to use only SMN data, which can be explained by the additional local information introduced by the MG stations. Performances were in some cases even slightly better than for RCK in which both variables are considered separately. However, and as

expected from the data analysis presented in Section 2 (Study area and data), this joint use of SMN and MG data resulted in negative biases. This effect is well visible in particular for events 3 and 4 (Fig. 12), where values exceeded -0.6 dB corresponding to a negative bias of about -13% . Consequently, this bias issue suggests to consider both variables only with methods accounting for this deviation, that means in the present case the RCK method.

The present study also aimed at providing a preliminary analysis of integrating stations from surrounding areas. This is justified by the need for accurate information in terms of precipitation estimates for real-time hydro-meteorological monitoring and forecasting. Fig. 13 shows for a time step of event 2 the interpolation results of RCK, using only SMN and MG data compared to the results obtained with integrating the data from all surroundings additional networks. With the additional stations, precipitation estimates are for example increased over the Aosta region south of the studied basin (see Fig. 13c).

For a more quantitative assessment, Fig. 14 gives the corresponding performance indicators, including different combinations of primary and secondary variables for the precipitation interpolation. The additional data have however not been used for the linear regression computation nor for the variogram fitting. This was motivated respectively to ensure an optimal radar regression over the studied basin and to reduce the risk of inconsistencies in the variogram model fitting, sensitive to discrepancies in even only one or two stations, potentially affecting the entire interpolation of a given time step.

The results show that adding additional networks has a limited effect. Bias tends to be the most reactive indicator, even though differences are small. For the other indicators, as well as for the total precipitated volume, differences can be considered as limited, and it is difficult to define if it is rather a gain or a loss in terms of performance.

For some time steps, some stations of the additional networks reported no precipitation whereas the radar reported heavy precipitation, suggesting some possible quality issues. For operational purposes, the quality of these additional networks should be further investigated.

5. Discussion

The performance analysis used in this paper, based on leave-one-out cross-validation, did not allow a direct comparison with outputs of previous works, for example with the *CombiPrecip* product as described in Sideris et al. (2014a). In fact, the stations used in the cross-validation evaluation are used in the computation of the product, thus no comparison was possible. However, visual analysis of the interpolated precipitation fields revealed that the spatial patterns were very similar for a very large fraction of the time steps. Integration of the discussed interpolated precipitation fields into a hydrological model could allow a quantitative comparison between the products from a hydrological point of view. Furthermore, the analysis was carried out over the set of recent most heavy precipitation events, which were not evenly spread through all seasons, with events 1 to 4 (period 2014–2017) occurring from fall to spring and with events A to C (period 2012–2014) only in summer. This could have an impact on the analysis but should not modify the general conclusions from the comparison between methods.

The choice of performance indicators can also slightly modify the results of the analysis. For example, we decided to work with a bias indicator based on a ratio between estimated and observed values, indicator also used by several other authors (Sideris et al., 2014a; Goudenhoofd and Delobbe, 2009). However, alternative versions exist, based for example on a differential bias (Cecinati et al., 2017b), less sensitive to small denominators.

Two aspects of the presented precipitation interpolation deserve further discussion, namely the integration of different rain gauge networks and remaining challenges, due mainly to radar visibility.

Regarding the integration of the data from the private Meteogroup (MG) raingauges, it is important to point out here that their added value is probably somewhat underestimated in the presented results. In fact,

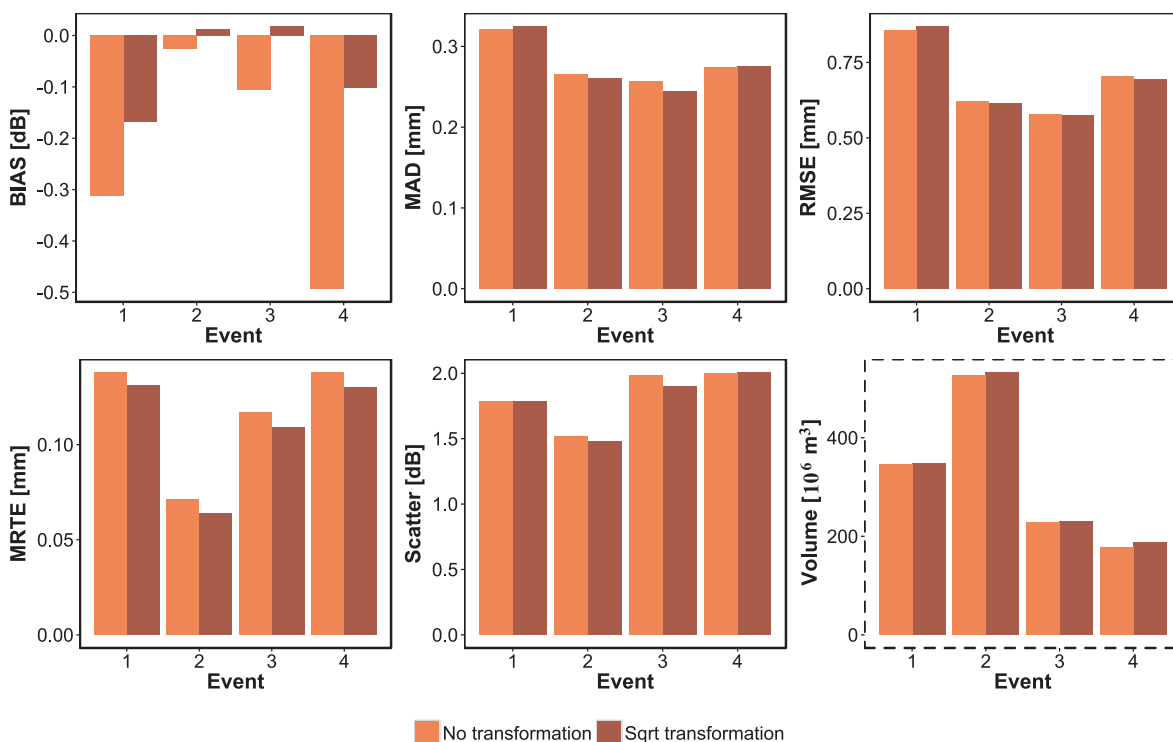


Fig. 11. Assessment of transforming or not the data when using the RCK(SMN, MG) method.

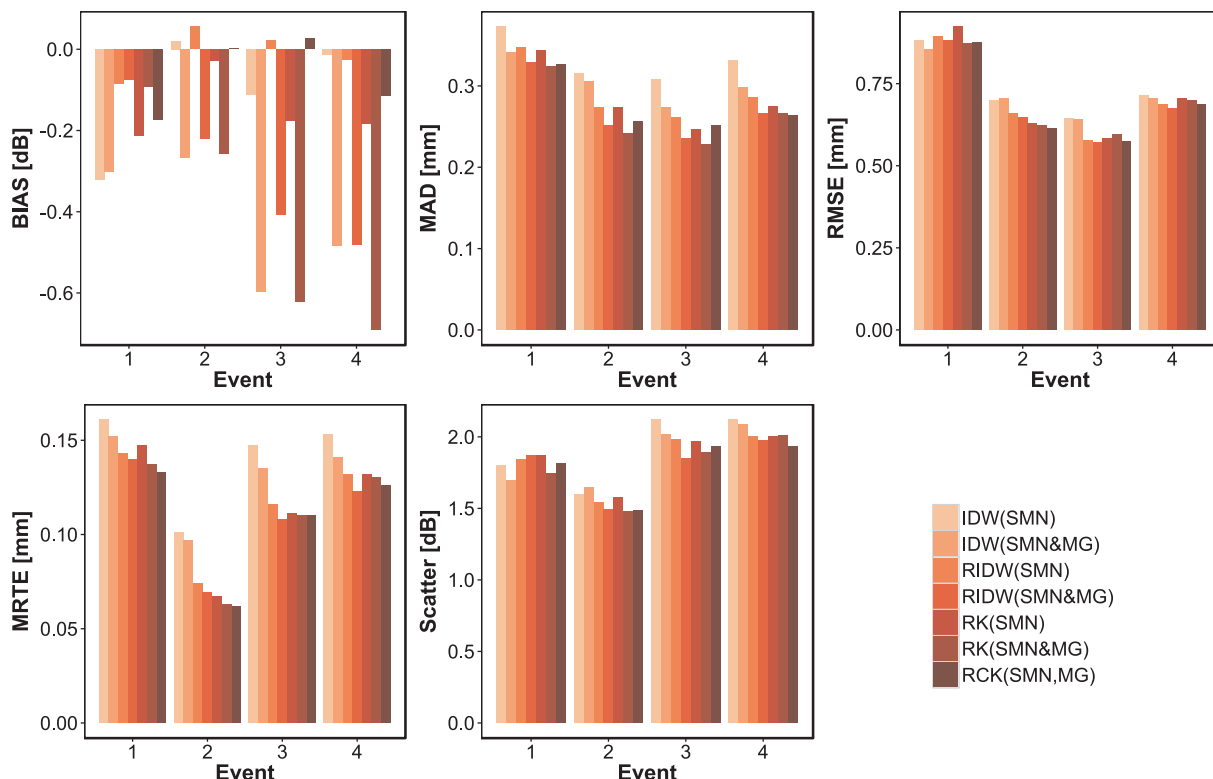


Fig. 12. Performance indicators over the 4 events, exploring combination of SMN and MG as primary variable for IDW, RIDW and RK methods.

their contribution to the overall interpolation quality is analyzed only via cross-validation applied to the MeteoSwiss (SMN) stations. This cross-validation does probably not show a complete picture of the contribution brought by the MG stations as (i) the MG stations have been selected to complete the SMN network in areas without SMN stations and (ii) the MG stations contribute to the final interpolated

precipitation field mostly in their immediate vicinity.

As expected, including the radar data as external drift considerably improved the precipitation interpolation for all tested methods. However, any radar data set in a comparably complex area is highly likely to suffer from several quality issues such as radar beam shielding by mountain peaks located in close vicinity of the radars. For our case

Table 6
List of methods and data used for analysing the combination of SMN and MG data as a unique variable. For methods abbreviations, see Table Table 3.

Application	Radar	Primary variable	Secondary variable
IDW(SMN)	No	SMN	–
IDW(SMN&MG)	No	SMN + MG	–
RIDW(SMN)	Yes	SMN	–
RIDW(SMN&MG)	Yes	SMN + MG	–
RK(SMN)	Yes	SMN	–
RK(SMN&MG)	Yes	SMN + MG	–
RCK(SMN,MG)	Yes	SMN	MG

Table 7
Table of variables.

Variable	Description
a	Regression coefficient for trend computation
b	Bin size for variogram computation
$C(h)$	Covariance at distance h
c_a	Covariance vector between the location of interpolation and the monitored locations of variable A
C_{aa}	Covariance matrix between the residuals of variable A
C_{bb}	Covariance matrix between the residuals of variable B
C_{ab}	Cross-covariance matrix between the residuals of variable A to the residuals of variable B
C_{ba}	Cross-covariance matrix between the residuals of variable B to the residuals of variable A
C_{ij}	Covariance between the residuals at locations i and j
d	Distance separating two locations
D	Spatial domain
g	Rain gauge observation
h	Distance lag between pairs of locations
K_0	Nugget value
K	Partial sill
m	Trend component
N	Number of available rain gauge measurements
p	Precipitation depth
r	Radar estimate
s	Spatial coordinates
s	Spatial coordinates vector
s_0	Spatial coordinates of interpolation location
t	Period of time
T	Temporal domain
x	x coordinate
y	y coordinate
Y	Square-root-transformed random variable
Y^2	Back-transformed random variable
Z	Random variable
α	Variogram model range
β	Power coefficient for the IDW method
ϵ	Residual component: observation - trend component
$\gamma(h)$	Variogram model
$\gamma_a(h)$	Univariate variogram
$\gamma_{ab}(h)$	Cross-variogram
$\gamma_{ab}^*(h)$	Pseudo cross-variogram
λ	Interpolation weights
μ_Y	Mean of the square-root-transformed kriging prediction
ρ	Research radius
σ_Y	Standard deviation of the square-root-transformed kriging prediction
σ_Z^2	Variance of the observations
τ	Precipitation intensity threshold for computation of variance to add in the back-transformation

study, the Mont Bonvin (2994 m asl.), located two kilometers south-east of the radar of Pointe de la Plaine Morte (2926 m asl.), creates such a blind zone due to radar shielding in south-eastern direction from the radar location (visible in Fig. 15). In this area, precipitation is highly likely to be underestimated by the radar. This effect remains visible in the final estimation method retained here (RCK on the radar residuals with SMN as primary and MG as secondary variable) and is visible on Fig. 13. A similar effect can be seen on Fig. 6(b) for a second radar, the

Monte Lema radar (south-east of the case study basin, see Fig. S.2 in Supp. Mat.). In fact, before the installation of the new radar at Pointe de la Plaine Morte, such shielding beams were already common over the studied basin as illustrated in the Supplementary Material (Figs. S.3 and S.4).

The radar network configuration in terms of installed devices is supposed to not evolve in the near future. The most promising directions to further improve precipitation interpolation under the current configuration are, thus, the following:

- (i) Better accounting for radar shielding effects; the replacement by MeteoSwiss of their radar precipitation estimates product, used for the present study, by a new version, optimized for the new network configuration with 5 weather radars, will certainly contribute positively to this issue. Further investigations could e.g. consist in developing a raster of radar data quality based on the visibility of the weather radars or by analyzing the annual radar precipitation estimates. Such a method to account for radar quality should also consider temporal variations of the radar network configuration resulting from temporary inactivity of individual weather radars (due e.g. to technical failures or scheduled maintenance);
- (ii) Improvement of the regression of the radar data on the rain gauge data, e.g. by including a second coefficient in the linear regression (Eq. 7), by developing a more local regression method that could account explicitly for summer convective precipitation or by integrating other covariates (e.g. topography).

In addition, latest developments in the field of hydrometeor type classification from radar data (Grazioli et al., 2015), might open up new perspectives on precipitation-radar data integration for mixed snow and rain events in the near future, as well as higher quality radar precipitation estimates during snow fall.

A final point worth mentioning is the potential integration of secondary rain gauge networks composed of non-heated stations that can only observe liquid precipitation, such as the Agrometeo network (Agroscope, 2017) or the IMIS network (SLF, 2017) to further increase the density of rain observation stations. This is readily possible with the retained interpolation methodology and could potentially reduce the precipitation estimation error during rainfall events. However, 75.1 percent of the studied area lies above 1500 m asl., where precipitation occurs regularly in the form of snow between November and March (Marty, 2008). In addition, with the high density of higher quality data already available, it is not sure that this would improve the performance.

6. Conclusion

This paper proposes a new method named Regression co-kriging for spatial interpolation of observed precipitation from two non-collocated rain gauge networks of different quality with radar data. Compared to the precipitation fields routinely produced in real-time by the Swiss national meteorological service MeteoSwiss (Sideris et al., 2014a) based on the observed precipitation data from their SwissMetNet (SMN) network, the final interpolation method retained here, additionally integrates data from the network of the private company MeteoGroup Switzerland AG (MG).

The performance of the interpolated precipitation fields is assessed for four events over a Swiss Alpine region, the Upper Rhône River basin, using inverse distance weighting applied directly to the rain gauge observations as baseline scenario. A series of well-established precipitation interpolation methods are tested, including methods that use (i) the radar data as an external drift to compute an overall precipitation trend and (ii) the rain gauge data to form local residuals that are spatially interpolated and added to the trend. Since the station locations of the two networks do not coincide, the concept of pseudo cross-variogram is employed to compute the linear model of coregionalization

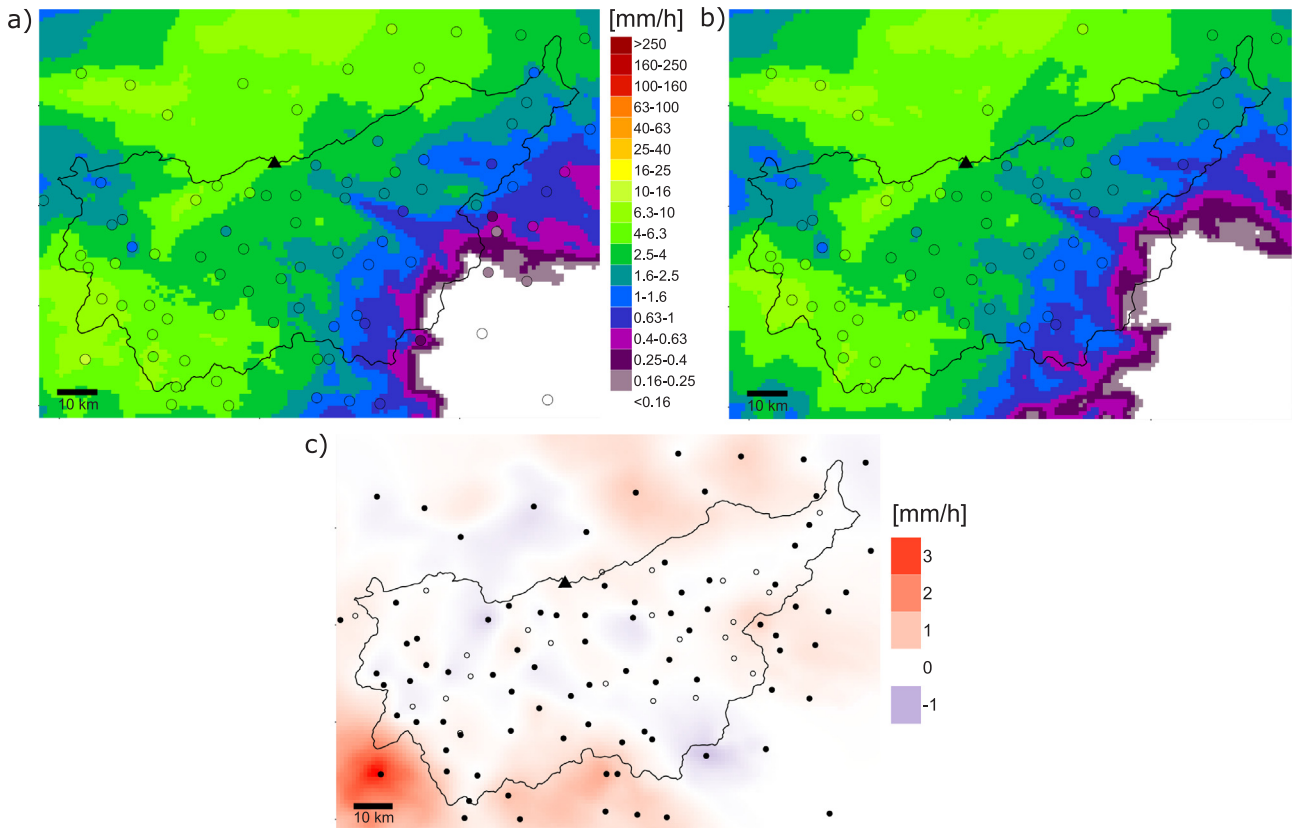


Fig. 13. Hourly precipitation interpolated using RCK(SMN,MG) (a) considering all station networks around the basin (see Table 1) together with the SMN stations as a single (primary) variable (time step: 01-05-2015 2200 UTC + 1); (b) as (a) but without surroundings station networks; (c) difference between (a) and (b). On (a) and (b), the circles represent the primary stations. On (c), the filled circles represent primary stations, the empty circles the secondary stations. The triangle represents the location of the radar of Pointe de la Plaine Morte.

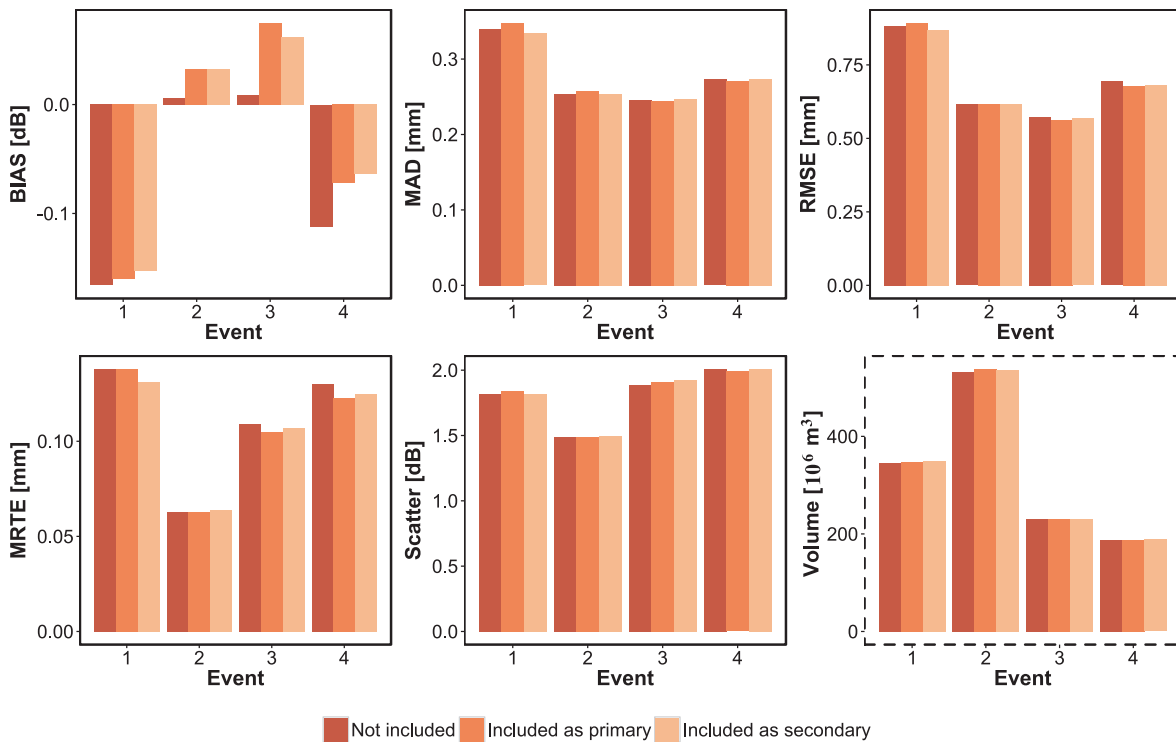


Fig. 14. Performance indicators comparison for RCK(SMN,MG) including or not the neighbouring networks, and using them as primary, respectively secondary network.

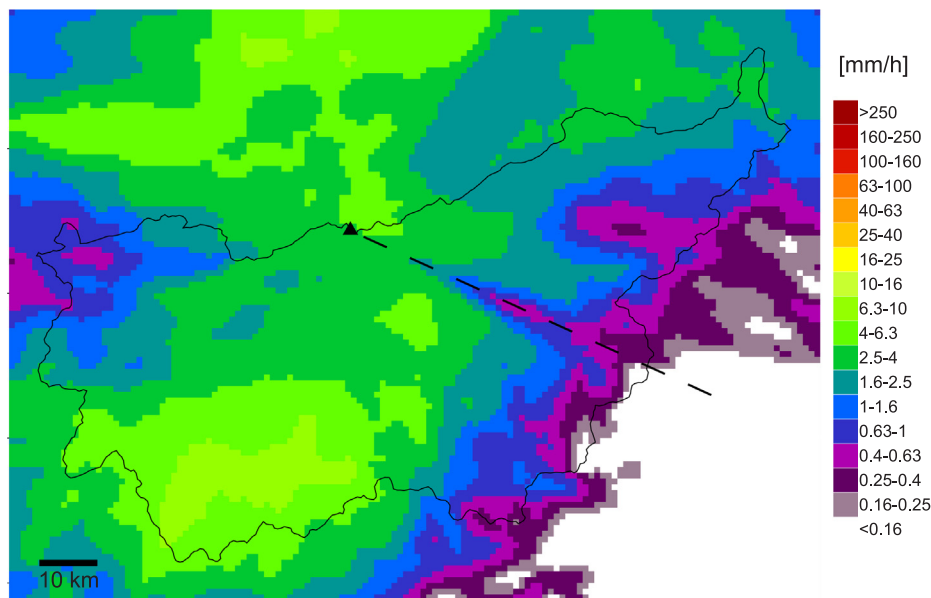


Fig. 15. Example of a raw radar data with the blind zone in south-east direction of the radar of Pointe de la Plaine Morte (time step: 01-05-2015 2200 UTC + 1). The black triangle represents the weather radar. The dashed-line indicates the blind zone direction.

used for the co-kriging interpolation.

The completed detailed tests demonstrated that regression co-kriging using the SMN data as primary variable and MG data as secondary variable to interpolate the local precipitation residuals provides the best performance for the study area. The method even proved to clearly outperform the Inverse distance weighting method for historical data availability scenarios, before the radar network was completed and with lower rain gauge station density. This result is important for hydrological applications where data over many years are required. The gain introduced by the co-kriging approach is demonstrated by showing a bias issue when considering both networks jointly linked to a difference in the networks quality. Regardless of the spatial scale, data combination must therefore consider with care the quality of the sensors providing the data when elaborating a combination methodology. The results of the analysis also showed that even with up-to-date modern weather radar equipments, radar-gauge combination in a complex topography such as the Swiss Alps requires a high-level treatment of the data. This is particularly true for reducing the artefacts due to beam shielding by the topography.

An interesting side-result of this study is the fact that if a single rain gauge network (SMN stations) is combined with radar data, a kriging-based residual interpolation does not clearly outperform a simple inverse distance weighting of the residuals. This is probably explained, at least partly, by the relatively low number of rain gauges that report precipitation for some time steps over the considered domain, which is often near the limit or even below the minimum required number to obtain robust variograms (which is particularly limiting for RCK where two variables need to meet this criterion).

Overall, the presented results underline the importance of analyzing in detail the evolving data situation to propose robust precipitation interpolation methods. This not only holds for regions where the rain gauge and radar network is evolving; any existing network might indeed suffer from device failures and ensuing missing data.

In general, the detailed analysis of different rain gauge networks provided here (including networks of neighbouring regions, networks of different quality), illustrates that integration of several networks for operational interpolation purposes is not straightforward. Since the available meteorological data (quantity and quality) is permanently increasing, there is ample room for further studies on improving quantitative precipitation estimates for complex Alpine environments. Based on our analysis, the most promising research direction is

certainly the pre-processing of the radar data in particular to account for known beam shielding effects and to take advantage of recent progress in the field of hydrometeor type classification for radar data.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.jhydrol.2018.05.027>.

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AMÉLIORATION DU CALAGE DU MODÈLE HYDROLOGIQUE DU BASSIN DE LA GRANDE-EAU EN SUISSE AVEC DES PRODUITS SPATIALISÉS DE PRÉCIPITATION, TEMPÉRATURE ET COUVERTURE DE NEIGE

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La prévision hydrologique en milieu alpin continue de représenter un défi majeur malgré le développement technologique, notamment en lien avec la forte variabilité spatiale des précipitations ainsi que l'importance de la fonte nivale au printemps. Cet article explore l'utilisation de divers produits de précipitation pour le calage d'un bassin alpin en Suisse, le bassin de la Grande-Eau (153.9 km²). Deux réseaux de stations de mesure ainsi que deux produits d'estimation quantitative de précipitation sont examinés. Parallèlement à cette variation des données d'entrée, deux approches de calage sont explorées. La première approche, conventionnelle, utilise les données de débit pour caler les paramètres du modèle hydrologique. La seconde étudie une division en deux phases du calage : dans un premiers temps, les coefficients de fonte nivale sont estimés à l'aide de données satellitaires ; les autres paramètres sont ensuite calés comme dans l'approche conventionnelle en utilisant les données de débit. Les résultats du cas d'étude montrent que l'utilisation de produits spatialisés de précipitation ne permet pas forcément d'améliorer la valeur des indicateurs de performance. Sur le bassin étudié, l'utilisation de ces produits semble renforcer le problème de biais négatifs en termes de volume déjà observé en utilisant les valeurs aux stations météorologiques. Concernant la division en deux phases de la procédure de calage, une légère amélioration des indicateurs de performance est observée.

MOTS CLEFS : modèle hydrologique, précipitations spatialisées, équivalent en eau de la neige.

Improved calibration of the hydrological model of the Grande-Eau catchment in Switzerland with spatialized products of precipitation, temperature and snow cover

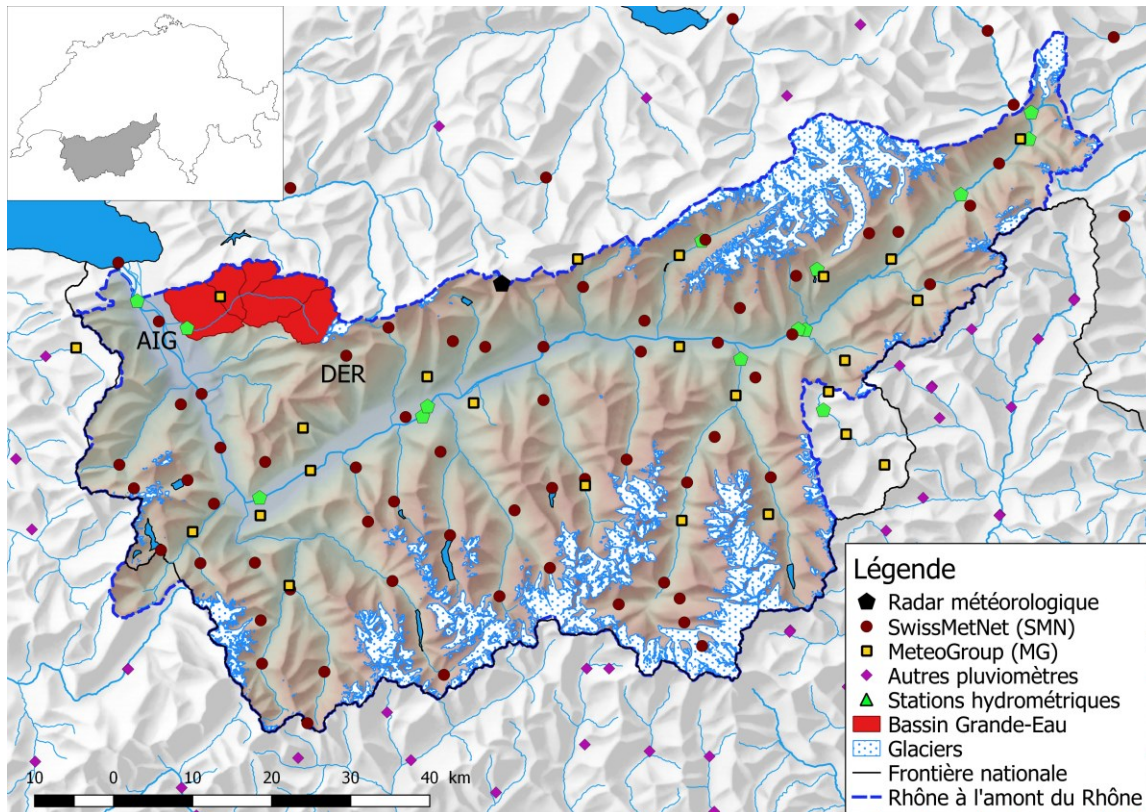
Hydrological forecasting in Alpine environments continues to represent a major challenge despite of technological development. The spatial variability of precipitation as well as the importance of snow-melt in spring are two major issues. The present article explores the use of various precipitation products for the calibration of an Alpine catchment in Switzerland, the Grande-Eau catchment (153.9 km²). On one side, it analyses the combination of two networks of different quality. On the other side, it studies the use of two products of quantitative precipitation estimates. In addition to this input variation, two calibration approaches are explored. The first approach consists of a traditional calibration of the parameters of the model using discharge data. In the second approach, a division into two steps of the calibration is investigated. In a first step, the snow-melting coefficients are estimated using data from the Moderate-Resolution Imaging Spectroradiometer (MODIS) on board the Terra and Aqua satellites. The analysis is done pixel by pixel using spatialized products of precipitation, temperature and snow cover. Pixel values are then aggregated over altitude bands to be used in the semi-distributed model used for the hydrological simulation. In the second step, the other parameters are calibrated as in the traditional approach with discharge data. In order to allow a comparison between the precipitation products, the multiplier coefficient of precipitation is maintained fixed to 1 for all the methods. The results of the case study show that the use of spatialized products of precipitation does not necessarily improve the performance of the hydrological model. Over the studied basin, the use of these quantitative precipitation estimates seems to increase the negative bias issue in the simulated flow already observed when using data from the meteorological stations. Regarding the 2-step calibration, a slight improvement in the performance indicators is observed, which tends to support the explored approach.

KEY WORDS : Hydrological model, spatial interpolation of precipitation, snow water equivalent.

50 **I INTRODUCTION**

51 Le projet MINERVE pour la prévision et la gestion des crues dans le bassin du Rhône à l'amont
52 du Lac Léman (Valais, Suisse) a débuté en 2002. Un modèle hydrologique-hydraulique capable de
53 modéliser à l'aide d'une approche semi-distribuée des bassins complexes ainsi qu'un système
54 d'aide à la décision pour la gestion des barrages ont été développés [Jordan, 2007 ; Tobin, 2012 ;
55 García Hernández et al., 2014]. Depuis 2011, le système est opérationnel et génère chaque deux
56 heures une nouvelle prévision hydrologique pour l'ensemble du bassin.

57 Le bassin du Rhône à l'amont du Lac Léman (Figure 1) se situe dans les Alpes Suisses et couvre
58 la majeure partie du Canton du Valais et une partie du Canton de Vaud. La surface du bassin est de
59 5524 km², dont environ 10% est couverte de glaciers. L'altitude varie entre 372 et 4634 m s.m.



60
61 Figure 1 Bassin du Rhône à l'amont du Lac Léman et le sous-bassin de la Grande-Eau en rouge. L'abréviation des
62 stations SwissMetNet d'Aigle (AIG) et de Derborence (DER) sont indiquées. Source de données: Swisstopo [2017a]
63 pour les rivières et lacs, Swisstopo [2013] pour les glaciers (avec modifications), Swisstopo [2005] pour le modèle
64 numérique de terrain, Swisstopo [2012] pour le relief et Swisstopo [2017b] pour la frontière nationale.

65 Le système MINERVE est une source d'information essentielle pour les organes compétents du
66 Canton du Valais en lien avec la prise de décision telle que la vidange préventive d'aménagements
67 hydro-électriques ou l'évacuation de zones habitées. Le système exploite les observations
68 météorologiques de deux réseaux de stations de mesure (le réseau SwissMetNet (SMN) de l'Office
69 Fédéral de météorologie et climatologie MétéoSuisse et le réseau de la société privée MeteoGroup
70 (MG) Switzerland AG) ainsi que le produit opérationnel d'estimation quantitative de précipitation
71 de MétéoSuisse [Sideris et al., 2014] combinant les données radar et les mesures du réseau SMN.
72 Le système utilise également les données de débit de l'Office fédéral de l'environnement (OFEV)
73 ainsi que les prévisions météorologiques de MétéoSuisse (produits COSMO-1 et COSMO-E).

74 Sur la base de ces données, le système MINERVE génère, à l'aide d'un modèle hydrologique, des
75 prévisions de débit pour l'ensemble du bassin. Un système d'envoi automatique de messages
76 informe du dépassement de seuils prédéfinis aux principaux points de contrôle du bassin.

77 La présente étude, appliquée au bassin de la Grande-Eau, vise d'une part à évaluer le gain
78 potentiel d'une décomposition en deux phases de la procédure de calage en découplant l'évaluation

79 des coefficients de fonte nivale du reste du calage hydrologique. Elle explore, d'autre part,
80 l'utilisation de différents jeux de données d'entrée de précipitation.

81 Parajka et Blöschl [2008] ont démontré que l'utilisation des données de couverture neigeuse du
82 *Moderate-Resolution Imaging Spectroradiometer* (MODIS), embarqué sur les satellites Terra et
83 Aqua [Hall et al. 2016], permet une amélioration des performances de la modélisation de la neige.
84 He et al. [2014] proposent une méthode pour l'estimation sans calage des facteurs degré-jour à
85 partir de la couverture neigeuse de MODIS et de mesures au sol de la hauteur de neige. Pistocchi et
86 al. [2017] ont également obtenus de bons résultats en utilisant des valeurs journalières de
87 température et de précipitation et les données MODIS. Ils ont mis en avant l'importance de la
88 qualité des précipitations et des températures utilisées comme données d'entrée. Contrairement à He
89 et al [2014], la présente étude utilise uniquement les données MODIS et non pas de hauteurs de
90 neige mesurées au sol. De plus, une différence avec Pistocchi et al. [2017] réside dans l'utilisation
91 de données horaires plutôt que journalières ainsi qu'un pas de temps horaire pour les simulations.

92 **II BASSIN D'ÉTUDE ET DONNÉES D'ENTRÉE**

93 Le bassin de la Grande-Eau, un sous-bassin du bassin MINERVE situé dans sa partie nord-ouest,
94 couvre une superficie de 153.9 km² dont seulement environ 1% est couvert par de la glace.
95 L'altitude varie entre 378 et 3200 m s.m. L'écoulement y est légèrement perturbé par une
96 installation hydro-électrique mais l'effet étant limité, cela n'a pas été modélisé.

97 Le bassin de la Grande-Eau ne dispose pas à l'intérieur de son territoire de station du réseau
98 SwissMetNet (SMN), considéré comme le réseau de référence de par la qualité des équipements
99 installés. Deux stations SMN, Aigle et Derborence (respectivement AIG et DER sur la Figure 1)
100 sont cependant proches du bassin. La station Leysin du réseau MeteoGroup (MG) est quant à elle
101 située dans le bassin. Il faut cependant noter ici qu'une comparaison entre les deux réseaux de
102 stations météorologiques a démontré une tendance des stations MG à relever moins de précipitation
103 que les stations du réseau SMN [Foehn et al., 2018]. Deux cas de figure sont donc explorés :
104 i) utilisation des données SMN uniquement ; ii) utilisation des données SMN et MG combinées.

105 En plus des réseaux de mesure au sol, deux produits d'estimations quantitatives de précipitation
106 sont employées dans cet article: 1) le produit opérationnel horaire de MétéoSuisse [Sideris et al.,
107 2014], ci-après noté EQP1, combinant les données des radars météorologiques de MétéoSuisse avec
108 les données du réseau SMN ; 2) le produit décrit dans Foehn et al. [2018], ci-après noté EQP2,
109 utilisant les mêmes données que EQP1 mais intégrant également les données du réseau MG comme
110 variable secondaire dans un co-krigeage avec régression. Dans les deux cas, la résolution spatiale
111 des produits est de 1km·1km et la résolution temporelle de 1 heure. Il faut relever que le produit
112 EQP1 ne fournit pas de valeur pour 50 à 80 heures par année en moyenne, soit entre 0.5 et 1% du
113 temps. Une pluie de 0 mm/h sur tout le territoire est attribuée pour ces heures.

114 Concernant les températures, un produit spatialisé de température (PST) a été calculé à partir des
115 stations météorologiques à disposition sur le bassin. L'interpolation de ce produit a été réalisée avec
116 un krigeage avec dérive externe utilisant un modèle numérique de terrain. Cela permet de fournir
117 des valeurs de température avec la même résolution temporelle et spatiale que les produits de
118 précipitation.

119 **III MODÉLISATION HYDROLOGIQUE**

120 Le bassin d'étude est modélisé avec les modèles hydrologiques semi-distribués SOCONT et GSM
121 [García Hernández et al., 2018], illustrés dans la Figure 2. Le Tableau 1 fournit une description des
122 principaux paramètres de chaque modèle.

123 Pour la modélisation hydrologique du bassin, ce dernier a été divisé en 6 sous-bassins, sous-
124 divisés en 23 bandes d'altitude non-glaciaires (SOCONT) et 2 bandes d'altitude glaciaires (GSM).
125 L'utilisation de bandes d'altitude permet de reproduire de manière adaptée les processus liés à la
126 température et donc à l'altitude, telles que la fonte nivale ou glaciaire.

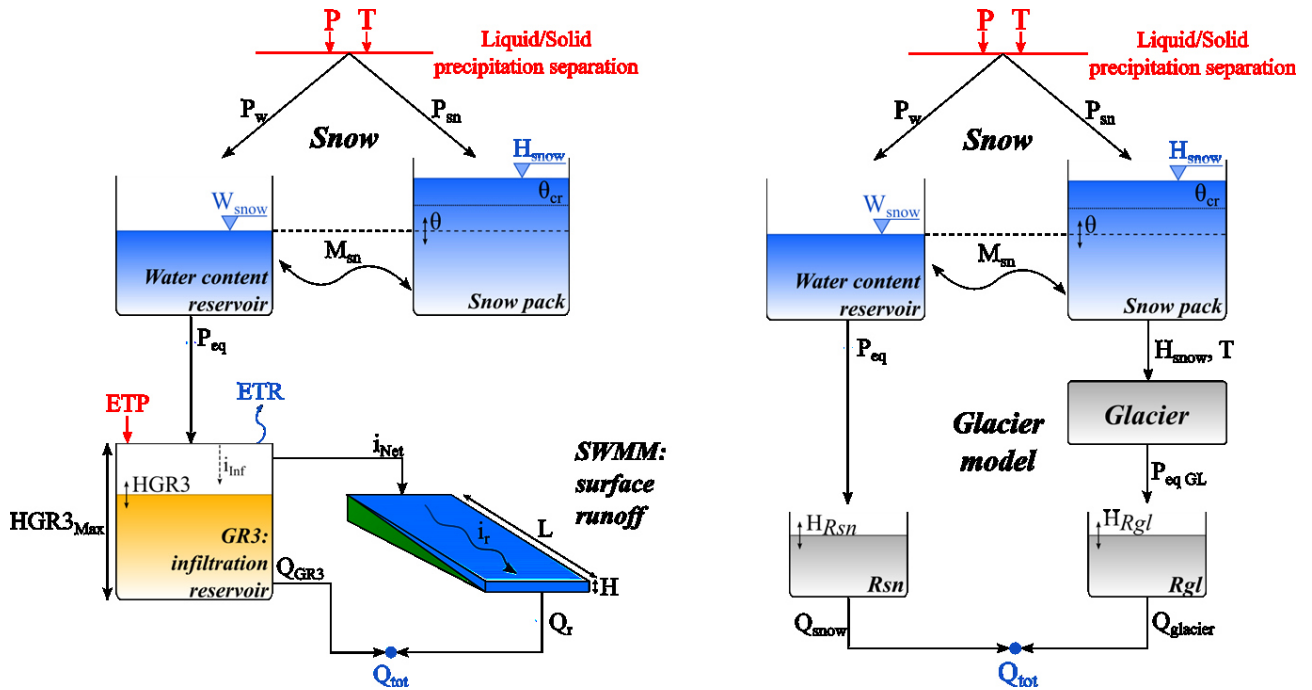


Figure 2 Modèle SOCONT (gauche) et GSM (droite). Source : García Hernández et al. [2018].

Tableau 1 Principaux paramètres des modèle SOCONT et GSM.

Variable	Unité	Modèle SOCONT
Asn	mm/°C/j	Coefficient degré-jour de fonte nivale
HGR3Max	m	Hauteur maximale du réservoir d'infiltration
KGR3	1/s	Coefficient de vidange du réservoir d'infiltration
Kr	m ^{1/3} /s	Coefficient de Strickler pour l'écoulement de surface
Variable	Unité	Modèle GSM
Asn	mm/°C/j	Coefficient degré-jour de fonte nivale
AgI	mm/°C/j	Coefficient degré-jour de fonte glaciaire

L'implémentation et les calculs sont réalisés avec le logiciel RS MINERVE [Foehn et al., 2018; García Hernández et al., 2018], basé sur la programmation orientée objet et permettant la modélisation hydrologique et hydraulique avec une approche semi-distribuée. En plus de simuler les processus hydrologiques tels que les écoulements de surface et de sub-surface ou la fonte nivale et glaciaire, le logiciel permet également d'incorporer des éléments de contrôle hydraulique comme des barrages, déversoirs, dérivations, turbines ou pompes. Les données météorologiques (précipitation et température) sont estimées pour chaque bande d'altitude à partir des données fournies. L'évapotranspiration est estimée pour chaque bande d'altitude et pour l'ensemble de la période de simulation à partir des données de température selon la formule de Turc [1961].

Toutes les autres opérations, incluant l'acquisition de données, la génération d'images ou l'interaction avec le logiciel RS MINERVE sont effectuées à l'aide du langage de programmation R [R Core Team, 2018].

IV MÉTHODOLOGIE DE CALAGE ET DE VALIDATION

Les différents produits de précipitations présentés précédemment sont utilisés pour le calage selon 2 approches. La première approche consiste en un calage conventionnel des paramètres sur la base des données de débit à l'exutoire du bassin. La seconde approche découple la procédure de calage en ajoutant une première phase permettant d'évaluer les coefficients de fonte nivale sur la base de données satellitaires, avant de caler dans la seconde phase le restant des paramètres sur la base du débit observé. Le Tableau 2 liste les paramètres calés dans chaque phase pour les deux approches.

150 Tableau 2 Les deux approches de calage avec les paramètres calés dans chaque phase.

	Paramètre calé dans la phase 1	Paramètres calés dans la phase 2
Calage conventionnel	-	HGR3Max ; KGR3 ; Kr ; Asn ; Agl
Calage en 2 phases	Asn	HGR3Max ; KGR3 ; Kr ; Agl

151

152 La première phase considère une variabilité spatiale du paramètre Asn. La seconde phase, et donc
153 le calage conventionnel, fixe par contre une valeur unique sur l'ensemble du bassin pour chaque
154 paramètre calé.

155 Pour le calage basé sur les observations de débit, les périodes listées dans le Tableau 3 ont été
156 considérées. Une période d'initialisation d'un an a été considérée autant pour le calage que la
157 validation, afin de définir des conditions initiales adéquates pour le modèle.

158

159 Tableau 3 Période utilisée pour le calage et la validation du modèle hydrologique.

Utilisation	Période
Calage	1.9.2015 – 1.9.2017
Validation	1.9.2012 – 1.9.2015

160

161 La fonction objectif permettant à l'algorithme de calage d'évaluer la performance de chaque
162 itération est composée de deux indicateurs [García Hernández et al., 2018] :

163 Fonction objectif = $0.5 \cdot \text{Nash-Sutcliffe} + 0.5 \cdot \text{coefficient de corrélation de Pearson}$.

164 Pour l'approche en deux phases (Figure 3), l'évaluation des valeurs de Asn s'effectue sur la base
165 d'une analyse pixel par pixel, en calant le paramètre de fonte de neige afin de reproduire le
166 comportement de la couverture neigeuse fourni par le *Moderate-Resolution Imaging*
167 *Spectroradiometer* (MODIS) [Hall et al. 2016]. Les valeurs journalières du Normalized Difference
168 Snow Index (NDSI), entre 0 et 100, peuvent être considérées comme un pourcentage
169 d'enneigement, et sont fournies par chacun des deux satellites. Elles sont combinées pour fournir
170 une valeur journalière de couverture neigeuse. La résolution spatiale du produit MODIS est de
171 500m·500m et définit la résolution spatiale utilisée pour la présente étude.

172 Pour chaque pixel, les valeurs de précipitation, de température et de couverture neigeuse sont
173 extraites d'une base de données spatiale. Le modèle de fonte nivale des modèles SOCONT et GSM
174 est ensuite utilisé pour simuler un équivalent en eau de la neige sur la période considérée. Afin de
175 permettre une comparaison avec les valeurs de couverture neigeuse, ces dernières ne fournissant pas
176 d'estimation quantitative de l'équivalent en eau de la neige, une binarisation de l'information est
177 réalisée. Pour ce faire, les seuils présentés dans le Tableau 4 sont utilisés pour définir la présence ou
178 l'absence de neige [Parajka et Blöschl, 2008].

179

180 Tableau 4 Seuil pour définir la présence de neige ou non.

Variable	Seuil
Equivalent en eau simulé	0.1 mm
NDSI (MODIS)	25%

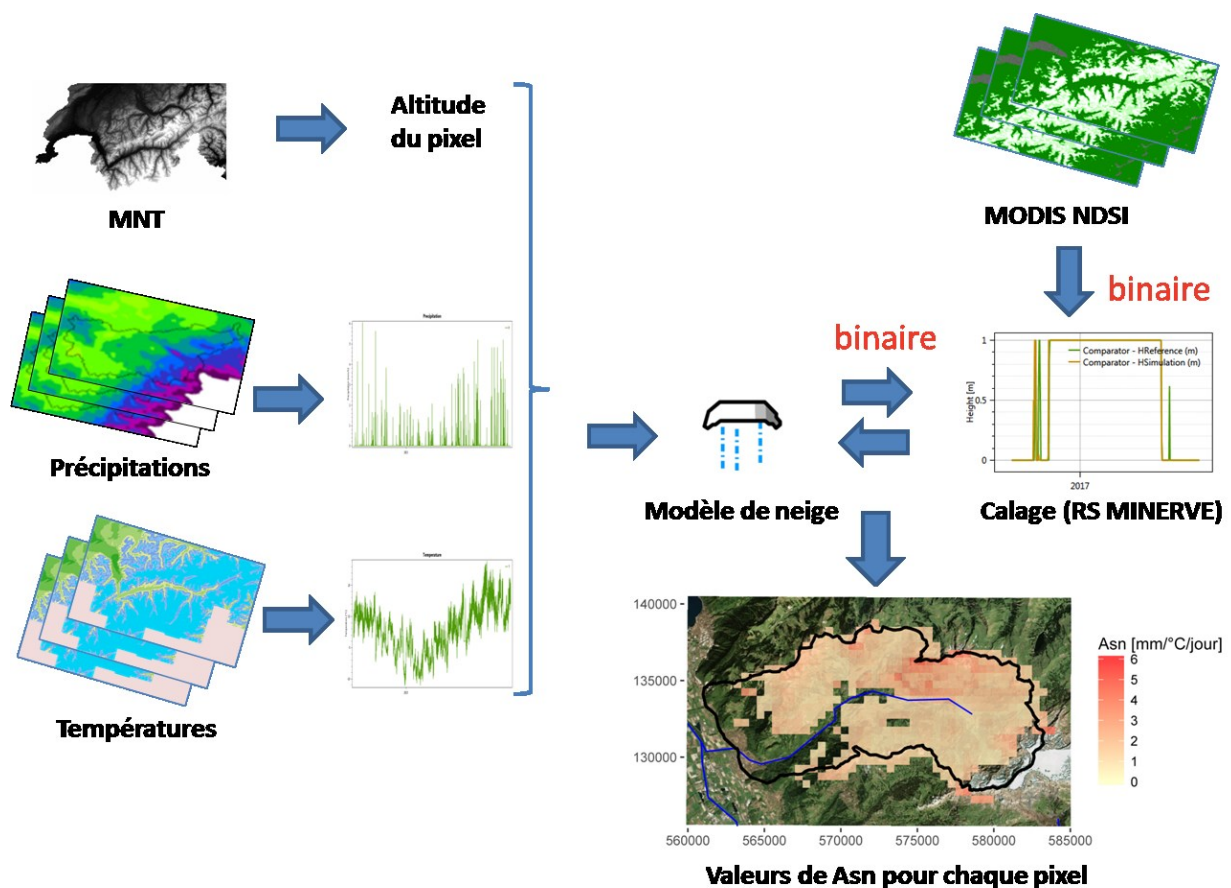


Figure 3 Schéma du calage du paramètre Asn (Phase 1 du calage en 2 phases).

181
182

183 Le paramètre Asn est ensuite calé de manière automatique à l'aide de la fonctionnalité du logiciel
184 RS MINERVE permettant de travailler en ligne de commande [García Hernández et al., 2018]. Le
185 calage se base sur le coefficient de performance de Nash-Sutcliffe (NS) comme unique indicateur et
186 est réalisé sur une période de 5 ans (1.9.2012-1.9.2017). Le calcul est réalisé sur tous les pixels du
187 bassin à l'exclusion des pixels glaciaires. En effet, la présence de glace toute l'année ne permet pas
188 de déterminer la présence de neige.

189 Une fois le calage réalisé sur tous les pixels, les valeurs sont agrégées par bande d'altitude. Afin
190 de ne considérer dans l'agrégation que les pixels pour lesquels le comportement observé a pu être
191 bien reproduit, seuls les pixels ayant obtenu une valeur de NS de 0.6 ou plus sont utilisés. Le seuil
192 de 0.6 a été défini sur la base d'une analyse pour assurer notamment l'exclusion des pixels les
193 moins élevés en altitude et sur lesquels les jours avec neige étaient trop peu nombreux pour
194 permettre un calage robuste. De plus, un minimum de 5 pixels valables par bande d'altitude est
195 exigé. Pour les bandes d'altitude en contenant moins, la valeur agrégée de la bande d'altitude la plus
196 proche respectant cette condition est considérée. Pour les bandes glaciaires, la valeur de Asn est
197 définie en considérant la valeur de la bande d'altitude non-glaciaire la plus proche.

198 Afin de permettre une comparaison entre les produits, aucun coefficient multiplicateur des
199 précipitations n'a été appliqué lors du calage. La valeur de ce coefficient est donc fixé à 1 afin
200 d'identifier d'éventuels problèmes de biais dans les résultats. En considérant les différents jeux de
201 données d'entrée et les différentes approches de calage précitées, six méthodes de calage ont été
202 retenues et sont présentées dans le Tableau 5.

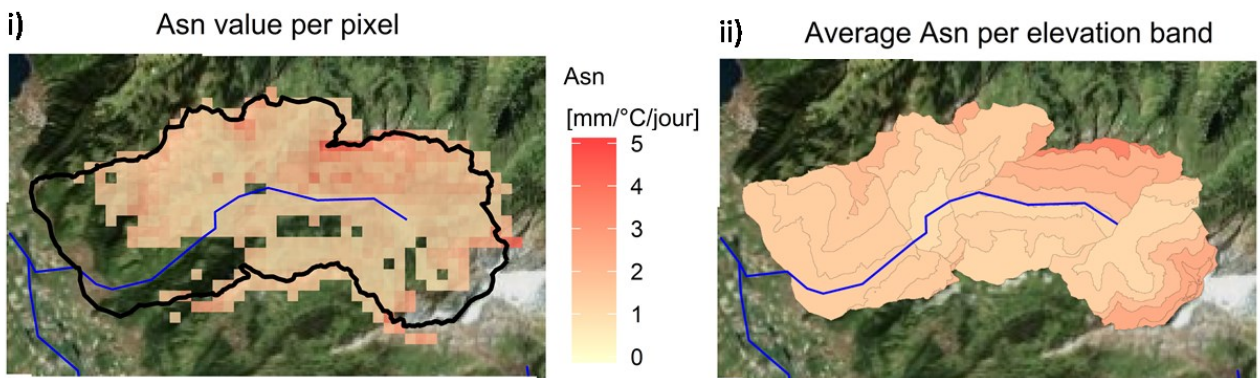
203 V RÉSULTATS

204 La première partie de cette section détaille les résultats concernant le calage des coefficients de
205 fonte de neige. La seconde partie présente les résultats globaux, avec une comparaison entre les
206 différentes méthodes ainsi qu'une discussion du gain du calage en deux phases.

Méthode	Données Précipitation	Données Température	Approche
Stations_SMN	Stations (SMN)	Stations (SMN)	Calage conventionnel
Stations_SMN+MG	Stations (SMN + MG)	Stations (SMN + MG)	Calage conventionnel
EQP1_1step	EQP1 (radar ; SMN)	PST (MNT ; SMN + MG)	Calage conventionnel
EQP2_1step	EQP2 (radar ; SMN + MG)	PST (MNT ; SMN + MG)	Calage conventionnel
EQP1_2steps	EQP1 (radar ; SMN)	PST (MNT ; SMN + MG)	Calage en 2 phases
EQP2_2steps	EQP2 (radar ; SMN + MG)	PST (MNT ; SMN + MG)	Calage en 2 phases

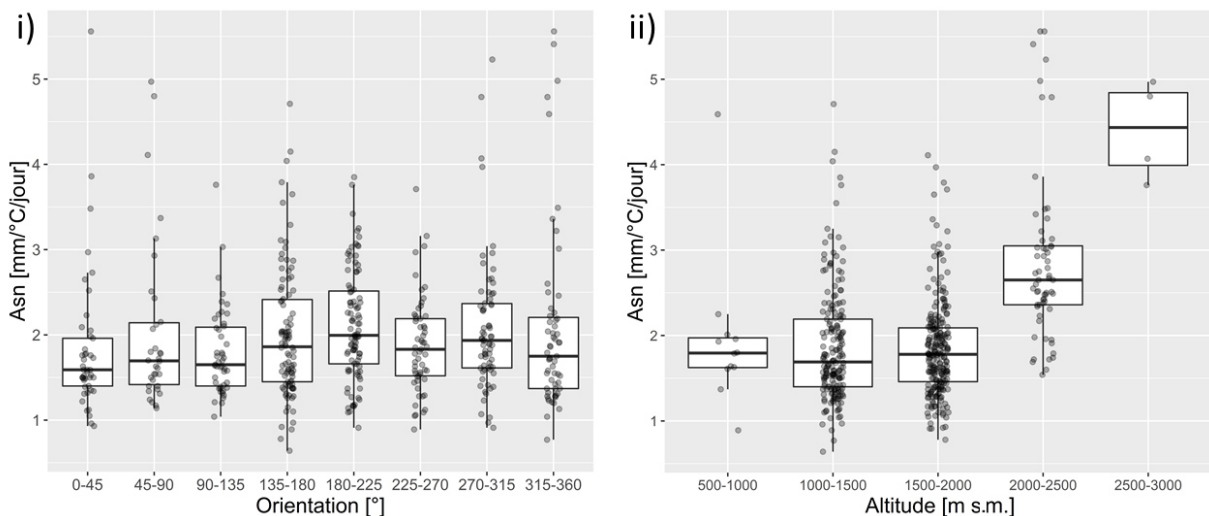
208 **V.1 Calage des coefficients de fonte de neige**

209 Nous présentons ici les résultats obtenus pour l'estimation des coefficients de fonte de neige avec
 210 les méthodes EQP1_2steps et EQP2_2steps. La Figure 4 présente les valeurs obtenues avec la
 211 méthode EQP1_2steps (gauche) et le résultat après agrégation par bande d'altitude (droite). Seules
 212 les valeurs des pixels ayant obtenu une valeur de NS supérieure à 0.6 lors du calage sont affichées.



213 Figure 4 Valeurs du coefficient Asn obtenus i) pixel par pixel avec la méthode EQP1_2steps ; ii) par bande d'altitude
 214 après agrégation des pixels présenté en i). Source de données : Bing Maps pour le fond de carte.
 215

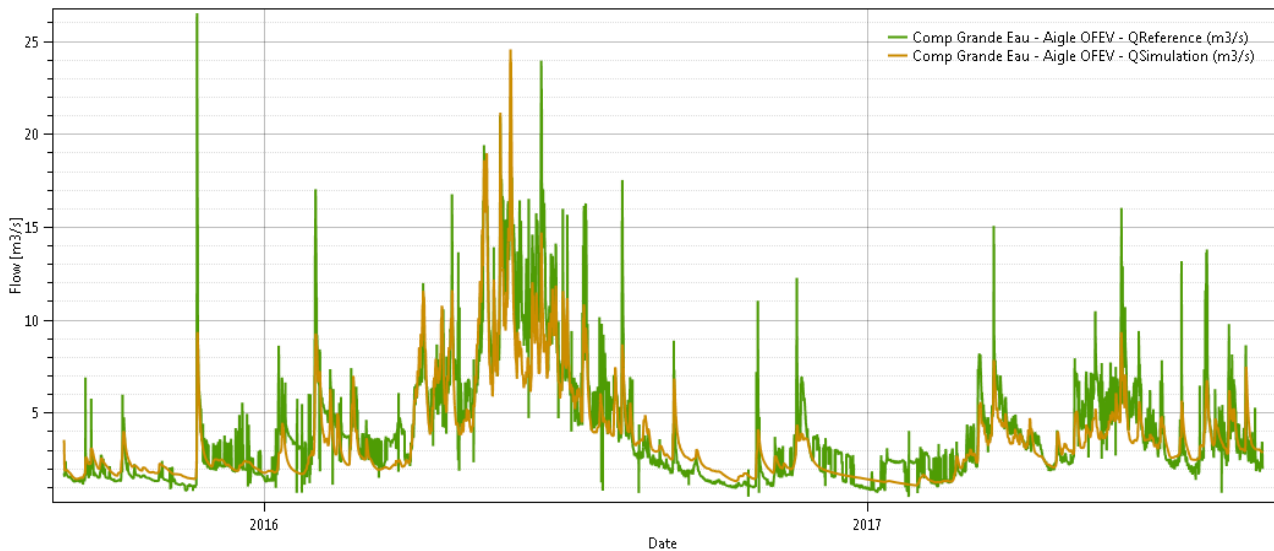
216 La Figure 5 présente la distribution des valeurs de Asn en fonction de l'orientation (par rapport au
 217 nord et dans le sens horaire) et de l'altitude. L'orientation de chaque pixel a été définie à partir
 218 d'une analyse du modèle numérique de terrain en considérant des pixels de 150m·150m. La
 219 comparaison avec l'orientation illustre l'ensoleillement plus important sur les faces orientées sud,
 220 traduit par des valeurs de Asn plus élevées, synonymes d'une fonte plus rapide. Concernant
 221 l'altitude, les valeurs ont tendance à augmenter avec l'altitude, peut-être expliqué en partie par un
 222 effet proportionnellement plus important en altitude du rayonnement par rapport à la température.



223 Figure 5 Distribution des coefficients Asn en fonction de i) l'orientation et ii) l'altitude. Chaque point correspond à un
 224 pixel de l'analyse. Seuls les pixels ayant obtenu une valeur de NS supérieure à 0.6 sont affichés.
 225

226 **V.2 Résultats du calage avec les données de débit**

227 Pour toutes les méthodes listées dans le Tableau 5, le calage basé sur les données de débit a été
 228 réalisé. Pour les méthodes avec un calage en 2 phases, les valeurs pour le paramètre Asn obtenues
 229 lors de la première phase ont été intégrées dans le modèle avant le calage sur les débits (seconde
 230 phase). La Figure 6 fournit le résultat de la validation pour la méthode Stations_SMN, résultat d'un
 231 calage uniquement sur les données de débit et employant les données du réseau SMN comme
 232 données d'entrée. Une bonne correspondance entre débits simulé observé est constatée. Pour les
 233 autres méthodes, la correspondance est légèrement moins bonne, avec des débits simulés tendant à
 234 être inférieurs que les débits observés, essentiellement les six premiers mois de chaque année.



235 Figure 6 Débits observé et simulé pour la méthode Stations_SMN, résultat d'un calage en une phase utilisant
 236 uniquement les données de débit comme référence et alimenté par les données du réseau SwissMetNet pour les données
 237 d'entrée météorologiques.
 238

239 L'analyse des indicateurs de performance obtenus (Tableau 6) montre que l'utilisation de produits
 240 d'estimation quantitative des précipitations n'entraîne pas forcément une augmentation de la
 241 performance. En effet, lors du calage, la meilleure valeur a été obtenue par la méthode n'utilisant
 242 que les valeurs du réseau SMN. Cela n'est par contre pas le cas pour la validation, où les méthodes
 243 utilisant les produits spatialisés de précipitation fournissent en partie de meilleures performances.

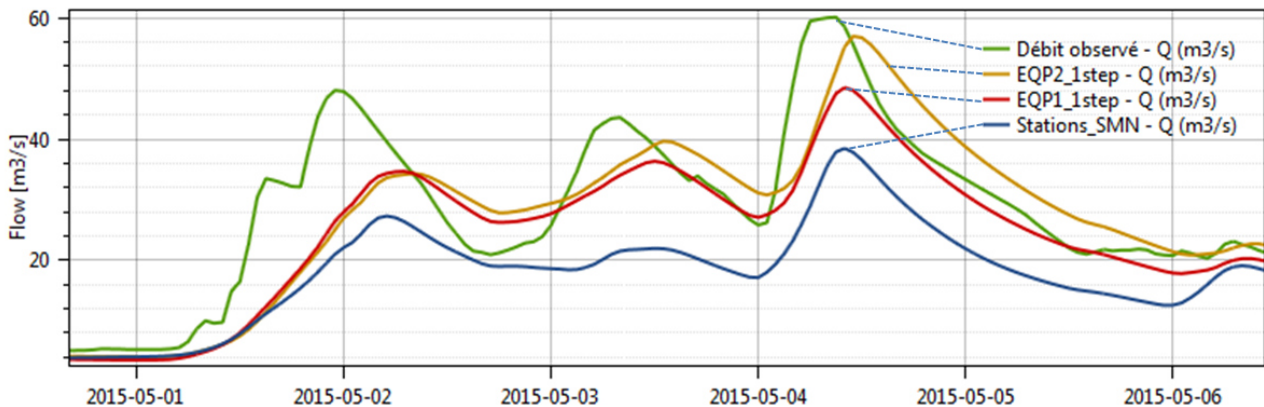
244 Un autre résultat évident est la sous-estimation des volumes totaux constatée pour toutes les
 245 méthodes. La différence s'observe notamment de janvier à juin et suggère une sous-estimation de la
 246 fonte nivale, vraisemblablement expliquée par une sous-estimation des précipitations solides.

247
 248 Tableau 6 Valeurs obtenues pour les indicateurs de performance lors du calage et de la validation.

Méthode	Calage (2015-2017)				Validation (2012-2015)		
	Fonction objectif	NS	Corrélation de Pearson	Biais de volume [%]	NS	Corrélation de Pearson	Biais de volume [%]
Stations_SMN	0.85	0.80	0.91	-9.9	0.60	0.85	-24.8
Stations_SMN+MG	0.84	0.78	0.91	-18.2	0.58	0.87	-31.6
EQP1_1step	0.75	0.62	0.88	-28.1	0.62	0.89	-31.7
EQP2_1step	0.75	0.62	0.88	-27.3	0.64	0.85	-17.4
EQP1_2steps	0.76	0.61	0.91	-30.0	0.60	0.88	-33.2
EQP2_2steps	0.76	0.63	0.89	-27.1	0.69	0.87	-17.0

251 Concernant le calage en 2 phases, l'approche semble fournir de meilleurs résultats que le calage
252 conventionnel selon l'indicateur de performance NS, mais tend à péjorer la performance selon le
253 coefficient de corrélation de Pearson. Ces résultats encouragent à poursuivre le développement de
254 cette approche. Il faut cependant noter que la présente analyse se base uniquement sur une période
255 limitée et que la méthode devra être appliquée à d'autres bassins avant de pouvoir tirer des
256 conclusions plus générales.

257 De plus, dans une perspective de prévisions de crues, la seule crue survenue durant la période de
258 validation, en mai 2015, a été analysée (Figure 7). Les produits spatialisés ont permis une
259 reproduction bien meilleure du débit observé et du pic de crue, la méthode Stations_SMN souffrant
260 notamment d'une forte sous-estimation du débit sur l'événement étudié.



261 Figure 7 Comparaison entre le débit observé et les débits simulés selon différentes méthodes pour la crue de mai 2015
262 (période de validation).
263

264 VI CONCLUSION

265 Le présent article étudie l'utilisation de différents produits de précipitation pour le calage d'un
266 bassin hydrologique, avec d'une part des mesures ponctuelles et d'autre part l'utilisation de produits
267 spatialisés de précipitation. L'analyse explore également une division en deux phases du calage
268 hydrologique, avec l'introduction d'une première phase permettant de caler les paramètres de fonte
269 de neige sur la base de données satellitaires.

270 Les résultats montrent que l'utilisation de produits spatialisés de précipitation n'entraîne pas
271 forcément de meilleures performances du modèle. Par contre, lors d'une crue en 2015 (période de
272 validation), l'utilisation de produits spatialisés de précipitation a permis une meilleure
273 représentation des débits observés. Un biais négatif en termes de volume est en outre observé sur le
274 bassin d'étude pour toutes les méthodes.

275 Concernant le calage en 2 phases, l'estimation a priori des coefficients de fonte de neige a permis
276 d'obtenir en partie de meilleures performances lors de la validation que le calage basé uniquement
277 sur les données de débit. La méthode devra encore être appliquée à d'autres bassins et sur une plus
278 longue période afin de pouvoir tirer des conclusions plus générales.

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APPLICATION OF AN ENSEMBLE KALMAN FILTER TO A SEMI-DISTRIBUTED HYDROLOGICAL FLOOD FORECASTING SYSTEM IN ALPINE CATCHMENTS

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KEY WORDS

Data assimilation, hydrological modelling, data uncertainty, data perturbation

ABSTRACT

One of the key success factor for hydrological forecasts is the establishment of initial conditions that represent well the conditions of the simulated basin at the beginning of the forecast. Real-time Data Assimilation (DA) has been shown to allow improving these initial conditions. In this article, two DA approaches are compared with the reference scenario working without DA (Control). In both approaches, discharge data at gauging station are assimilated. In the first approach, a volume-based update (VBU) compares the simulated and observed volumes over the past 24 hours to compute a correction factor used to update the soil water saturation in the upstream part of the semi-distributed hydrological model. In the second approach, an Ensemble Kalman Filter (EnKF) is implemented to account for the uncertainty in precipitation, temperature and discharge data. The comparison is carried out over 2 sub-basins of the Upper Rhône River basin upstream of Lake Geneva, where the MINERVE flood forecasting and management system is implemented. Results differ over the two studied basins. In one basin, the two data assimilation perform better than the Control simulation with the lowest error given by the VBU up to a forecast horizon of 35 hour and by the EnKF for higher forecast horizons. In the second basin, EnKF gives the lowest error over the few first hours of forecast, but then provides the weakest performance. The lowest error is given by the Control simulation, because the model already performs very well on the event without data assimilation.

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1. INTRODUCTION

Severe flooding events in recent decades have increased the need for reliable forecasting system in Alpine catchments. Following the major flood of October 2000 in the Canton of Valais (Switzerland), an operational forecasting system (MINERVE) has been set-up in 2013 and provides a tool for decision-making tasks [Jordan2008, García2001, García2014].

Despite efforts on the calibration of the model, the hydrological forecasts are subject to a number of uncertainties [Srikanthan2008]. First, meteorological inputs suffer from uncertainties both on the measurements and the meteorological forecast. This is true for the precipitation, but also for the temperature that can be difficult to estimate accurately in alpine catchments. Second, the model represents a simplification of the real system which implies errors in the simulated discharges. Third, the discharge measurements also suffer from uncertainties. All the uncertainties must be considered when analyzing the performances of a hydrological forecasting system.

Data assimilation techniques are mathematical tools developed to operationally correct the model results using the newly available system observations and taking into account explicitly the different sources of uncertainty. One of the first developed techniques was the Kalman filter (KF) [Kalman1960], largely used for linear models. To allow working with non-linear models, alternative methods have been developed. Among them, the Ensemble Kalman filter (EnKF) is a Monte Carlo approach of the KF, performing an ensemble of model runs [Evensen1994]. Weerts et al. 2006 compared the EnKF with Particle filtering and showed that EnKF was more robust and outperformed the two other analyzed filters. In this study, an implementation of EnKF with updating of state variables is explored using the SOCONT and GSM semi-distributed conceptual models. The performance gain is evaluated over two flood events concerning two different rivers located within the Upper Rhone River basin in Switzerland.

2. MATERIAL AND METHODS

2.1 Watersheds and data

The analysis concerns the simulation of the streamflow at the outlet of two sub-catchments of the Upper Rhone River basin over which an episode of high flow occurred over the period of availability (in 2012 for Reckingen and 2015 for Aigle). The characteristics of the sub-catchments are given in **Table 1**.

Station	River	Area [km ²]	Catchment mean elevation [m asl.]	Glaciation [%]	Return period of the studied event [years]
Reckingen	Rhone	214	2305	11.8	36
Aigle	Grande Eau	132	1562	0.8%	10

Table 1: Main characteristics of catchments

Both rivers are equipped each with a small run-of-river hydropower plant. The one over the Rhone has an equipped discharge of 5.7 m³/s (2012 yearly average: 10.6 m³/s). The Grande-Eau catchment receives water diverted from the Lac d'Arnon, a reservoir located in a nearby catchment with a capacity of 11 million m³. When the natural discharge in the Grande-Eau river is below the installed capacity of the two successive run-of-river hydropower plants, the water from the external reservoir is turbined in a third more upstream hydropower plant with a capacity of 1.75 m³/s (2015 yearly average: 4.02 m³/s).

Precipitation data are taken from a spatial product of precipitation following the regression co-kriging approach presented in Foehn2018, in which radar data are combined with two networks of ground stations data into a 1km x 1km gridded data with a one hour temporal resolution.

The temperature data are taken from a spatial product of temperature obtained through a kriging with external drift using elevation. The vertical lapse rate for temperature is computed each hour using a moving window of 150 m of altitude range and applying a signal filter. Most of the time, the temperature dispersion

at a given altitude is limited and the points are close to the regression line. However, this is not always true and the temperature distribution with altitude can be much more spread. In that case, the quality of the interpolated data is lower with a higher uncertainty.

In order to evaluate the performance of the data assimilation method, the mentioned spatial products of precipitation and temperature are used both for the assimilation and forecast simulation. Therefore, the simulations are based on observed data and are not subject to the uncertainty of meteorological forecasts. However, because uncertainties in these input data remain high in particular due to the complex topography of the Upper Rhone River basin, perturbed inputs are considered in the EnKF simulations (see Section 3.3).

2.2 GSM-SOCONT model

Simulations are performed with the rainfall-runoff semi-distributed conceptual GSM-SOCONT (Glacier and SnowMelt – Soil CONTRibution) model [Schaepli2005, GarcíaHernández2019], illustrated in **Figure 1**. The main parameters of the model are given in **Table 2**.

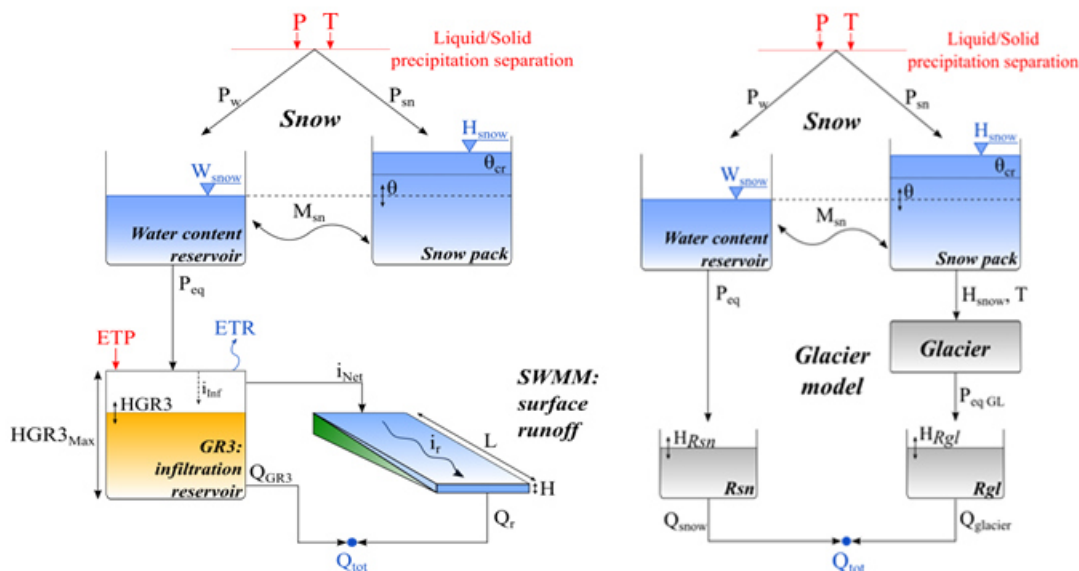


Figure 1: Parameters of the SOCONT rainfall-runoff model ([GarcíaHernández2019])

Parameters	Units	Model SOCONT
Asn	mm/d/°C	Reference degree-day snowmelt coefficient
HGR3 _{Max}	m	Maximum height of infiltration reservoir
KGR3	1/s	Release coefficient of infiltration reservoir
Kr	m ^{1/3} /s	Strickler coefficient of surface runoff
Variable	Units	Model GSM
Asn	mm/d/°C	Reference degree-day snowmelt coefficient
Agl	mm/d/°C	Reference degree-day glacier melt coefficient

Table 2: Main parameters of models SOCONT and GSM

The studied catchment is divided into elevation bands with an elevation range not exceeding 500 m. This allows in particular accounting for the vertical evolution of temperature. The GSM model is used for glacial elevation bands and the SOCONT model for non-glacial elevation bands. For both models, the snowmelt rate is controlled by the snowmelt coefficient. For the GSM model, when the surface is free of snow, glacial melting is considered based on the glacier melt coefficient and the temperature. For the SOCONT model, the generated discharge at the outlet of the basin is controlled by the absorption capacity of the soil, the release coefficient of the infiltration reservoir as well as the roughness of the surface runoff surface.

The model has been calibrated using the same spatial products of precipitation and temperature used for the assimilation.

2.3 Data assimilation techniques

Two data assimilation techniques are explored in this work to improve the values of the system state variables at the beginning of each forecast. The first method is based only on a volume comparison between simulated and observed discharges over the past 24h. This method has been used operationally for 3 years in the MINERVE system. The second method consists in an Ensemble Kalman filter, where an ensemble of possible model trajectories are corrected by assimilating the last available discharge observation.

The objective of the data assimilation is reducing the discrepancy between the simulated state variables and the actual state of the system as measured in real-time. This step would improve the performance of the model during the forecast. To do so, the state variables of the model are updated using the available system observations.

In the GSM-SOCONT model, the state variables that need to be updated are the water level in the soil reservoir (HGR3), the surface runoff water level (Hr) and the Snow water equivalent (SWE), which are evaluated at each spatial node of the model. In the following we will indicate with \mathbf{x}_t the system state vector of dimension $nstate=3 \times nnodes$, which elements are the state variables HGR3, Hr, SWE in all modeled nodes. The temporal evolution of the state vector obtained with GSM-SOCONT is formally represented by the following dynamical model

$$\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) \quad (1)$$

where the function f is the set of equations linking the state of the system from time t to $t+1$, \mathbf{u}_t^i represents the vector of model inputs (here, spatial maps of temperature and precipitation), \mathbf{w}_t is the possible occurrence of system noise (not directly considered in this analysis).

The assimilation procedure is performed using real measurements of the system, discharge data based on water level observations at the outlet of the watershed, provided by the Swiss Federal Office for the Environment (FOEN). To do so, the initial discharge of the (kinematic wave) river reaches (Qini) of the model are also considered as state variables. Observations are indicated with the vector \mathbf{y}_t of dimension $nobs$ (here $nobs=1$, since the observation is the discharge at time t at a unique gauging station). The link between the state variables \mathbf{x}_t and the observations, \mathbf{y}_t , is provided by the following observation operator:

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t + \mathbf{v}_t \quad (2)$$

where \mathbf{H} is a projection matrix (dimension $nobs \times nstate$), and \mathbf{v}_t represents possible measurement errors (see Section 3.1.3). Matrix \mathbf{H} is constructed with a value of 1 in correspondence of the state variable being observed, and 0 elsewhere [Clark2008].

In the following we describe the three assimilation procedures considered here to produce the forecasts of discharge.

2.3.1 Control simulation (Control)

The reference scenario is computed by running the model (eq. 1) without any perturbation of the input data (i.e., \mathbf{u}_t corresponds to the nominal values of precipitation and temperature) and without considering the discharge measurements performed during the simulation (no data assimilation). This simulation corresponds to what is frequently called the open loop scenario.

2.3.2 Volume-based update (VBU)

The first data assimilation approach is the volume-based update (VBU), which is based on the comparison between the volumes of the observed and the simulated discharges. The updated state variable is the soil moisture (HGR3) of the SOCONT models. The value of the corresponding HGR3 at the start of the VBU simulation (24 hours before the beginning of the hydrological forecast) is iteratively changed (up to ten iterations) so that the simulated flows throughout the simulation are as close as possible to the observed ones. The implemented approach limits the saturation at the start of the VBU simulation to 75% of the maximum water content in the soil, in order to avoid a too much reactive results. Note that VBU does not take into consideration the uncertainties in the input, model, and observations. The update takes into consideration all the observations collected during the 24 h before the forecast. Similarly to the control simulation, VBU provides as output only one model trajectory.

2.3.3 Ensemble Kalman filter (EnKF)

The second data assimilation approach is an implementation of Ensemble Kalman filter (EnKF), which better allows the update of the state variables taking into consideration model and measurements uncertainties. EnKF is an adaptation of the Kalman filter in which the covariance matrix is replaced by the sample covariance computed from an ensemble of possible state vectors. EnKF is based on the sequential repetition of two steps: the prediction (or forecast) step and the analysis (or update) step. In the prediction step the different members of the ensemble are independently advanced in time by running the model (eq. 1) using different random samples of the uncertain forcing terms:[Srikanthan2008, Abaza2015]:

$$\mathbf{x}_{t+1}^{i,f} = f(\mathbf{x}_t^{i,a}, \mathbf{u}_t^i, \mathbf{w}_t), \quad i = 1, \dots, nens \quad (3)$$

where $\mathbf{x}_{t+1}^{i,f}$ is the i^{th} member forecasted state at time $t+1$, $\mathbf{x}_t^{i,a}$ is the i^{th} updated ensemble state at time t , \mathbf{u}_t^i represents a possible occurrence of the model and/or input uncertainties (here, a perturbation of temperature and precipitation, see Section 3.1). The index “f” indicates the prediction and the index “a” the analysis.

In the analysis step, the predicted state variables $\mathbf{x}_{t+1}^{i,f}$ are updated using the newly available observation, \mathbf{y}_{t+1} . The $nens$ ensemble members are combined into the $nstate \times nens$ model state matrix, that is:

$$\mathbf{X}_{t+1}^f = (\mathbf{x}_{t+1}^{1,f}, \mathbf{x}_{t+1}^{2,f}, \dots, \mathbf{x}_{t+1}^{nens,f}) \quad (4)$$

where $nstate$ is the number of state variables and $nens$ is the number of ensemble members. The ensemble mean is given by

$$\bar{\mathbf{x}}_{t+1}^f = \frac{1}{N} \sum_{i=1}^{nens} \mathbf{x}_{t+1}^{i,f} \quad (5)$$

and it is used to compute the model error for each ensemble member i :

$$\mathbf{E}_{t+1}^f = (\mathbf{x}_{t+1}^{1,f} - \bar{\mathbf{x}}_{t+1}^f, \mathbf{x}_{t+1}^{2,f} - \bar{\mathbf{x}}_{t+1}^f, \dots, \mathbf{x}_{t+1}^{nens,f} - \bar{\mathbf{x}}_{t+1}^f) \quad (6)$$

The ensemble model covariance matrix ($nstate \times nstate$) can then be defined as follows:

$$\mathbf{P}_{t+1}^f = \frac{1}{N-1} \mathbf{E}_{t+1}^f \mathbf{E}_{t+1}^{fT} \quad (7)$$

In order for the EnKF to maintain sufficient spread in the ensemble and prevent filter divergence [Burgers1998], observations are perturbed in accordance with the measurement error (eq. 2) to create a $nobs \times nens$ vector of observations \mathbf{Y}_{t+1} . The analysis equation is then given by the EnKF update, which is optimal in the case of errors with a Gaussian distribution:

$$\mathbf{X}_{t+1}^a = \mathbf{X}_{t+1}^f + \mathbf{K}_{t+1}(\mathbf{Y}_{t+1} - \mathbf{H}_{t+1}\mathbf{X}_{t+1}^f) \quad (8)$$

where the matrix \mathbf{K}_{t+1} ($nstate \times nobs$) is called the Kalman gain:

$$\mathbf{K}_{t+1} = \mathbf{P}_{t+1}^f \mathbf{H}_{t+1}^T (\mathbf{H}_{t+1} \mathbf{P}_{t+1}^f \mathbf{H}_{t+1}^T + \mathbf{R}_{t+1})^{-1} \quad (9)$$

and where \mathbf{R}_{t+1} is the $nobs \times nobs$ observation error covariance matrix.

Note that each ensemble member is updated separately. Moreover, the forecast computed after an EnKF update consisted of an ensemble of model trajectories, from which it is possible to quantify the uncertainty associated to the forecast. In the EnKF implementation realized in this study, a new assimilation is performed every two hours.

3. EXPERIMENTAL SET-UP

3.1 Uncertainties in input and output

Model uncertainties are quantified by the ensemble Kalman filter through the empirical probabilistic distribution of the ensemble members. Input forcing data (precipitation and temperature in this study) are perturbed to provide each member a different input and thereby ensures spread in the ensemble. Ensembles are initialized with a perturbation of the main state variables of the model.

3.1.1 Precipitation uncertainty

Precipitation measurements are a large source of uncertainty, here described with a temporally-correlated lognormal random variable. During the prediction step of EnKF, the nominal value of precipitation is perturbed with a multiplier coefficient as follows:

$$P_t^i = P_t \times e_t^i \quad (10a)$$

with

$$e_t^i = \exp(z_t^i) \sim \log N(1, \sigma_e) \quad (10b)$$

where P_t is the measured precipitation at time t , e_t^i is the multiplier coefficient for the i^{th} member at time t , P_t^i is the perturbed precipitation for the i^{th} member at time t and $z_t^i \sim N(m_z, \sigma_z^2)$.

At time $t=0$, z_0^i is sampled from $z_0^i \sim N(m_z, \sigma_z^2)$. Parameters m_z and σ_z are computed imposing that $m_e = 1$ mm/h and $\sigma_e = 0.7$. This value of σ_e is in agreement with the Root Mean Squared Error (RMSE) computed in a previous validation study [Foehn2018] based on the cross-validation of a spatial product of precipitation over 4 events of heavy precipitation over the basin.

At time $t>0$, in order to ensure a temporal correlation of the perturbation in a given member, the time evolution of model errors is simulated as follows [Clark2008]:

$$z_t^i = \rho z_{t-1}^i + \sqrt{1 - \rho^2} \omega_t^i \quad (11a)$$

$$\omega_t^i \sim N(0, \sigma_z^2) \quad (11b)$$

$$\rho = 1 - \frac{\Delta T}{\tau} \quad (11c)$$

where ω_t^i is the sample white noise, ρ is the temporal persistence parameter, ΔT is the simulation time step and τ the decorrelation time step. In the present study, ΔT is one hour and τ is fixed to 24 hours (following Clark2008).

3.1.2 Temperature uncertainty

Temperature is perturbed using an additive term following a normal distribution:

$$T_t^i = T_t + s_t^i \quad (12a)$$

$$s_t^i \sim N(0, \sigma_s^2) \quad (12b)$$

For time $t>0$, a temporal correlation of the perturbation is considered following Eq. (9a) to (9c). The decorrelation time is fixed to 12 hours for the temperature.

3.1.3 Measurement uncertainty

Errors in the streamflow measurements can result from both errors in the level measure and uncertainties in the rating curve used to transform water level into discharge data. The perturbed discharges are computed with an additive term as following:

$$y_t^i = y_t + \beta_t^i - \gamma \quad (13a)$$

$$\beta_t^i \sim N(0, \sigma_\beta^2) \quad (13b)$$

$$\sigma_\beta = \varepsilon_y \times y_t \quad (13c)$$

where ε_y is a hyper-parameter allowing to define the perturbation proportionally to the discharge values and γ corresponds to a correction for possible external discharge contributions to the basin, like in the case of the Grande-Eau (1.75 m³/s from the Lac d'Arnon located outside of the basin). The γ correction is randomly sampled to represent the installed discharge capacity of the diversion for half of the members and to 0 m³/s for the other members.

3.1.4 Members initialization

Before the first assimilation, initial conditions of the state variables are also perturbed. Level in infiltration reservoir, level of surface runoff and snow water equivalent height are perturbed using a normal distribution with mean 0 and a standard deviation corresponding to 40% of the original state variable value.

The original initial values are computed with a one year warm-up simulation using the same precipitation and temperature data.

3.2 Performance evaluation

Here we consider two precipitation events and we use VBU and EnKF to assimilate streamflow measurements every 2 hours. After each assimilation, a new streamflow forecast of 3 days is produced using the actual precipitation and temperature, so that the results are not subject to the uncertainty due to meteorological forecasts. The performances of the control scenario, VBU and EnKF are evaluated by computing the root mean squared error (RMSE) between the forecasted and measured streamflows at different lead times L (each hour) during the forecast as follow:

$$RMSE_L = \sqrt{\frac{\sum_{j=1}^n \{Q_{L,j}^f - Q_{L,j}^{obs}\}^2}{n}} \quad (12)$$

where n is the number of forecasts produced during the single precipitation event.

4. RESULTS AND DISCUSSION

Simulations have been run for the two events presented in **Table 1**.

Figure 2 shows the forecasted flow about 24 hours before the peak flow for the high flow event at station Reckingen (Rhone River). Over the assimilation period, the difference between the VBU (green line) and the Control (blue line) are well visible, with the VBU line much closer to the observations. The red line, existing only over the two hours preceding the assimilation time (corresponding to the propagation of the members) is close to the observed discharge value of the assimilation time (dashed line).

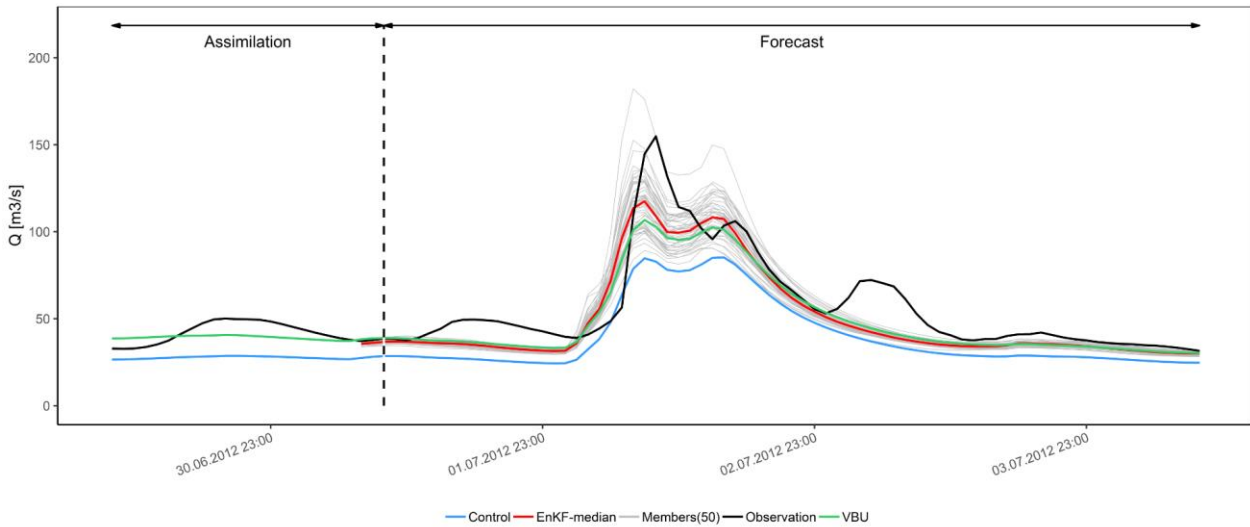


Figure 2: Forecasted discharges for the three different approaches at the Reckingen station on the Rhone River. The dashed line corresponds to 2012-07-01T10+01:00.

The RMSE values obtained for the event are presented in **Figure 3**. The two assimilation methods clearly outperform the Control simulation for the entire forecast period (72 hours). Interestingly, the VBU approach provides better performances up to a forecast horizon of 40 hours. For higher temporal horizons, the EnKF approach gives the lowest error.

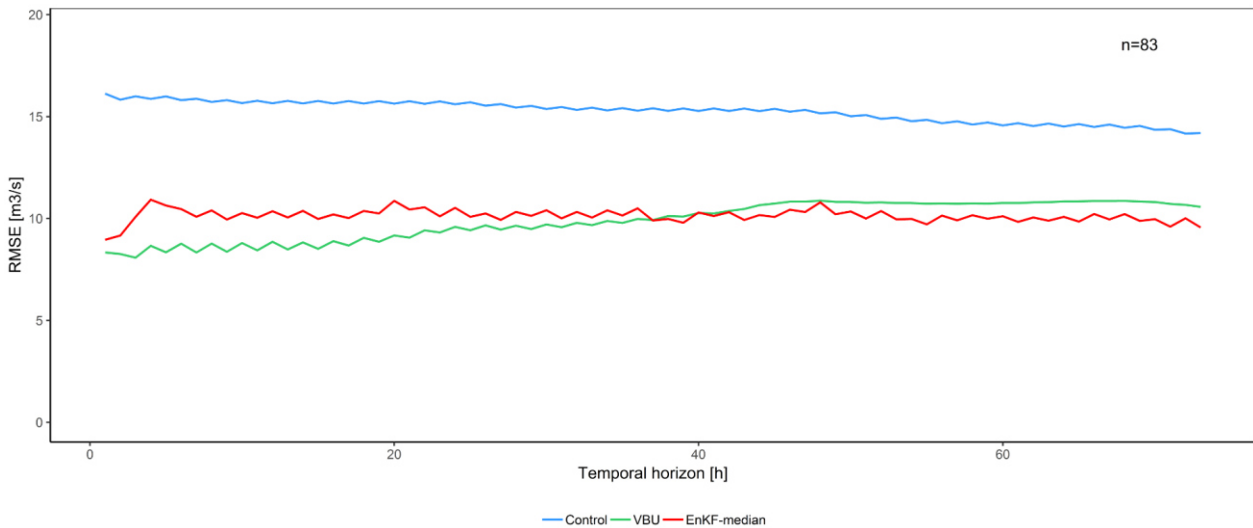


Figure 3: RMSE values obtained for the three approaches for the high flow event at the Reckingen station on the Rhone River. The n value indicated the number of run considered in the computation of the RMSE value of each temporal horizon.

Over the second studied high flow event, concerning the Grande-Eau basin, results are quite different (Figure 4). In that case, the Control simulation provides the best performance except for the few first hours, where EnKF performs best. Rapidly, the error of the EnKF increases with temporal horizon and exceeds the error of the VBU approach.

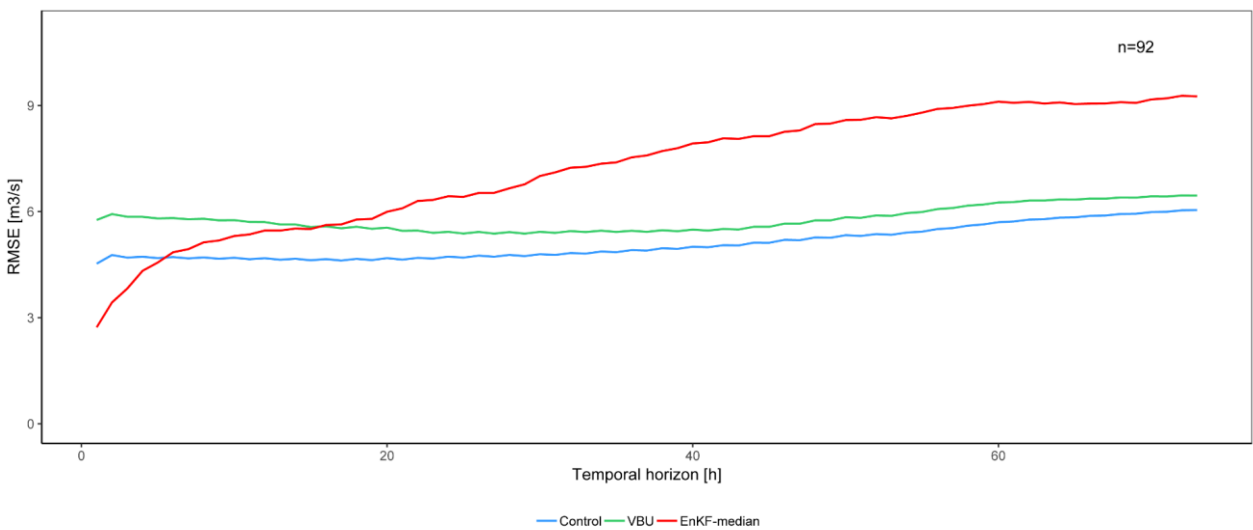


Figure 4: RMSE values obtained for the three approaches for the high flow event at the Aigle station on the Grande-Eau River. The n value indicated the number of run considered in the computation of the RMSE value of each temporal horizon.

To better understand the reason of this low performance of the EnKF, **Figure 5** illustrates the discharge simulated with the forecast generated about 36 hours before the start of the precipitation. The discharge forecasted by the EnKF approach is closer to the observed discharge over the first 30 hours of the forecast, the Control and VBU underestimating the base flow. Indeed, the EnKF has increased the soil saturation to have a base flow corresponding to the discharge given by the data. When the precipitation starts, the discharge forecasted by the EnKF overestimates the peak flow, in addition to a temporal delay of the simulated peak for all three approaches. An analysis of the initial conditions of the Control and the VBU has revealed that the VBU does not approach more the observed discharge values because it reaches 75% of soil saturation over the entire basin (constraint fixed in the VBU approach).

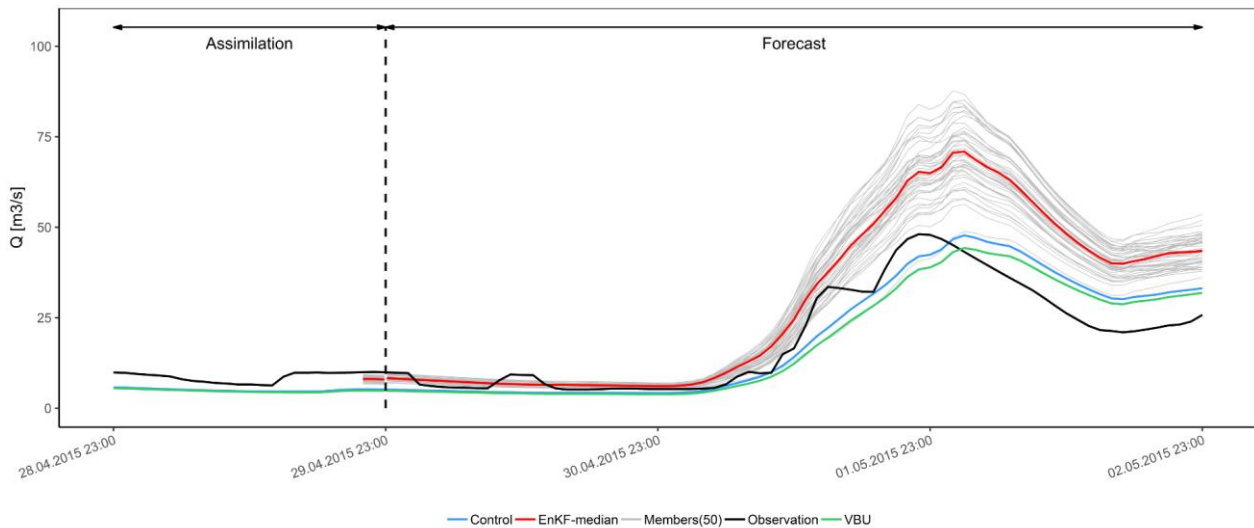


Figure 5: Forecasted discharges for the three different approaches at the Aigle station on the Grande-Eau River. The dashed line corresponds to 2015-04-30T00+01:00.

The overestimation by the EnKF approach remains valid over the entire event, composed of three successive fronts of precipitation that resulted in three successive increase of the discharge (**Figure 6**).

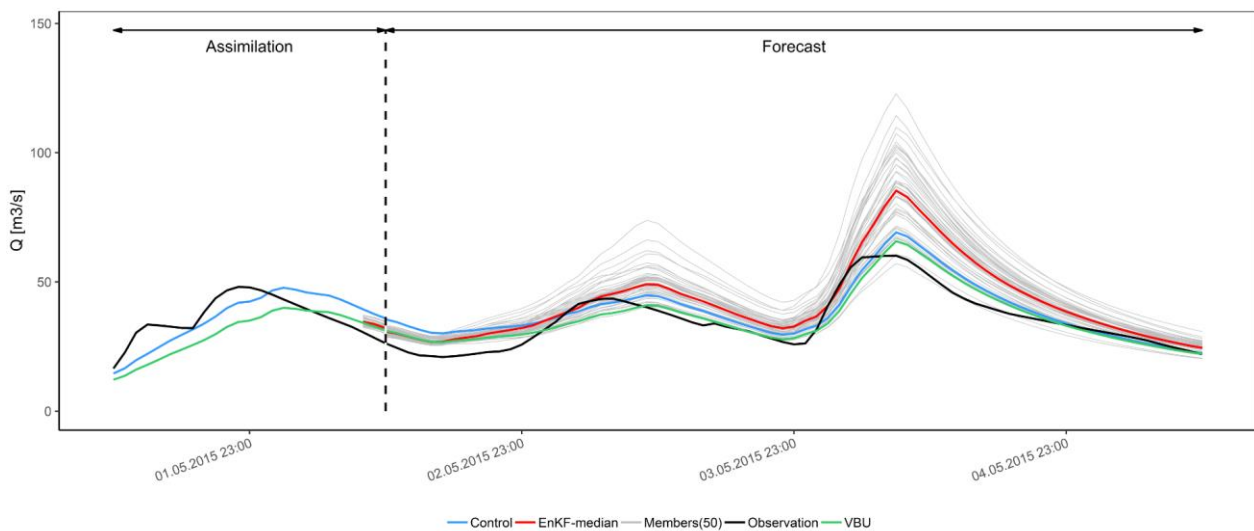


Figure 6: Forecasted discharges for the three different approaches at the Aigle station on the Grande-Eau River. The dashed line corresponds to 2015-05-02T12+01:00.

Further investigation will be required to understand the reason of this overestimation. However, one can already say that likely, the inadequacy of the model to reproduce the low flow before the precipitation event results in a correction by the EnKF that does not correspond to the state of the soil before the event. The correction brought by the EnKF probably results in an excessive increase of the soil saturation. This excessive increase might be linked to the low maximum height of the infiltration reservoir which is only of 0.2 m. Therefore, a slight change in the soil saturation can have a considerable effect on the basin reaction when receiving precipitation.

5. CONCLUSION

Two data assimilation methods are explored in this study to improve the initial conditions of the model state variables with the objective of improving the quality of hydrological forecasts. The first method updates the soil saturation based on a volume-based update (VBU) over the 24 hours preceding the forecast. The second is an implementation of the Ensemble Kalman filter (EnKF). The semi-distributed conceptual hydrological model GSM-SOCONT is used for the simulations.

The methods are applied to two events of high flow events over two different catchments of the Upper Rhone River basin in Switzerland. Spatial products of observed precipitation and temperature data are used both for the assimilation and forecast parts. The performance is evaluated with the Root Mean Square Error at hourly forecasting horizon up to 72 hours.

The results differ over the two basins. Over one basin, the two data assimilation methods provide better result than the Control simulation corresponding to a simulation of the model without data assimilation. The VBU performs better up to a forecast horizon of 35 hours, above which the EnKF then results in lower errors. Over the second basin, the results are completely different. The EnKF performs best over the first few hours but then provides the highest error. The best performance is obtained by the Control simulation, thanks to the ability of the model to reproduce the event without any assimilation. The EnKF results in a clear overestimation of the discharge, resulting from an adaptation of the soil saturation to reproduce the base flow that affects the ability of the model to absorb part of the incoming precipitation.

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