Verification of Regional Deterministic Precipitation Analysis products using snow data assimilation for application in meteorological network assessment in sparsely gauged Nordic basins

Kian Abbasnezhadi[1,2,*,†] Alain N. Rousseau[1], Étienne Foulon[1], and Stéphane Savary[1]

1 Institut National de la Recherche Scientifique, Centre eau terre et environnement, Québec, Québec, Canada

2 YukonU Research Centre, Yukon University, Whitehorse, Yukon, Canada

* Corresponding author: Climate Research Division, Science and Technology Branch, Environment and Climate Change Canada, 4509 Dufferin St., Toronto, ON M3H 5T4
kian.abbasnezhadi@canada.ca
† Former address: Institut National de la Recherche Scientifique, Centre Eau Terre Environnement (INRS-ETE), 490 rue de la Couronne, Québec, QC G1K 9A9, Canada.

Early Online Release: This preliminary version has been accepted for publication in *Journal of Hydrometeorology,* may be fully cited, and has been assigned DOI 10.1175/JHM-D-20-0106.1. The final typeset copyedited article will replace the EOR at the above DOI when it is published.

Abstract

Sparse precipitation information can result in uncertainties in hydrological modelling practices. Precipitation observation network augmentation is one way to reduce the uncertainty. Meanwhile, in basins with snowpack-dominated hydrology, in the absence of a high-density precipitation observation network, assimilation of in situ and remotely sensed measurements of snowpack state variables can also provide the possibility to reduce flow estimation uncertainty. Similarly, assimilation of existing precipitation observations into gridded numerical precipitation products can alleviate the adverse effects of missing information in poorly instrumented basins. In Canada, the Regional Deterministic Precipitation Analysis (RDPA) data from the Canadian Precipitation Analysis (CaPA) system have been increasingly applied for flow estimation in sparsely gauged Nordic basins. Moreover, CaPA-RDPA data have also been applied to establish observational priorities for augmenting precipitation observation networks. However, the accuracy of the assimilated data should be validated before being applicable in observation network assessment. The assimilation of snowpack state variables has proven to significantly improve streamflow estimates, and therefore, it can provide the benchmark against which the impact of assimilated precipitation data on streamflow simulation can be compared. Therefore, this study introduces a parsimonious framework for performing a proxy-validation of the precipitation assimilated products through the application of snow assimilation in physically-based hydrologic models. This framework is demonstrated to assess the observation networks in three boreal basins in Yukon, Canada. The results indicate that in most basins, the gridded analysis products generally enjoyed the level of accuracy required for accurate flow simulation and therefore were applied in the meteorological network assessment in those cases.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

1. Introduction

The spatio-temporal representativeness of liquid and solid precipitation data is among the most crucial factors in every flow simulation practice. Sporadic meteorological observations, among other data constraints, can result in uncertainties in many hydrological modelling practices performed for flow and inflow forecasting. This is also the case with the HYDROTEL system (Bouda et al., 2012; Bouda et al., 2014; Fortin et al., 2001a; Turcotte et al., 2003; Turcotte et al., 2007) set up for the watersheds in Yukon in northwestern Canada, where data constraints due to sparsely distributed precipitation information in major basins of interest have adversely affected the performance of the modelling system. Therefore, it is obvious that augmenting the precipitation observation network could greatly reduce the uncertainty involved with meteorological forcing.

In many forecasting centers around the globe where streamflow simulation is performed in basins with a hydrology dominated by snowpack melt during spring freshet, in the absence of a high-density precipitation observation network, assimilation of *in situ* and remotely sensed measurements of snowpack state variables has become increasingly important for accurate flow estimation (Helmert et al., 2018). Li et al. (2019) have shown that in snow dominated basins, where the meteorological uncertainty during the forecast period is significant (which is the case for sparsely gauged networks), reinitializing the model based on observed snow water equivalent (SWE) information can significantly improve streamflow forecasts. Similarly, in the absence of a high-density precipitation observation network, assimilation of snowpack state variables can provide the possibility to handle different sources of uncertainty by merging the value of observed information into the model in order to correct the effects of model errors and improve forecasting capabilities (Turcotte et al., 2010).

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

SWE reinitialization through various data assimilation (DA) approaches has been proven to be an effective approach to improve the degree of agreement between the simulated and observed discharge values (see, e.g., Clark et al., 2006; De Lannoy et al., 2012; Leisenring and Moradkhani, 2011; Nagler et al., 2008; Liu et al., 2013; Saloranta, 2016). Several DA techniques are available for updating snow state variables, including direct insertion (Liston et al., 1999), Cressman interpolation (Drusch et al., 2004), optimal interpolation (Brasnett, 1999), nudging (Boni et al., 2010), particle filtering (Arulampalam et al., 2002), and various types of Kalman filtering approaches with different levels of complexity (Gelb, 1974; Miller et al., 1994; Moradkhani, 2008; Evensen, 1994). Among these approaches, Kalman filtering, and its Monte Carlo-based implementation, the Ensemble Kalman Filtering (EnKF) approach, have been widely applied in different hydrological modelling studies (see, e.g., Andreadis et al., 2006; Clark et al., 2006; De Lannoy et al., 2012; Durand and Margulis, 2008; Huang et al., 2017; Magnusson et al., 2014; Piazzi et al., 2018; Slater and Clark, 2006; Su et al., 2008).

Currently, to gain a proper insight into short-term, seasonal, and long-term flow forecasting in northern and mid-cordilleran alpine, sub-alpine, and boreal watersheds in Yukon, where the flow regime is dominated by snowpack melt, and also to alleviate the adverse effects of scarce precipitation datasets, two independent DA routines are combined in HYDROTEL. These DA tasks are performed to update: (i) flow states, including soil temperature, soil moisture, overland flow routing, and river flow routing, based on *in situ* discharge measurements, and (ii) snow states, including snow depth, SWE, snowpack thermal deficit, snowpack liquid water content, and surface albedo, based on snow survey data. The first DA routine was implemented by Samuel et al. (2019), where the North American Ensemble Forecasting System (NAEFS) precipitation products are merged into the operational flow forecasting platform in HYDROTEL through EnKF. The snow

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

DA routine, on the other hand, performs a distributed snow correction of the simulated snowpack based on available *in situ* measurements. When snow surveys are available, the simulated state variables including SWE and snow depth are corrected based on site measurements. The correction is performed by interpolating the three nearest sites, where measurements are taken from, over the entire watershed (Turcotte et al., 2007). Thus, the application of the snow DA routine in HYDROTEL is in line with the same practice followed by a number of other forecasting centers (see, e.g., Brasnett, 1999; Barrett, 2003; Drusch et al., 2004).

There are other sources of information, such as gridded numerical products, which can reduce the input data uncertainty. For instance, the numerical weather prediction datasets produced by Environment and Climate Change Canada (ECCC), which are adjusted through an assimilation technique known as statistical interpolation (SI), represents a prime example of such atmospheric analysis gridded precipitation products. Currently, these adjusted products are created by the Canadian Precipitation Analysis (CaPA) system (Fortin et al., 2015; Mahfouf et al., 2007), the product of which is known as the Regional Deterministic Precipitation Analysis (RDPA). The CaPA-RDPA products are currently available in grib2 format on a polar-stereographic grid with a 10-km resolution (true at 60°N) at two temporal resolutions (6 hourly and 24 hourly). A high-resolution version of the system, known as High Resolution Deterministic Precipitation Analysis (CaPA-HRDPA) System is also in operation since 2018 and takes the HRDPS 2.5-km resolution field as the trial.

The CaPA system has gained considerable momentum in recent years, and the suitability of its precipitation products for application in hydrological modelling studies in Nordic watersheds in Canada have been the subject of a number of studies (e.g., Deacu et al., 2012; Eum et al., 2014; Gbambie et al., 2016; Haghnegahdar et al., 2014; Hanes et al., 2016; Wong et al., 2017; Zhao,

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

2013). Boluwade et al. (2018) compared the performance of CaPA-RDPA data against precipitation observations in the Lake Winnipeg basin, which entails many of the hydro-climatological characteristics associated with the northern Great Plains and concluded that CaPA-RDPA data is a reliable precipitation product in sparsely gauged basin. Xu et al. (2019) evaluated daily total precipitation data derived from CaPA-RDPA, ERA-Interim, ERA5, JRA-55, MERRA-2, and NLDAS-2 over the Assiniboine River Basin, and concluded that in general, except for convective rainfalls in summer, CaPA-RDPA products demonstrated the best performance among all.

CaPA-RDPA data have also been used for establishing observational priorities in poorly-instrumented basins in Canada. For instance, Abbasnezhadi et al. (2019) used the SI technique and simulated the products and by-products of the CaPA system to design a stochastic meteorological network density assessment scheme. In this approach, the network assessment is undertaken with the objective to maximize the accuracy of precipitation products for hydrological modelling applications. This scheme can be used to find the optimal density of a new observation network, only if the RDPA products in the sparsely gauged region, where the observation network is investigated for augmentation, are *assumed* to represent the truth. Given such a proposition, a controlled assessment approach (one in which observation uncertainty is accounted for), as suggested by Abbasnezhadi et al. (2019), would then be necessary to find the optimal station density. However, the benchmark that the snow assimilation routine in HYDROTEL provides for accurate flow estimation would mean that the accuracy of the CaPA-RDPA products could be first validated prior to undertaking the network assessment. In other words, it is possible to claim or at least expect that the current SWE correction performed in HYDROTEL can result in accurate streamflow estimates against which the simulated streamflow for given CaPA-RDPA forcing can

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

be compared. Such an evaluation would provide us with valuable information (i.e., benchmark) with respect to the accuracy or the intrinsic added-value of using the CaPA-RDPA products in sparsely gauged basins for meteorological network assessment. Given this approach, it would then be possible to perform the precipitation observation network assessment through a parsimonious approach. Therefore, this study was designed to provide a framework for performing a proxy-validation (i.e., indirect validation of gridded weather products by means of hydrological modelling) of the RDPA products through the application of snow assimilation in physically-based hydrologic models. The proxy-validation experiment and the network assessment framework designed in this study can therefore be undertaken to complement the precipitation network assessment approach designed by Abbasnezhadi et al. (2019). The assessment scheme introduced in this study may also be implemented autonomously in sparsely gauged basins; providing that snow survey data would be readily available.

The remainder of the paper is organized as follows. In Section 2, the study area is described and specific details with respect to the hydrometeorological data used in the study are provided. Section 3 describes the HYDROTEL model and outlines the approaches carried out to: (a) perform HYDROTEL parameter sensitivity analysis and optimization, (b) validate the CaPA-RDPA products through the application of the snow data assimilation routine in the model, and (c) undertake the network assessment. Thereafter, results are presented and discussed in Section 4, and conclusions are drawn in Section 5.

2. Study area and data characteristics

2.1 Study basins

Fig. 1 illustrates the location of the three study basins in Yukon, Canada, including the Mayo River basin, Aishihik (/eyzhak/) River basin, and Upper Yukon River basin. These watersheds are

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

located in northern and mid-cordilleran alpine, sub-alpine, and boreal ecoclimatic regions (Strong, 2013) of central and southern Yukon. The Mayo basin covers a drainage area of roughly 2,670 km^2. The mean annual precipitation and mean daily 2-m temperature are 456 mm (257 mm as rain; 199 mm as SWE) and −5.9°C, respectively (true for 1981-2018). The flow volume varies on a seasonal basis, peaking in summer between June and July and dropping during winter in January and December. There are two generating stations in Mayo: Mayo A and Mayo B. The Aishihik basin covers a larger drainage area in the order of 4,550 km^2 and is housing the Aishihik hydroelectric Facility. The mean annual precipitation is around 302 mm (126 mm as rain; 176 mm as SWE), and the mean daily annual 2-m temperature is in the order of –6.6°C (true for 1981-2018). The streamflow peaks in June, and the flow volume is relatively higher between May and October (Brabets and Walvoord, 2009). The Upper Yukon River basin is the largest of the three and covers a drainage area of around 19,600 km^2. The basin is mountainous and is largely covered by sporadic permafrost. Runoff in the Upper Yukon is derived primarily from snowmelt and rainfall. The mean annual precipitation is around 299 mm (101 mm as rain; 198 mm as SWE), and the mean daily annual 2-m temperature is in the order of –3°C (true for 1981-2018). The streamflow peaks in August and is low between November and May. There is a generating station in Whitehorse and one control structure on Marsh Lake. For all three basins, the dominant hydrological processes are governed by snow accumulation and melting that produce high flow volume which peaks in summer. In addition, the Upper Yukon River summer runoff involves glacier melting from the southwest region of the basin.

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Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

2.2 Meteorological data

Table 1 provides a list of the meteorological stations located within and in the vicinity of the boundaries of each basin. Except for MAYOMET and AISHMET stations, which are operated by Yukon Energy (YE), the other stations are operated by the Meteorological Survey of Canada (MSC).

-- Table 1 here --

Fig. 2 shows the distribution of the meteorological stations within and in the vicinity of the study basins. In Mayo, the precipitation gauge at the Mayo airport (Mayo A), which is located just in the outskirts of the basin, is the only historical active weather station with close to 100 years of available record. The MAYOMET station located near the outlet of Mayo Lake was installed in late 2018 and is the only active station within the basin. In Aishihik, the majority of the stations (17 out of 27) have less than 25 years of available data. There are three active MSC stations within a 75-km distance from the basin boundaries, including Carmacks CS (recording since 1999), Haines Junction (recording since 1944), and the one at Burwash airport, which is 50 km east of Aishihik, providing more than 50 years of historical precipitation data in conjunction with its nearby stations (Burwash & Burwash A). Within the basin boundaries, however, there are only two weather stations available (AISHMET & Otter falls NCPC), of which Otter falls NCPC has not been recording since 2015, and AISHMET is the one which was activated in late 2018. In Upper Yukon, more than 65% of the stations have less than 20 years of record, the majority of which have been installed in the past 10 years. The MSC station at Atlin is the only historical active station with more than 120 years of recorded precipitation amounts. It should be reminded that solid precipitation undercatch is rather an important issue to consider when assimilating snow measurements. Pierre et al. (2019) assessed the undercatch to be as much as 20-70% of the solid

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

precipitation, which is, to the authors' knowledge, the most recent assessment available. This can justify and explain why snow assimilation is necessary and beneficial.

-- Fig. 2 here --

The grib2 CaPA-RDPA v3.0.0 data from 2010 to 2018 at daily time steps were also downloaded from ECCC ftp repository and decoded using NOAA/National Weather Service wgrib2 program. The decoded data sets were then converted from the polar-stereographic grid onto a rectangular grid covering each basin's drainage area with a spatial resolution of 0.10° in latitude and 0.15° in longitude (roughly 10 km in both directions at 60°N).

2.3 Hydrometric data

Table 2 provides a list of available hydrometric stations at which streamflow measurements are taken in each basin (see Fig. 2 for the specific location of the hydrometric stations). The inflows to Aishihik Lake and Mayo Lake do not represent naturally observed discharge values and were reconstructed based on recorded water levels (see Samuel et al. (2019) for a detailed description of the reconstruction methodology). For Mayo Lake, water level data obtained from the 09DC005 station and streamflow observed at the YECMAYO station were used for reconstructing inflows. Similarly, water levels recorded at station 08AA005 and streamflow recorded at 08AA008, 08AA009, and 08AA010 stations were used to reconstruct the inflows to Aishihik Lake. All flows and water levels were provided by the Water Survey of Canada (WSC), except for those at reconstructed stations #0000003, ##0000003, and YECMAYO, which are recorded by YE.

-- Table 2 here --

2.4 Snow readings

Table 3 provides the metadata of the snow depth and SWE monitoring networks managed by the Water Resources Branch (WRB) of Environment Yukon as well as the Gamma Monitoring

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

(GMON) automatic snowpack sensor readings provided by YE. The GMON (a.k.a. Campbell Scientific CS725) sensor measures SWE by detecting the attenuation of naturally occurring electromagnetic energy from the ground. This contactless approach can offer highly reliable and accurate local SWE measurements with an uncertainty level that does not exceed ±5% at maximum snow depth. Traditional SWE measurement approaches, such as the application of snow pillows, by which the snowpack weight is directly measured, are prone to higher uncertainty levels since snowpack properties (e.g., radiation characteristics) can be altered during the measurement. The GMON gauge, which monitors snowpack properties in a contactless mode, does not suffer from the same disadvantages. During the past few years, a number of GMON gauges were installed at those locations identified in Table 3 and Fig. 2 (five stations were initially installed in Upper Yukon, but two were removed and relocated; one in Mayo; and one in Aishihik). Once monitored, the collected information is transmitted via satellite connection and goes through quality control. Added and relocated GMON gauges intend to complete the existing snow survey site or at least offer specific measurements within the basin limit (in Aishihik, Mayo). *In situ* snow measurements are relevant and aim to capture snow evolution, but local measurements may not be representative for the entire basin conditions.

-- Table 3 here --

3. Models and methodology

3.1 HYDROTEL: Sensitivity analysis and model calibration

The semi-distributed physically based HYDROTEL model can simulate a variety of hydrological processes. These processes and the physically-based approaches used to simulate each one along with a list of parameters associated with each process used in the version of HYDROTEL utilized in this study are listed in Table 4. In HYDROTEL, the vertical water budget

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

is computed over a computational unit called the Relatively Homogeneous Hydrological Unit (RHHU), which represents either a hillslope or elementary sub-watershed and are derived based on a digital elevation model and a digital network of lakes and river sections using PHYSITEL, a specialized GIS for distributed hydrological models (Turcotte et al., 2001; Rousseau et al., 2011; Noël et al., 2014), both of which overlaid by a multi-layer soil model. The soil column of a RHHU is stratified into three layers. The first soil layer (Z1) governs infiltration, and the other two layers (Z2 and Z3) control interflow and baseflow. The interpolation of meteorological variables is based on the weighted mean of the nearest three stations to resolve the amount of total precipitation, which is then partitioned into rain and snow according to a threshold temperature and a simple weighted scheme based on daily minimum and maximum temperatures, on each RHHU. For missing station values, HYDROTEL fills the gap by using the values available at the three nearest stations based on the inter-station temperature and precipitation altitude variations. The accumulation and melt of snowpack processes are based on a mixed degree-day energy budget approach and determine the timing and peak of the spring freshet. In the glacier module, a mixed degree-day energy budget approach is also used in the exact same fashion used for the snowmelt process. In the soil temperature and soil frost process, the only associated parameter (soil freezing temperature threshold) is not distributed over the entire RHHUs, and therefore, is not recommended to be modified. The next process is designed to identify the potential evapotranspiration which is dominantly going to impact the total annual runoff and baseflow in summer. The flow process at the RHHU scale simulates the water flux towards the river network using a hydrogeomorphological unit hydrograph (a.k.a., HGM).

-- Table 4 here --

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

While other studies have performed different types of sensitivity analyses of HYDROTEL on other basins (e.g., Bouda et al., 2013; Turcotte et al., 2003), a global sensitivity analysis was performed using the Variogram Analysis of Response Surfaces (VARS) toolbox (Razavi et al., 2019). The toolbox allows the user to identify the parameters by the importance level (i.e., model sensitivity to changing parameter conditions) through a multi-method approach that unifies different theories and strategies. With sensitive parameters in hand, the model calibration becomes a less challenging task. However, since calibration of HYDROTEL, in essence, is a multi-objective optimization problem (due to the number of stream gauges reporting flows in the basin for which several error criteria might be assessed), defining what makes the model calibrated is not a straightforward task. Moreover, other factors affecting the quality of the calibration result include error due to lake/reservoir inflow reconstruction and the quality of precipitation or temperature forcing data (elaborating on these concerns is beyond the scope of the current study). To properly respond to these challenges, model calibration was completed in OSTRICH (Optimization Software Toolkit for Research Involving Computational Heuristics), which is a model-independent and multi-algorithm optimization tool (Matott, 2017). The toolkit, which supports both single- and multi-criteria optimization options, can be used for the weighted non-linear least-squares calibration of the model parameters or for constrained optimization of a set of design variables according to pre-defined cost functions. OSTRICH can incorporate different algorithms to search for the optimal value of the objective functions and to identify the set of parameter values associated with such optima. There are several optimization algorithms available in the toolkit, which can be classified as either deterministic local or heuristic global search methods incorporating elements of structured randomness. For multi-criteria optimization, the Pareto Archive Dynamically Dimensioned Search (PA-DDS; Asadzadeh and Tolson, 2009, 2013) and the

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

simple multi-objective optimization heuristic algorithms are available, while for uncertainty-based calibration, several sampling-based algorithms (i.e., Generalized Likelihood Uncertainty Estimation and Metropolis-Hastings Markov Chain Monte Carlo) are available. In addition, the asynchronous parallel processing architecture provided by OSTRICH, which is based on the industry standard Message Passing Interface (MPI), provided the means to speed up the calibration procedure.

The model was calibrated for the period of 2010-2018 using PA-DDS by maximizing the Kling-Gupta Efficiency (KGE; Gupta et al., 2009) and minimizing the root mean squared errors (RMSE). HYDROTEL was forced with CaPA-RDPA and meteorological data, including daily precipitation and maximum and minimum temperatures time series described in Table 1, as well as snow survey observations provided in Table 3. Daily historical discharge data measured at the location of available hydrometric stations described in Table 2 and identified in Fig. 2 were obtained from WSC, while the reconstructed inflows were calculated and used for model calibration.

3.2 Impact of snow data assimilation and CaPA-RDPA forcing

In order to investigate the impact of SWE assimilation on model performance, and also to understand how robust the accuracy of CaPA-RDPA products were over the three study basins for hydrologic application purposes, two separate sets of modelling experiments were designed. In the first set (experiment Set 1), the model was trained with forcing CaPA-RDPA, while in the second set (experiment Set 2), MSC meteorological data were used as input. Depending on whether the GMON and snow survey monitoring information were assimilated during the calibration and the ‘stand-alone’ run (i.e., when the model runs once the calibration is completed), two separate runs were considered for each set (see Table 5). In Exp. 1.1, the model was calibrated while assimilating

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

SWE measurements. The assimilation was then switched off and the calibrated model was forced with CaPA-RDPA once again for the same time period (2010-2018) (Exp. 1.2). This experiment was designed to indicate the extent by which the model would be able to preserve the flow estimation accuracy with forcing precipitation analysis products only. The second set of experiments (Exp. 2.1 and Exp. 2.2) are similar to those in the first set except that CaPA-RDPA data were replaced with gauged meteorological forcing. For each experiment, goodness-of-fit metrics can be used to quantitatively measure the representativeness of the experimental flow estimations to the hydrometric observations (the metrics used in this study can be found in the supplementary materials provided in the online version of this paper). Such an evaluation helped us perform an inter-comparison of the results between the two sets of experiments.

-- Table 5 here --

3.3 Network assessment

Depending on whether the former assessment of the CaPA-RDPA forcing in HYDROTEL may suggest if the gridded analysis products can be adequately used for streamflow simulation, a simple network density sensitivity analysis based on CaPA gridded products was proposed for flow simulation in HYDROTEL. Such an assessment was designed to guide future network assessment procedures. Therefore, a network assessment procedure similar to that of Abbasnezhadi et al. (2019) was followed here, except that the assessment did not include artificially generated reference fields. Rather, a subset of grid points was extracted to create network scenarios of different resolutions from the RDPA domain over each basin, while the respective precipitation analysis was directly used during the assessment. Such an uncontrolled framework could be specifically useful for the case of this study as the SWE DA-CaPA coupling could prove to output such streamflow estimation that could closely match flow observations.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Sampling grids (Θ^{ν}), where ν is the resolution of the pseudo-network in decimal arc-degrees, pertaining to each study basin are defined in Table 6 (refer to the supplementary materials to see individual scenarios for each basin).

-- Table 6 here --

4. Results and Discussion

4.1 Sensitivity analysis and model calibration

The results of the sensitivity analysis provided by VARS indicated that among the parameters used to regulate the vertical water budget, the second soil layer thickness (Z2), which affects flow peaks, is a sensitive parameter. The third soil layer thickness (Z3), which mostly affects baseflow, was identified to be a less sensitive parameter in this group. Also, the recession coefficient (CR), which affects summer baseflow and works with Z3, was found to be a relatively sensitive parameter. Among the parameters used for calculating the weighted mean of the nearest three stations, VARS indicated that the third parameter in this group (PPN) has more impact on the results, and the first two (GT and GP) are almost equal in sensitivity. Also, for the snow processes, the melting temperature thresholds and rates for all three land classes in this group (SFC, SFF, SFD, TFC, TFF, TFD) were shown to have equal sensitivity levels. Both glacier melting parameters (MR and TT) were found to be sensitive too, and the multiplicative coefficient (FETP) applied to the Penman-Monteith equation was found to be the only sensitive evapotranspiration parameter. None of the parameters related to the flow process at the RHHU scale was found to be sensitive, while any modification to these parameters would force the model to recalculate the HGM file which would be time-consuming. The parameters associated with the channel flow process, computed using the kinematic wave equation, were also not found to be sensitive.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Previous VARS applications performed by Foulon et al. (2019) in two basins in southern Québec yielded different results for the vertical water budget parameters. Z1 was shown to be the least sensitive soil layer thickness, while Z2 and Z3 were the second most and the most sensitive parameters, respectively. Also, the recession coefficient (CR) was indicated to be one of the most sensitive parameters in the model. This signifies that HYDROTEL is rather sensitive to basin location and governing hydrological processes. In fact, Yukon and southern Québec are both governed by snow accumulation and melt, yet summer baseflow plays a more prominent role in southern Québec.

With sensitive parameters in hand, comprising of a set of 16 parameters indicated in Table 4 by those with the importance level of 1, the model was calibrated in OSTRICH. The standard upper and lower bound values used for each parameter in OSTRICH are provided in Table 4, which are based on the physical meaning of each parameter and the works of Fortin et al. (2001b) and Turcotte et al. (2003). Also, the initial estimates for each parameter were based on those derived in previous calibration efforts, in which each parameter was manually adjusted in order to achieve the desired hydrological performance. The toolbox utilized eight computational cores for asynchronous parallel processing at the budget of 2-18 hours (depending on the basin's drainage area) for 1000 iterations.

In Mayo, the model calibration was completed in OSTRICH based on the inflow time-series into Mayo Lake associated to YE gauge ##0000003 (see Fig. 2). In Aishihik, the model calibration was completed in two stages. In the first stage, the model was calibrated for Sekulmun River streamflow time-series at the outlet of Sekulmun Lake observed at WSC Gauge 08AA008 (see Fig. 2). The Sekulmun portion of the Aishihik model was isolated and separated in HYDROTEL GUI (graphical user interface) to decrease the model run time. In the second stage, the model was

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

setup to simulate the reconstructed inflow time series to Aishihik Lake associated with YE gauge #0000003. The original reconstructed inflow data display high-intensity fluctuations and were not deemed suitable for the calibration. Instead, they were first smoothed by using a 7-day moving average window (windows of longer durations were also tested and did not show to enhance the calibration results). In Upper Yukon, the model calibration was also performed in two stages. In the first stage, the model was calibrated separately for three gauged sub-basins, including Atlin River (WSC gauge 09AA006), Tutshi River (WSC gauge 09AA013), and Wheaton River (WSC gauge 09AA012) (see Fig. 2). In the second stage, the model was then setup to simulate the flow time series in Yukon River at Whitehorse observed at WSC gauge 09AB001.

Fig. 3 shows the flow duration curves for Mayo, Aishihik (including the Sekulmun sub-basin), and Upper Yukon (including the Atlin, Tutshi, and Wheaton sub-basins) (refer to the supplementary materials provided in the online version of this paper to see discharge time-series). In Mayo, the simulation has fully preserved the exceedance probability of observed flows. In Aishihik and Sekulmun, other than some overestimation of winter low flows, the remainder has been well captured by the model. In Upper Yukon, in general, the exceedance probabilities of the simulated flows closely resemble the observed ones although the low flows are underestimated in sub-basins with small drainage areas (Tutshi and Wheaton), which has similarly impacted the low flows in Yukon too. In Atlin, the exceedance probability of the observed high flows (corresponding to the flow peaks) is marginally underestimated.

-- Fig. 3 here --

4.2 Proxy validation of CaPA-RDPA

The impact of the snow DA routine in HYDROTEL and CaPA-RDPA forcing data on modelling results were assessed based on the set of experiments discussed in Section 3.2. Fig. 4

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

compares the metrics in Mayo for the first and the second sets of experiments (for the full description of the metrics used in the figures of this section, see the supplementary materials in the online version of this paper). The metrics reported by the experiments indicate that the calibration results for the case when CaPA-RDPA are used as input (Exp. 1.1 and Exp. 1.2) surpass, in both cases, those derived by station observations (Exp. 2.1 and Exp. 2.2). In addition, the best outcome is obtained with Exp. 1.1 when the model calibration is performed with CaPA-RDPA forcing and the snow DA routine in active mode. Exp. 1.2 (CaPA-RDPA forcing and no snow DA), on the other hand, indicates that the model's performance is not undermined if the snow DA routine is turned off in HYDROTEL (when the model has already been calibrated with the snow DA routine in active mode). In other words, for this experiment, the assimilation of snow monitoring data has relatively no impact on the flow estimation accuracy if CaPA-RDPA data are used as input. In contrast, the metrics obtained from the second set of experiments indicate that when the model is calibrated using MSC meteorological data as input and with the snow DA routine in active mode (Exp. 2.1), the metrics are on the ballpark of an acceptable level, while still falling short of those obtained with CaPA-RDPA. However, as Exp. 2.2 indicates, if the snow DA routine is turned off, the flow estimation accuracy declines significantly. This illustrates that for the second set of experiments with sparsely gauged meteorological input data, the snow DA routine has a compensating impact on the flow estimation accuracy.

Although the new GMON stations do not provide a long record of measurements yet, the snow course sites in all three basins provide long-enough and continuous records of snow depth and SWE measurements. Results from the second set of experiments shown in Fig. 4 indicate that, in Mayo, these snow course measurements provide valuable information by which the SWE data simulated using the meteorological network can be corrected through the snow assimilation routine

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

in HYDROTEL. In other words, the flow estimation accuracy in Mayo is highly dependent on the external information from the snow survey sites. Although this outcome does not indicate the representativeness of the snow survey sites, it hints at their value. The same debate is found in the literature where hydrological models, for example, are run by interpolating snow depth measurements from a few selected sites to larger areas despite their limited spatial representativeness (Grünewald and Lehning, 2015; López-Moreno et al., 2013). Other studies have quantified the issue of snow sites representativeness. For example, Winstral and Marks (2014) proved that an index site representative of the basin conditions can be valid for a basin wide SWE in most years.

On the other hand, the proxy validation of the CaPA-RDPA in Mayo based on the reconstructed inflow associated with gauge ##0000003 shows that the analysis is accurate enough to the extent that would not call for any correction through snow measurements. To this point, these results indicate that in Mayo: (a) CaPA-RDPA products can be used for flow estimation, (b) given the fact that very few precipitation stations are currently assimilated in CaPA, if the current network is extended, the modelling accuracy will improve, and (c) in the absence of a precipitation observation network with an optimal density, the snow assimilation routine plays a significant role to compensate for proper precipitation information.

-- Fig. 4 here --

Fig. 5a compares the metrics in Aishihik for the first and the second sets of experiments, while the performance of the model in response to the set of experiments completed in Sekulmun are shown in Fig. 5b. The results reported for both Aishihik and Sekulmun are not identical to those of Mayo and the experiments rather exhibit a contrasting outcome. While in Mayo, deactivating the snow assimilation routine in HYDROTEL when forcing the model with CaPA-RDPA

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

(Exp. 1.2) would marginally impact the metrics compared to the case when the snow assimilation routine was active (Exp. 1.1), in Aishihik (including the Sekulmun sub-basin), deactivating the snow assimilation routine led the model performance to decay significantly. This suggests that the RDPA gridded products do not encompass the required accuracy over Aishihik, rendering the assimilation of snow readings an essential component for accurate flow estimation. The inadequacy of the RDPA estimates over Aishihik is an indication of the detrimental impact of the sparse precipitation network in Aishihik, which encompass a relatively larger drainage area, on CaPA products over the basin. In Sekulmun, Exp. 2.2 provides marginally better results than Exp. 2.1, demonstrating that the precipitation measurements taken at the MSC meteorological stations better represent the ground SWE accumulation than those recorded at the snow course sites. Nevertheless, in Sekulmun, when using CaPA-RDPA data as the input, the combined effect of incorporating the value of information from both the external assimilation of precipitation data in CaPA and the internal assimilation of snow readings in HYDROTEL has obviously improved the flow estimation accuracy (see Fig. 5b). In Aishihik, however, Exp. 2.1 displays a declined performance relative to Exp. 1.1, while Exp. 2.1 and Exp. 2.2 are relatively identical. These results, in total, revealed that in Aishihik and Sekulmun, the snow data are essential for accurate flow estimation if the model is forced with CaPA-RDPA, while the MSC precipitation input data seems to deliver sufficient accuracy (indicating the accuracy of the precipitation measurements taken as MSC stations which necessitates minimal correction by the data taken at the snow course sites). This, once again, indicates that the value of precipitation information from the MSC precipitation gauges is superior to those of CaPA-RDPA which illustrates the low accuracy of CaPA data over the basin.

-- Fig. 5 here --

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Fig. 6 compares the metrics in Upper Yukon, including those for Atlin, Tutshi, and Wheaton for the first and the second sets of experiments. In Atlin (Fig. 6a), there are marginal differences between the results derived from all four experiments. This agreement could be the outcome of several factors, including: (a) co-location of the snow course site and the MSC gauge in Atlin, (b) existence of a MSC gauge which is assimilated in CaPA (see Fig. 2); forcing the respective RDPA over the basin to become more or less identical to that of gauge reading, (c) the impact of the nearby MSC gauges on the northeast side of the basin (just beyond the basin boundary) on the accuracy of precipitation estimate over the basin. In Tutshi and Wheaton, however, a different outcome is evident. The impact of drainage area on the flow estimation accuracy for the given activity state of the snow assimilation routine seems to be a factor of importance. For instance, for a sub-basin such as Tutshi (Fig. 6b) with a small drainage area, the impact of the only snow course site in the basin (site #09AA-SC3) on the flow accuracy can be comprehended by the fact that deactivating the snow assimilation in Exp. 2.2 has significantly decayed the flow accuracy by almost half. On the other hand, in Wheaton (Fig. 6c), a sub-basin with a comparable drainage area to that of Tutshi, in the absence of any snow course site, Exp. 2.2 has apparently yielded about the same metrics obtained from Exp. 2.1. In general, the results of the experiments performed in Upper Yukon indicate that since the basin generally enjoys a higher number of weather stations (including those assimilated in CaPA and snow course sites), the results demonstrate better metric values.

-- Fig. 6 here --

Table 7 summarizes the significance of the snow assimilation routine for each basin for the given meteorological forcing. In short, activating the snow assimilation routine would have a significant impact on the flow estimation only in Mayo when forcing HYDROTEL with the MSC meteorology and in Aishihik when forcing the model with CaPA-RDPA data. Hence, it appears

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

that snow survey sites are more representative of the watershed snow conditions than the meteorological conditions recorded at the MSC stations or embedded into CaPA-RDPA.

In Upper Yukon, sub-basins did not yield consistent results. It was shown that the model does not necessarily need the assimilation of snow products when the model is forced with either gauged or analysis precipitation products (for 3 out of 4 sub regions). While medium-size watersheds (as Tutshi) could benefit from snow survey measurements, the others could not. For larger watershed with denser meteorological networks, snow assimilation may prove to be superfluous. Overall, where snow assimilation significantly improves the results, it can be concluded that the corresponding meteorological forcing does not have the expected accuracy for hydrologic modelling purposes, including the assessment of the meteorological network density which is the subject of the next analysis in this study.

-- Table 7 here --

4.3 Network sensitivity analysis

The information gained from the validation stage was used to decide whether the assessments should be undertaken with/without the assimilation of snow course data. The proxy validations indicated that at least in Aishihik, CaPA data do not have the required accuracy, while the validations in the other two basins (Mayo and Upper Yukon) were promising. Therefore, in Aishihik, the network assessment was carried out while assimilating the snow course measurements. In Mayo and Upper Yukon, no snow assimilation was performed when evaluating the impact of different network scenarios. Even though any proposed additional station would probably be equipped with various measuring apparatus for different meteorological variables, the network augmentation assessment was carried out with the assumption that the network would be

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

mainly measuring precipitation. This is mainly due to the fact that precipitation demonstrates a lot more spatial variability than other meteorological variables (e.g., temperature, wind).

Fig. 7 shows the variation of the NSE, KGE, and absolute PBias scores in Mayo, Aishihik, and Upper Yukon with the changing resolution of the pseudo-network scenarios (for descriptions of the scores, see the supplementary materials). In Mayo (thick lines in all figures), as the network resolution decreases (and so does the network density) from 0.10° to 0.35°, the scores go through two distinct areas of variation. First, decreasing the network resolution from 0.10° to 0.30° results only in marginal drops in all three performance scores. In comparison, the performance of the CaPA precipitation products for a network with a given resolution of 0.30° or higher is better than that of the current meteorological precipitation network (shown by horizontal lines). The fluctuations and the unexpected drops in performance scores in this range are an artifact of the spatial variability of precipitation that has not been fully resolved by certain grid points. This phenomenon which is known as singularity has been reported previously by Abbasnezhadi et al. (2019) and Dong et al. (2005). Decreasing the network density below 0.30°, results in substantial performance deterioration to an extent well below the current sparse MSC network. This indicates that the limit at which the CaPA gridded data can outperform the existing network in Mayo is limited to a network with a density of at least 0.30°.

-- Fig. 7 here --

The variation of the NSE, KGE, and absolute PBias in Aishihik with changing network resolution are shown by dashed lines and compares the performance of the pseudo-network scenarios constructed based on the CaPA grid definition with the current MSC network in the basin. The same overall trend of variation previously observed in Mayo is evident here too where the scores drop (although less abruptly) after negligible changes before the threshold network

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

density. The less sudden drop is an expected attenuation consequence of a larger drainage area which is more evidently manifested by the NSE scores which is known to be a sensitive parameter to peak discharge values (see Abbasnezhadi et al., 2019 for the same performance outcome). In Aishihik, the network resolution threshold cannot be explicitly inferred. The variation of the NSE indicates that for every decrease in resolution there is a decrease in performance that is rather of the same order of magnitude for all resolutions, whereas those of KGE and PBias assert the 0.4° pseudo-network to entail the optimal resolution below which the accuracy of the ensued flow simulations degrades significantly. Any higher-density network would cause the scores to level off and little would be gained by further increasing the network density. The asserted network density threshold of 0.4° derived for Aishihik resembles the performance established by the current MSC meteorological network in the basin. Moreover, this threshold value is also slightly higher than the one determined for Mayo. This was an anticipated outcome as in basins with a larger drainage area, representativeness errors are averaged out which makes missing a storm event less impactful on the overall network precision. In contrast, in smaller basins (as in Mayo), mesoscale precipitation systems are essentially significant for capturing proper flow statistics. Accordingly, a higher network threshold value can already be anticipated for Upper Yukon which has an even larger drainage area than that of Aishihik.

In Upper Yukon (thin lines), the same features previously observed in Mayo and Aishihik are apparent, while a higher network threshold value is resolved. Similar to what was indicated for Aishihik, a network resolution threshold cannot be explicitly inferred in Upper Yukon. Arguably, if Pbias changes are ignored (which asserts the 0.7° pseudo-network to entail the optimal resolution), it can be claimed that the 0.5° pseudo-network would be optimal. A pseudo-network with a density threshold value between 0.5° and 0.7° would as such provide an optimal resolution

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

range. Quite interestingly, the current MSC network maintains an accuracy which is comparable in performance to the highest network density of the original CaPA network.

5. Summary and Conclusions

This study is at the crossroad between meteorological data assimilation (in which precipitation observations are merged into numerically modelled precipitation data), and hydrological data assimilation (in which snow survey data are merged into streamflow forecast). Before applying assimilated precipitation products in meteorological network assessment, first it is required to validate the accuracy of these products. In this study, it is indicated that since assimilation of snow survey data could provide the benchmark for accurate flow estimation, it would then be possible to evaluate the accuracy of precipitation assimilation products through the proxy-validation of precipitation analysis in such a hydrologic system. The HYDROTEL model snow data assimilation (DA) routine is one such example which provides the opportunity to investigate the added value of using the CaPA-RDPA data for application in meteorological network assessment in sparsely gauged Nordic basins.

The hydrologic footprint of CaPA-RDPA data and MSC ground observations were validated against hydrometric observations. This validation was performed to examine whether assimilating snow monitoring information in HYDROTEL can offset the adverse effects of precipitation data scarcity in Yukon. When snow assimilation could significantly improve the flow simulation outcomes, it was concluded that the corresponding meteorological forcing (either CaPA-RDPA data or ground observations; in this instance, MSC stations) could not exclusively provide the required accuracy for hydrologic modelling purposes. The proxy validation of the CaPA-RDPA data indicated that the gridded analysis products enjoy the level of accuracy required for accurate flow simulation in Mayo and Upper Yukon which does not entail the application of snow

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

assimilation in HYDROTEL. In Aishihik, however, the validations demonstrated that the regional precipitation analysis does not have the required accuracy, and therefore, assimilation of observed snow course information had a significant impact on the flow estimation accuracy. Based on the results of these experiments, it can be concluded that although these basins are all located within similar ecoclimatic zones in southern Yukon and in the proximity of each other, the distribution of snow course sites and precipitation gauges have left a substantial impact on the accuracy of precipitation and snow assimilation procedures which directly affect the accuracy of flow simulations. These results indicate the importance of the snow assimilation routine in HYDROTEL to embed crucial information not readily available from precipitation forcing data. This approach and the lessons learned may also benefit watersheds in other parts of the world facing similar challenges related to incorporating accurate data when such information is not embedded within the forcing data.

With the experiments in hand, a network augmentation assessment was carried out subsequently by incorporating the value of data and products available from the CaPA assimilation system with the assumption that the network would be mainly measuring precipitation. The assessment indicated that a number of additional stations can be installed in each basin to increase the accuracy for streamflow simulation. It is worth reiterating that the analysis was performed based on CaPA-RDPA data and having real measurements on the ground could prove to require fewer stations, especially for Aishihik and Mayo. In addition, the network was assessed in an uncontrolled mode where no observation error was added during the analysis to simulate the impact of such errors (including those related to solid precipitation in winter and convective storms during summer). Instead, CaPA-RDPA data were used directly into the assessment since the assumption of accuracy was validated prior to undertaking the assessment. Given that in the CaPA

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

system, precipitation measurements are subjected to various quality control (QC) procedures before being assimilated, the RDPA products can, therefore, be assumed to be of relatively proper quality. However, the implication of such an assumption is that, the optimal number of stations derived for each basin is valid when those stations satisfy CaPA QC procedures too. In other words, if the quality of measurements available from the proposed extended network can satisfy CaPA QC, they could equally benefit the CaPA system. Moreover, it is ultimately beneficial if any additional precipitation station which can be directly used for flow forecasting in HYDROTEL may also be used for the similar purpose indirectly when embedded into the products of the CaPA assimilation system. Also, if existing snow survey sites could provide the required SWE data for hydrologic snow assimilation, the framework introduced in this study could be easily implemented. Otherwise, in case a network assessment is to be undertaken in a basin where such data are not readily available, proper arrangements should be made to first conduct snow surveys.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Acknowledgements

The authors wish to gratefully acknowledge the financial support from Natural Sciences and Engineering Research Council of Canada (NSERC) and Yukon Energy (YE) through Collaborative (#CRDPJ 499954-16) and Applied (#CARD2 500263-16) Research and Development grants. This project would not have been possible without substantial contributions from staffs at Yukon Research Centre, namely Brian Horton and Maciej Stetkiewicz; at INRS, Sébastien Tremblay; and at YE, Shannon Mallory, Kevin Maxwell, and Andrew Hall. We would like to also acknowledge the following organizations for their readily available online data used in this study: Meteorological Survey of Canada, Water Survey of Canada, Environment and Climate Change Canada, Water Resources Branch at Environment Yukon, Yukon Energy, and Natural Resources Conservation Service at United States Department of Agriculture. The authors declare no conflict of interests in this work.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

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Table 1. MSC* meteorological networks in Mayo, Aishihik, and Upper Yukon (see Fig. 2).

Basin	Station Name	Station No.	Period	Time Step	Type
Mayo	ELSA	2100500	1948-1989	Daily	Manual
	Mayo A	2100700	1924-2013	Hourly & Daily	Auto
	Mayo A	2100701	2013-Present	Hourly & Daily	Auto
	Steward Crossing	2101030	1953-2008	Daily	Manual
	MAYOMET	MAYOMET	2018-Present	Hourly & Daily	Auto
Aishihik	Aishihik A	2100100	1943-1966	Hourly & Daily	Manual
	Blanchard River	2100163	1986-2012	Daily	Auto
	Burwash A	2100181	2011-Present	Hourly & Daily	Auto
	Burwash A	2100182	1966-2015	Hourly & Daily	Auto
	Burwash Airport BC	2100184	2013-Present	Hourly & Daily	Auto
	Carmacks CS	2100301	1999-Present	Hourly & Daily	Auto
	Haines Junction	2100630	1944-Present	Hourly & Daily	Auto
	Pelly Ranch	2100880	1898-2015	Daily	Manual
	Takhini River Ranch	2101095	1980-2015	Daily	Manual
	Otter Falls NCPC	2100840	1980-2015	Daily	Manual
	AISHMET	AISHMET	2018-Present	Hourly & Daily	Auto
Upper Yukon	Atlin	1200560	1899-Present	Daily	Manual
	Teslin	2101102	1944-Present	Hourly & Daily	Auto
	Whitehorse A	2101303	2012-Present	Hourly & Daily	Auto
	Whitehorse Auto	2101310	2009-Present	Hourly & Daily	Auto
	Fantail Lower	FANTLOW	2012-Present	Hourly	Auto
	Fantail Upper	FANTUPP	2012-Present	Hourly	Auto
	Llewellyn Lower	LLEWLOW	2013-Present	Hourly	Auto
	Llewellyn Upper	LLEWUPP	2013-2016	Hourly	Auto
	Wheaton	WHEATON	2014-Present	Hourly	Auto

* MSC: Meteorological Survey of Canada

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Table 2. WSC* and YE* hydrometric networks in Mayo, Aishihik, and Upper Yukon basins. The gauges used for the HYDROTEL model calibration are in bold (see Fig. 2).

Basin	Station Name	Station No.	Period	Type
Mayo	Mayo Lake near the Outlet	09DC005	1979-Present	Water Level
	Mayo Lake at the Outlet	YECMAYO	1979-Present	Flow
	Inflow to Mayo Lake (reconstructed)	**##0000003**	**1979-Present**	**Flow**
Aishihik	Aishihik Lake near Whitehorse	08AA005	1972-Present	Water Level
	Sekulmun River at Outlet of Sekulmun Lake	**08AA008**	**1981-Present**	**Flow & Water level**
	Giltana Creek near The Mouth	08AA009	1980-Present	Flow & Water level
	Aishihik River below Aishihik Lake	08AA010	1980-Present	Flow & Water level
	Aishihik Lake near Aishihik	08AA012	1995-2015	Water Level
	Inflow to Aishihik Lake (reconstructed)	**#0000003**	**1980-Present**	**Flow**
Upper Yukon	**Atlin River near Atlin**	**09AA006**	**1950-Present**	**Flow**
	Wheaton River near Wheaton	**09AA012**	**1955-Present**	**Flow**
	Tutshi River near outlet of Tutshi Lake	**09AA013**	**1956-Present**	**Flow**
	Yukon River at Whitehorse	**09AB001**	**1902-Present**	**Flow**

* WSC: Water Survey of Canada; YE: Yukon Energy

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Table 3. WRB and YE snow course and GMON networks in Mayo, Aishihik, and Upper Yukon (see Fig. 2).

Basin	Station Name	Station No.	Period	Type	Sources*
	Calumet	09DD-SC01	1975-Present	Depth/SWE	WRB
	Edwards Lake	09DD-SC02	1987-Present	Depth/SWE	WRB
Mayo	Mayo Airport A	09DC-SC01A	1968-Present	Depth/SWE	WRB
	Mayo Airport B	09DC-SC01B	1987-Present	Depth/SWE	WRB
	MAYOMET	MAYOMET	2017-Present	GMON	YE
	Canyon Lake	08AA-SC01	1975-Present	Depth/SWE	WRB
Aishihik	Macintosh	09CA-SC02	1976-Present	Depth/SWE	WRB
	Aishihik Lake	08AA-SC03	1944-Present	Depth/SWE	WRB
	AISHMET	AISHMET	2017-Present	GMON	YE
	Tagish	09AA-SC1	2006-Present	Depth/SWE	WRB
	Montana Mountain	09AA-SC2	2006-Present	Depth/SWE	WRB
	Log Cabin (BC)	09AA-SC3	2006-Present	Depth/SWE	WRB
	Atlin (BC)	09AA-SC4	2006-Present	Depth/SWE	WRB
	Mt. McIntyre	09AB-SC1B	2006-Present	Depth/SWE	WRB
	Whitehorse Airport	09AB-SC2	2006-Present	Depth/SWE	WRB
Upper	Meadow Creek	09AD-SC1	2006-Present	Depth/SWE	WRB
Yukon	Moore Creek Bridge (AL)	0034K02	2006-Present	Depth/SWE	USDA-NRCS
	Eaglecrest (AL)	0034J03	2006-Present	Depth/SWE	USDA-NRCS
	Fantail Lower	FANTLOW	2012-2017	GMON	YE
	Fantail Upper	FANTUPP	2012-2017	GMON	YE
	Llewellyn Lower	LLEWLOW	2013-Present	GMON	YE
	Llewellyn Upper	LLEWUPP	2013-2016	GMON	YE
	Wheaton	WHEATON	2014-Present	GMON	YE

* WRB: Water Resources Branch, Environment Yukon; YE: Yukon Energy; USDA-NRCS: United States Department of Agriculture, Natural Resources Conservation Service

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Table 4. HYDROTEL parameter sets associated with each hydrological process. Importance Level-0 parameters refer to those often physically-based constant (non-calibrated parameters), while levels 2 and 3 indicate lower importance levels and were not calibrated. Parameters calibrated in OSTRICH are identified by the importance level of 1. The lower and upper bounds shown in the table are used in parameter optimization.

Process/Parameter	Unit	Lower Bound	Upper Bound	Importance Level	OSTRICH Code
Vertical water budget: *BV3C*					
Thickness of the first soil layer	m	0.05	0.60	1	Z1
Thickness of the second soil layer	m	0.05	0.60	1	Z2
Thickness of the third soil layer	m	0.05	0.80	1	Z3
Initial humidity of the first soil layer	--	0.90	0.90	0	--
Initial humidity of the second soil layer	--	0.90	0.90	0	--
Initial humidity of the third soil layer	--	0.90	0.90	0	--
Extinctive coefficient	--	0.3	0.9	2	--
Recession coefficient	m/h	0.0000001	0.00001	1	CR
Drying coefficient	--	0.5	1.0	2	--
Maximal variation of relative humidity of soil layer	--	0.2	0.4	2	--
Interpolation of meteorological variables: *Weighted mean of nearest three stations*					
Temperature gradient	°C/100 m	−1.5	0.0	1	GT
Precipitation gradient	mm/100 m	0.0	1.5	1	GP
Phase change temperature threshold	°C	−3.5	3.5	1	PPN
Snow accumulation and melt: *Mixed degree-day energy budget approach*					
Melting rate (soil/snow)	mm/day	0.5	0.5	0	--
Maximal snow density	Kg/m^3	466	466	0	--
Compaction constant	--	0.01	0.01	0	--
Evergreen forest melting temperature threshold	°C	−3.5	3.5	1	SFC
Deciduous forest melting temperature threshold	°C	−3.5	3.5	1	SFF
Open area melting temperature threshold	°C	−3.5	3.5	1	SFD
Evergreen forest melting rate	mm/day °C	1	20	1	TFC
Deciduous forest melting rate	mm/day °C	1	20	1	TFF
Open area melting rate	mm/day °C	1	20	1	TFD
Albedo threshold	--	1	1	0	--
Glacier melt: *Mixed degree-day energy-budget approach*					
Melting rate	mm/day	1	20	1	MR
Melting temperature threshold	°C	−3.5	3.5	1	TT
Soil temperature and soil frost: *Rankinen*					
Soil freezing temperature threshold	°C	−1	1	3	--
Potential evapotranspiration: *Penman-Monteith*					
Standard height for wind measurement	m	2	2	0	--
Standard height for humidity measurement	m	2	2	0	--
Wind speed at the Z elevation	m/s	2	2	0	--
Surface reference vegetation height	m	0.12	0.12	0	--
Stomatal resistance for reference surface	s/m	80	120	2	--
Multiplicative coefficient	--	0.25	1.30	1	FETP
Flow on sub-watersheds towards river network: *Kinematic wave*					
Manning coefficient for forest land cover classes	--	0.15	0.3	3	--
Manning coefficient for water land cover classes	--	0.015	0.03	3	--
Manning coefficient for other land cover classes	--	0.04	0.1	3	--
Channel flow: *Kinematic wave*					
Roughness optimization	--	1	1	0	--
Stream width optimization	--	1	1	0	--

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Table 5. Application of snow assimilation during the experiments. × : snow assimilation was performed during the calibration/stand-alone run, ✓ : snow assimilation was not performed during the calibration/stand-alone run.

Exp.		Meteorological Forcing	Snow Assimilation ✓: active / ×: inactive	
Set	Run		Calibration	Stand-alone Run
1	1.1	CaPA-RDPA	✓	✓
	1.2		✓	×
2	2.1	MSC Meteorology	✓	✓
	2.2		✓	×

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Table 6. Sampling grid of pseudo-network scenarios (Θ^{ν}) of different resolutions in decimal arc-degrees (ν) for each study basin, extracted from the CaPA grid. See individual scenarios in the supplementary material.

Basin	Sampling grid scenarios
Mayo	$\Theta^{\nu} \mid \nu \in [0.10^{\circ}, 0.15^{\circ}, 0.20^{\circ}, 0.30^{\circ}, 0.35^{\circ}]$
Aishihik	$\Theta^{\nu} \mid \nu \in [0.10^{\circ}, 0.20^{\circ}, 0.30^{\circ}, 0.40^{\circ}, 0.50^{\circ}]$
Upper Yukon	$\Theta^{\nu} \mid \nu \in [0.10^{\circ}, 0.20^{\circ}, 0.30^{\circ}, 0.40^{\circ}, 0.50^{\circ}, 0.60^{\circ}, 0.70^{\circ}, 0.80^{\circ}]$

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

Table 7. Significance of the snow assimilation routine in HYDROTEL given the meteorological forcing for each study basin. Basin denominations are in bold, sub-basins are not. ✓ indicates that performing snow assimilation for the selected basin has a significant impact, while × shows a nonsignificant outcome.

Basin	CaPA-RDPA	MSC meteorology
Mayo	×	✓
Aishihik	✓	×
Sekulmun	✓	×
Upper Yukon	×	×
Atlin	×	×
Tutshi	×	✓
Wheaton	✓	×

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

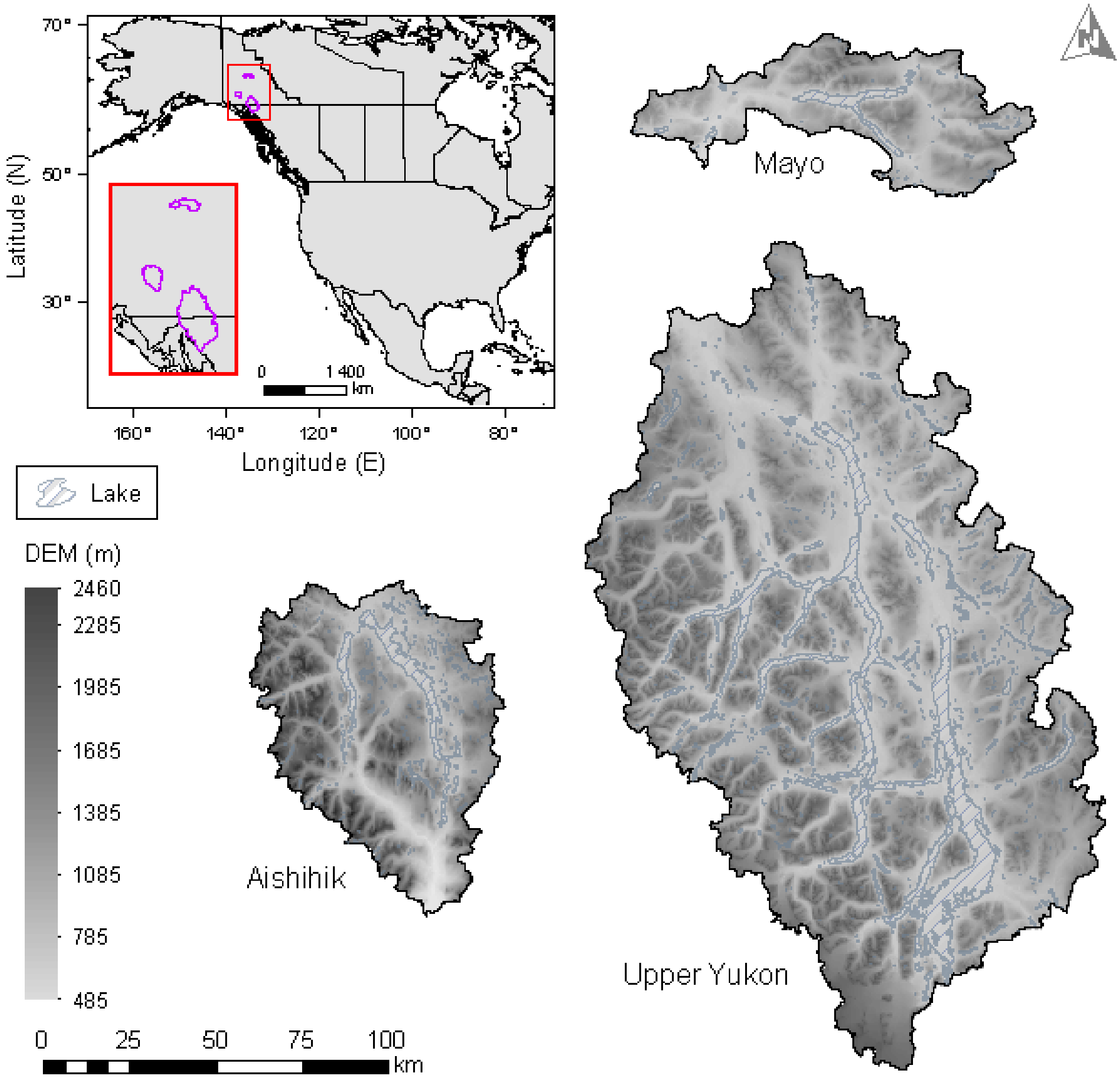


Fig. 1. The location of Mayo, Aishihik, and Upper Yukon River basins in central and southern Yukon. The southern half of the Upper Yukon basin is located within northern British Columbia.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

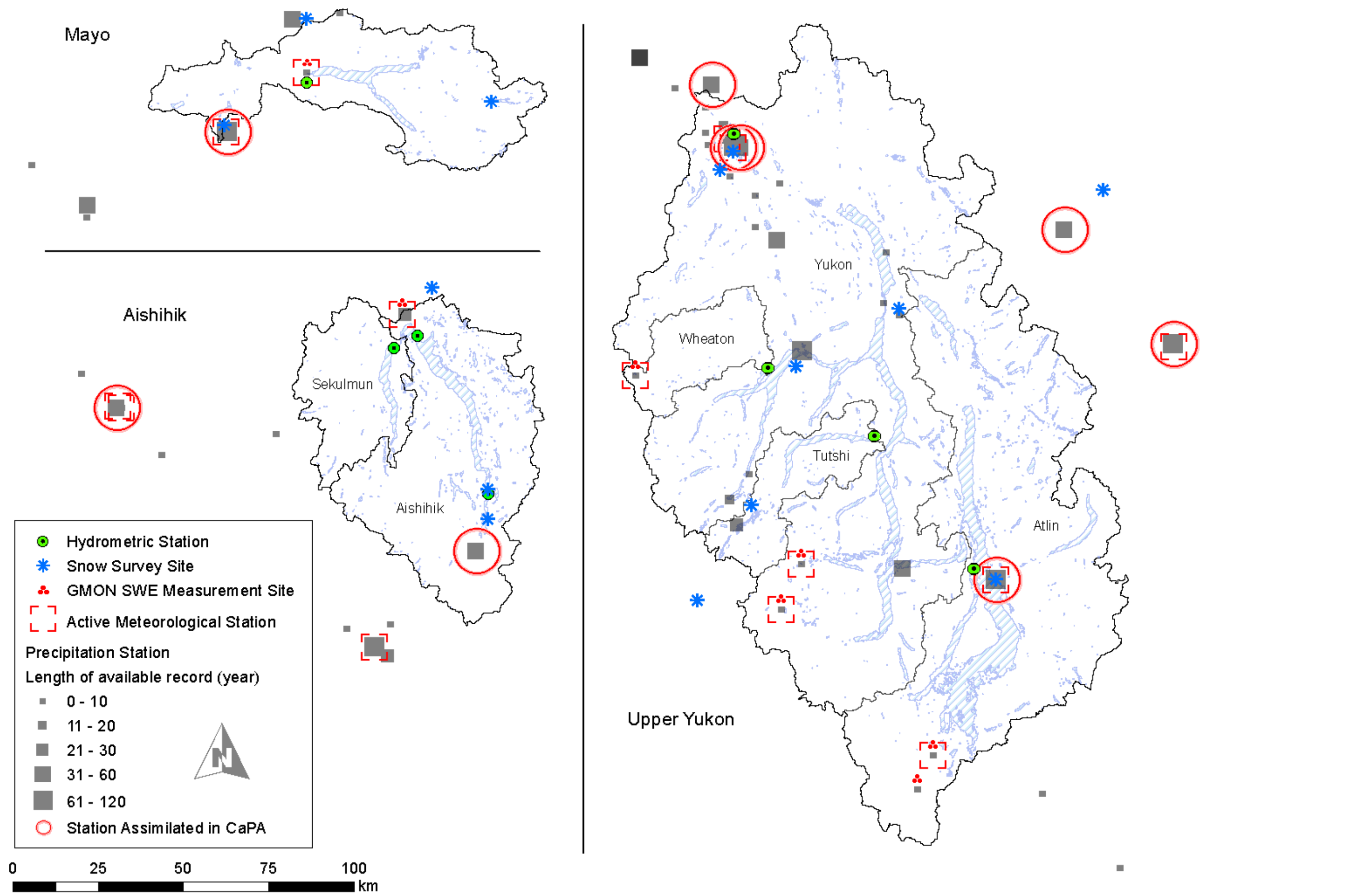
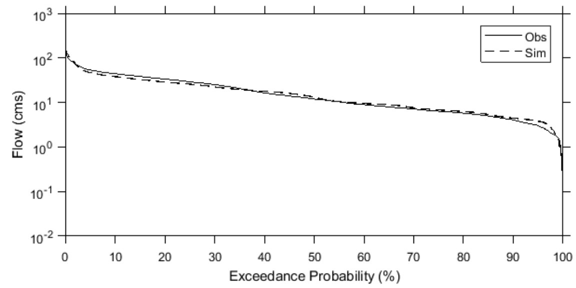
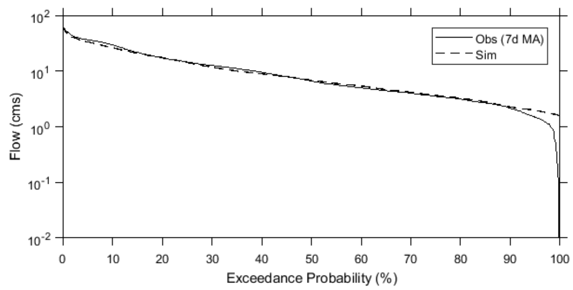


Fig. 2. The distribution of meteorological (solid black squares), hydrometric (co-centric green circles), snow course sites (blue asterisks), and GMON stations (solid red three-dot triangles) within and in the vicinity of the study basins (Mayo, Aishihik, and Upper Yukon). Meteorological stations are graduated based on the number of years of available record. Active meteorological stations (hollow red squares with dashed perimeter) and the synoptic weather stations currently assimilated in CaPA (hollow red circles) are identified.

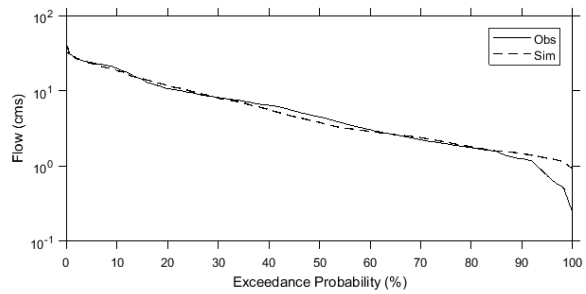
Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.



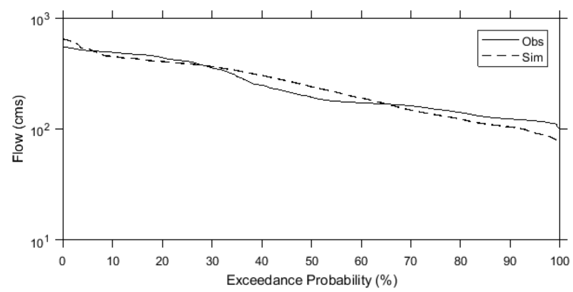
(a) Mayo (##0000003)



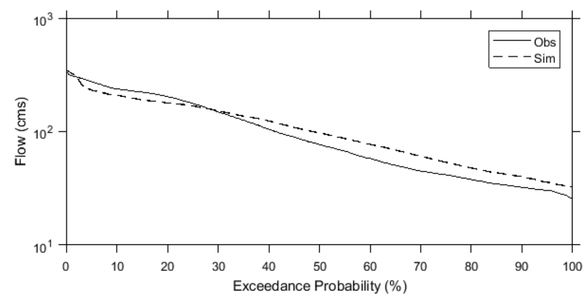
(b) Aishihik (#0000003)



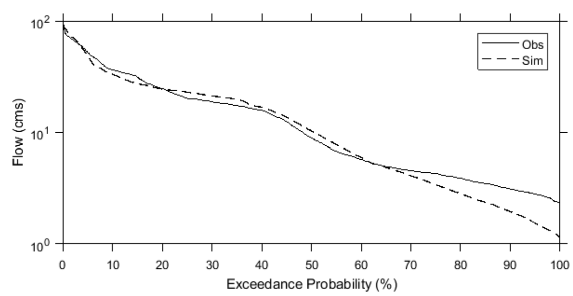
(c) Sekulmun (08AA008)



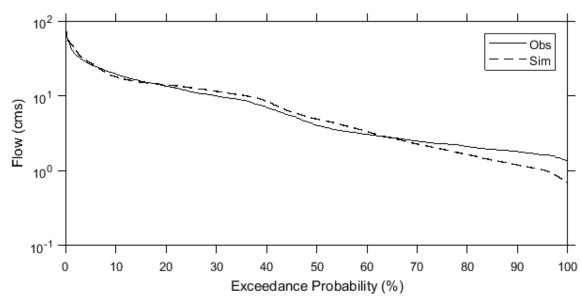
(d) Yukon (09AB001)



(e) Atlin (09AA006)



(f) Tutshi (09AA013)



(g) Wheaton (09AA012)

Fig. 3. Calibration flow duration curves for different hydrometric stations. Observations are shown as solid lines and simulations are dashed (refer to the supplementary materials provided in the online version of this paper to see flow hydrographs).

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

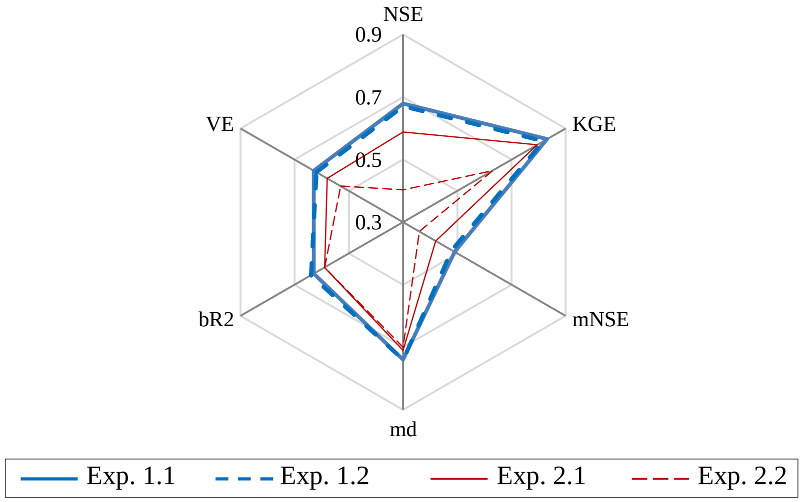


Fig. 4. Radial diagram for the performance of the model in response to the set of experiments completed in Mayo (Station ##0000003). NSE, VE, bR2, md, mNSE, and KGE stand for Nash-Sutcliffe Efficiency, Volumetric Efficiency, Modified Coefficient of Determination, Modified Index of Agreement Modified Nash-Sutcliffe Efficiency, and Kling-Gupta Efficiency, respectively.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

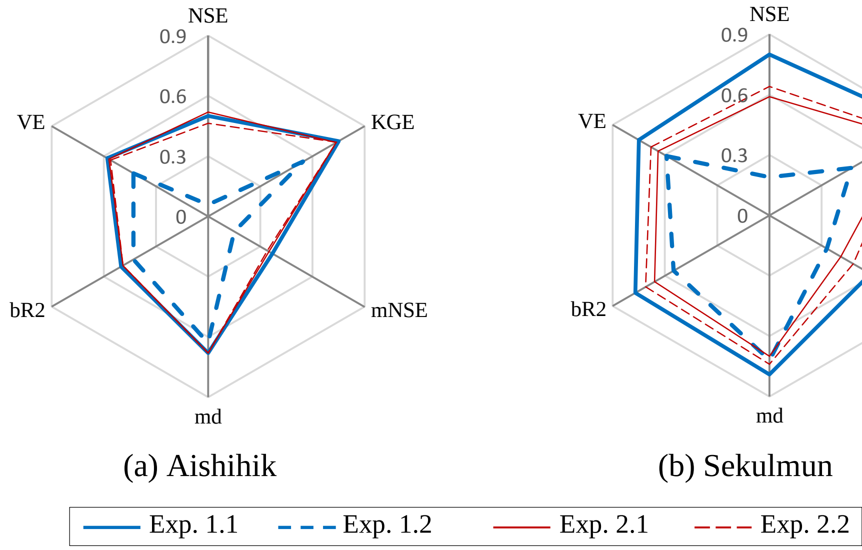


Fig. 5. Radial diagrams for the performance of the model in response to the set of experiments completed in Aishihik at (a) Aishihk (Station #0000003), and (b) Sekulmun (Station 08AA008). NSE, VE, bR2, md, mNSE, and KGE stand for Nash-Sutcliffe Efficiency, Volumetric Efficiency, Modified Coefficient of Determination, Modified Index of Agreement Modified Nash-Sutcliffe Efficiency, and Kling-Gupta Efficiency, respectively.

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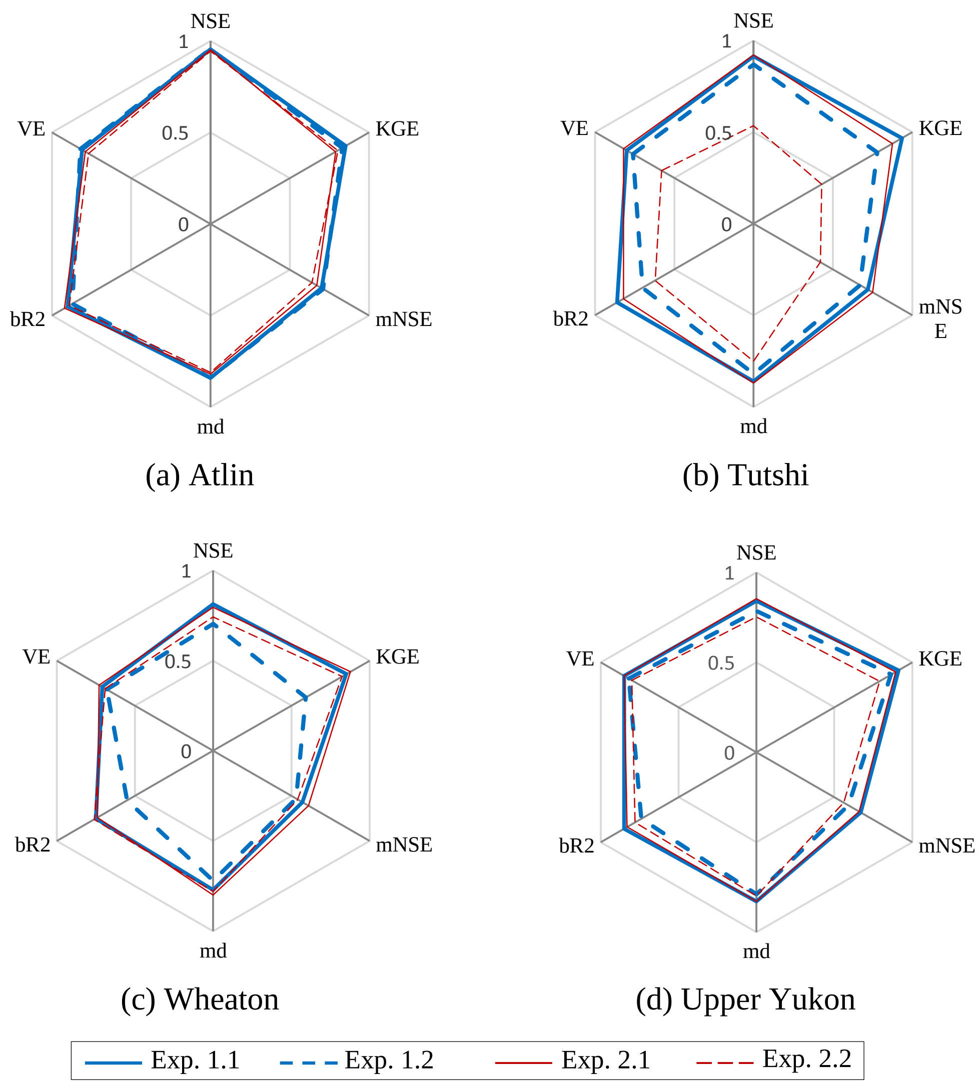

Fig. 6. Radial diagrams for the performance of the model in response to the set of experiments completed in Upper Yukon at (a) Yukon (Station 09AB001), (b) Tutshi (Station 09AA013), (c) Wheaton (Station 09AA012), and (d) Atlin (Station 09AA006). NSE, VE, bR2, md, mNSE, and KGE stand for Nash-Sutcliffe Efficiency, Volumetric Efficiency, Modified Coefficient of Determination, Modified Index of Agreement Modified Nash-Sutcliffe Efficiency, and Kling-Gupta Efficiency, respectively.

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.

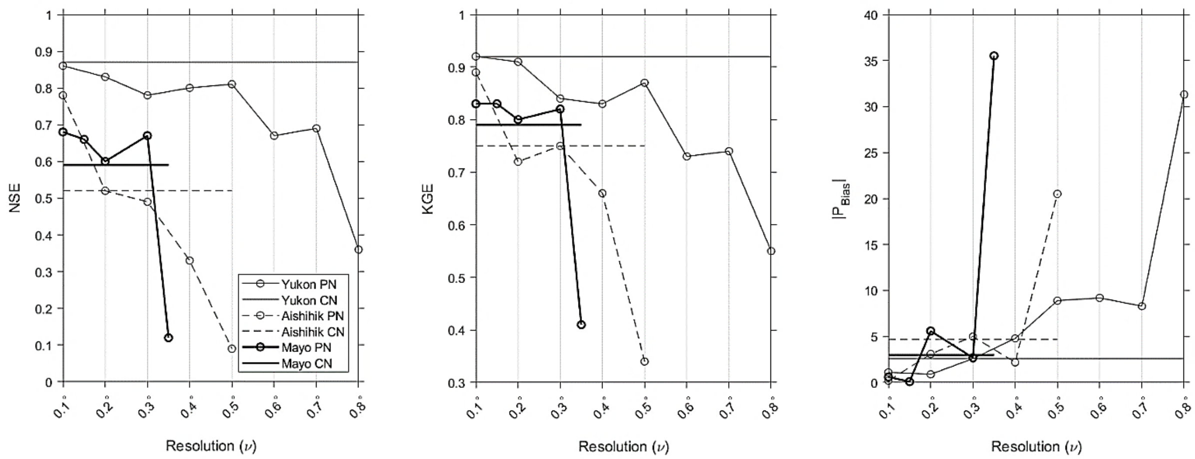

Fig. 7. Variation of the NSE (left), KGE (middle), and absolute PBias (right) in Mayo (thick lines), Aishihik (dashed lines), and Upper Yukon (thin lines) based on pseudo-networks (PN) resolution defined in Table 6. The revenue of the current network (CN) in each basin is also shown (horizontal lines).

Accepted for publication in *Journal of Hydrometeorology*. DOI 10.1175/JHM-D-20-0106.1.