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1 A current precipitation index-based model for continuous daily runoff simulation in seasonally 2 snow covered sub-arctic catchments

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7 Abstract

8 A new precipitation index-based model, which includes a snow accumulation and melt component, has
9 been developed to simulate hydrology in high latitude catchments. The model couples a point
10 snowmelt model with a current precipitation index (*CPI*) formulation to simulate continuous daily
11 runoff from catchments with seasonal snow cover. A new runoff conversion factor: C_T and L_f ,
12 threshold flow factor Th_Q and runoff transformation function *Maxbas* were introduced into the *CPI*
13 equation, which converts and transforms the routed daily *CPI* into daily runoff and maintains the daily
14 base flow in the catchment. The model was developed using twelve sub-arctic boreal catchments
15 located above and below the Arctic Circle in northern Finland, representing a region with considerable
16 seasonal snow cover. The results showed that the model can adequately simulate and produce the
17 dynamics of daily runoff from catchments where the underlying physical conditions are not known. An
18 open-access Excel-based model is provided with this paper for daily runoff simulations. The model can
19 be used to estimate runoff in sub-arctic regions where little data is typically available but significant
20 changes in climate are expected, with considerable shifts in the amount and timing of snowmelt and
21 runoff.

Keywords: current precipitation index; hydrological model; rainfall-runoff modeling; ungauged catchments

1 Introduction

An observatory network for runoff in boreal and arctic regions is often limited or inexistent (Lique et al., 2015). Small sub-catchments in these regions are usually ungauged due to the relatively high costs associated with stream gauging and monitoring. The sensitivity of these regions to natural and anthropogenic factors and the perceived impact of climate change on streamflow regimes here (Teutschbein et al., 2015) have made them the focus of the hydro-meteorological modeling community (Gusev et al., 2007). In future climate, increasing trends in air temperature and precipitation patterns are expected to cause wetter conditions in the northern hemisphere (Prowse et al., 2015; Bring et al., 2016), which will lead to considerable alterations in the hydrological cycle (Räsänen, 2007; Lique et al., 2015; Teutschbein et al., 2015). Thus there is an increasing need for robust tools to estimate daily runoff from snow-dominant high latitude ungauged catchments.

Although there is a wide range of physically and conceptually-based hydrological models for runoff modeling (Beven, 2001; Todini, 2007; Pechlivanidis et al., 2011; Devi et al., 2015), poor data coverage in high latitude regions (Gusev et al., 2007) makes the application of most of these models difficult and costly. Demand for more simplistic models with greater predictability is high, especially in ungauged regions. Empirical hydrological models provide a simplistic option, but most of the existing empirical models are event-based models (Pechlivanidis et al., 2011) and lack a snow accumulation and melt component, making them inapplicable to high latitude regions where snow contributes major volume of annual peak discharge in rivers (Woo and Young, 2004; Wilson et al., 2010). Empirical hydrological models that can simulate continuous daily runoff and account for snow accumulation and melt

processes can provide a less expensive and less data-driven method to estimate daily runoff from ungauged catchments in boreal and arctic regions.

One notable advance in the use of an empirical-deterministic model to simulate continuous daily runoff time series from ungauged catchments was made by Smakhtin and Masse (2000) in the use of the *CPI* formulation to generate precipitation time series that mimicked the general pattern of runoff variability. The duration curve derived from the simulated precipitation time series enabled them to estimate daily runoff from adjacent ungauged catchments using spatial interpolation technique (Hughes and Smakhtin, 1996; Smakhtin, 1999). This *CPI* formulation used by Smakhtin and Masse (2000) was a modification to the antecedent precipitation index (*API*) formulation used by Linsley et al. (1975). Although *API*-based continuous hydrological models have been used (Sittner et al., 1969), their use or the use of their improved form is mainly limited to storm runoff predictions (Fedora and Beschta, 1989; Ni-Lar-Win and Vandewiele, 1994). The modification made to the *API* formulation by Smakhtin and Masse (2000) enabled it to reflect not just the antecedent catchment conditions for any day, but also the current precipitation input. Although their *CPI* formulation produced precipitation time series resembling the general pattern of runoff variability, it lacks a snow accumulation and melt component, making it inapplicable in snow-dominated catchments. Furthermore, their formulation cannot be directly applied to simulate daily runoff hydrographs from ungauged catchments since it only simulates daily precipitation time series.

In this study, a new *CPI_{snow}* model was developed for simulating daily runoff hydrographs from snow-dominated catchments located in a boreal environment. The aim was i) to test model performance, ii) validate it with several boreal catchments, and iii) find limiting factors for model use. Guidelines for using the model in practice are also given and an open access Excel-based model is provided. To the

66 authors' knowledge, this is the first *CPI*-based model to account for snow accumulation and melt
67 processes.

68 2 Materials and methods

69 2.1 Study sites

70 The study was conducted using twelve boreal catchments located in Northern Finland (Fig. 1). Seven
71 of the catchments (Vääräjoki, Myllypuro, Kuusivaaranpuro, Vähä-Askanjoki, Myllyoja, Kotioja and
72 Laanioja) have areas of less than 100 km², whereas Kuoliojoki, Oulankajoki, Nellimjoki, Kajoönjärvi,
73 and Jongunjoki are larger catchments (Table 1). The Kotioja catchment was used for the sensitivity and
74 uncertainty evaluation of the model parameters, while the remaining catchments were used to test the
75 model performance in different catchment sizes and attributes. The Kotioja catchment was selected for
76 the sensitivity analysis since daily snow line measurements were available at the outlet of the
77 catchment. All of the catchments, with the exception of Kuoliojoki, Oulankajoki, Nellimjoki,
78 Kajoönjärvi, and Jongunjoki are part of the network of small basins research in the Finnish
79 Environment Institute (SYKE) (Seuna, 1983).

80 The catchments lie within humid climate regions with an aridity index of 0.7-0.9. Average annual
81 surface air temperature in the region is 1-2 °C while average snow depth by the end of March is 60-
82 80 cm (Irannezhad, 2015). The topography of the catchments is relatively flat with a maximum
83 elevation of around 500 m.a.s.l and a minimum elevation of around 100 m.a.s.l. Coniferous forest is the
84 dominant land use in the catchments. Most of the catchments have significant proportions of wetlands.
85 The catchments have zero lake percentages, except Oulankajoki, Kuoliojoki, Nellimjoki, Kajoönjärvi,
86 and Jongunjoki which have approximately 5 %, 10 %, 10 %, 14 %, and 5 % of their land area

respectively covered with lakes. The surface lithology of the catchments, with the exception of the Laanioja catchment, is mainly basal till covering over 50 % of their respective land areas. The Laanioja catchment has 53 %, 28 % and 18 % of its land area covered with migmatitic metapelite, basal till, and sand and gravel respectively. Other surface deposits in the catchments with insignificant proportions include quartzite, glaciofluvial sediments and hummocky moraine. The depth of superficial deposits is on average 10 m and the groundwater table is relatively shallow, at an average depth of 2 m from the surface. The land use data for the sites were sourced from the Finnish Environmental Institutes CORINE land cover data set 2012, the digital elevation model (10 m x 10 m) was from the National Land Survey of Finland database and the geological data were from the Geological Survey of Finland database.

The catchments were selected for the study based on the availability of long-term runoff measurements (at least 10 years of data) from the catchments in order to ensure that the model captured yearly climate variations in the catchments. The precipitation, temperature and snow line data used in the study were obtained from weather stations operated by the Finnish Meteorological Institute (Table 1) and Finnish Environmental Institute's open database (OIVA). The stations were at a distance of between 0 and 7.5 km from the catchments. For catchments not located near weather stations and snow line measurement points, the national 10 km x 10 km interpolated grid data from the Finnish Meteorological Institute was used and snow line data from stations in close proximity (about 10 km) was used. The runoff data were obtained from the open database (OIVA) of the Finnish Environmental Institute (SYKE). Runoff measurements were taken using weirs where water level is measured with limnigraphs (or pressure probes) (Mustonen, 1965). The runoff data is continually checked by the Finnish Environmental Institute for errors. Uncertainties associated with methods used for precipitation, temperature and

runoff measurements were not considered in the present study since the primary purpose of the study was to test the technical operations of the newly developed CPI_{snow} model.

2.2 Model development

The CPI_{snow} model was developed by coupling a simple degree day relation with the CPI algorithm, as shown in the flow diagram (Fig. 2). The coupling of the degree day method with the CPI formulation followed the snowmelt process model outlined by DeWalle and Rango (2008) in which the snowmelt-runoff computation is governed by five mathematical equations (Equations 1-5) that define the melting process, the refreezing process, the snow water equivalent of the snowpack and the liquid water-holding capacity of the snowpack at any given time. These equations and similar ones have been successfully applied in Finland (Kuusisto, 1980; Kuusisto, 1984; Irannezhad et al., 2015). The model outlined by DeWalle and Rango (2008) was selected for the present study owing to its successful application (Meriö, 2015) in the study region.

The model process starts with the input and correction of mean daily air temperature and precipitation. Precipitation is corrected by multiplying the daily values by a precipitation correction factor P_{corr} [-] and an elevation correction factor given by $1 + h * P_{\text{calt}}$, where h [m] is the elevation difference between the average elevation of the catchment and the average elevation of the precipitation stations and P_{calt} [-] is the elevation correction factor. The temperature is corrected by either adding or subtracting the elevation correction factor for temperature T_{calt} [-] from the original values, depending on the elevation difference between the average catchment elevation and the average elevation of the weather station. T_{calt} is typically given as 0.6 °C/100 m and P_{calt} is 0.1/100 m (Seibert, 2005; Akhtar et al., 2009).

The corrected precipitation is simulated as snowfall or rainfall depending on whether the air temperature T_a [°C] exceeds or equals a critical temperature T_{crit} [°C], which is a predetermined temperature value below which a precipitation event is considered as snowfall and above which a precipitation event is considered as rainfall and snowmelt occurs. Precipitations simulated as snowfall are multiplied by a snow correction factor S_{corr} [-] in order to take account of uncertainties in snowfall measurements. The snowfall event is accumulated in the model as the snow water equivalent SWE [mm] of the snowpack using the expression outlined in equation (1).

$$SWE_2 = SWE_1 + \Delta P + \Delta WHC - \Delta(M + P_r) \quad (1)$$

where ΔWHC [mm/d] is a change in the water-holding capacity of the snowpack, M [mm/d] is snowmelt, P [mm/d] is precipitation and P_r [mm/d] is rainwater. The accumulated snow melts when the air temperature T_a exceeds the critical temperature T_{crit} . Meltwater is computed as a multiple of a degree day factor DDf [mm/°C/d] and the difference between the air temperature T_a [°C] and the critical temperature T_{crit} [°C] (equation 2).

$$M = DDf \cdot (T_a - T_{crit}) \quad (2)$$

Meltwater is assumed to be retained in the snowpack as long as the amount does not exceed a certain fraction of the snow given as the liquid water-holding capacity of the snowpack WHC [mm/d] which is expressed as:

$$WHC_2 = WHC_1 + (f/100)\Delta P - \Delta(M + P_r) \quad (3)$$

where f [-] is a factor indicating the maximum percentage at which WHC can be reduced either through gradual melt or through rain, M [mm/d] is the melt, P [mm/d] is precipitation, and P_r [mm/d] is

rainwater. Refreezing of meltwater occurs when the snow surface temperature T_s [°C] decreases below the critical temperature and is given by the equation:

$$Ref = cfr \cdot DDf \cdot (T_{crit} - T_s) \quad (4)$$

where Ref [mm/d] is the refreeze meltwater and cfr [-] is the refreezing factor. An estimate of the snow surface temperature T_s at any given time is calculated using a simple temperature index approach used by Anderson (1973) and Marks et al. (1992) which is given as:

$$T_{s2} = T_{s1} + Ts f(T_{a2} - T_{s1}) \quad (5)$$

where T_{s1} [°C] and T_{s2} [°C] are snowpack surface temperatures at time t_1 [d] and t_2 [d] respectively, T_{a2} is the mean daily air temperature at time t_2 and Tsf [-] is the surface temperature factor. As recommended by Anderson (1976), the snow surface temperature was limited to a maximum of 0 °C and set as equal to the value of the mean daily air temperature on days with snowfall exceeding about 5 mm water equivalent since the assumption is that the new snowfall becomes the surface layer. The output liquid R_t (meltwater + rain) from the model was used as input to the CPI formulation (equation 6) to simulate the CPI time series for the catchment.

$$CPI_t = CPI_{t-1} K_r + R_t \quad (6)$$

The simulated CPI time series was then multiplied by conversion factors; C_T [-] (during winter and spring periods) and L_f [-] (during summer and autumn periods), which converted it to runoff time series (Fig. 2). The conversion factors take into account the evapotranspiration and infiltration losses in the catchment. As these clearly differed for the winter-spring periods and summer-autumn periods, different conversion factors were used for these periods. This helped to minimize underestimation of sharp hydrograph rises during snowmelt periods since evapotranspiration and infiltration rates are low

during these periods (Lafleur et al., 2005). In the model, the summer-autumn period was assumed to begin from the end of first 30 days period when average air temperature remained above 0 °C, and ends with the occurrence of the first zero or negative air temperature at the end of the year. The 30 days period was based on the average duration of snowmelt in northern Finland (calculated from 30 years discharge and metrological records).

Since the study catchments are in an energy-limited region of the globe, a threshold flow factor Th_Q [-] was introduced into the CPI algorithm in order to account for saturation excesses in the region, which maintains outflow from the catchments even in the absence of a precipitation event. Th_Q ensured that the simulated daily CPI was never below a certain value, which represented the minimum daily outflow from the catchments. The simulated CPI_t was passed to the runoff conversion stage of the model if its value was greater or equal to the threshold flow Th_Q . Otherwise, the threshold flow was added to the simulated CPI_t before passing it to the runoff conversion stage of the model (equation 7).

$$Q_{sim(t)} = \begin{cases} \left(\begin{cases} CPI_t * C_T & \text{if } CPI_t \geq Th_Q \\ (CPI_t + Th_Q) * C_T & \text{if } CPI_t < Th_Q \end{cases} \right) & \text{for winter – spring period} \\ \left(\begin{cases} CPI_t * L_f & \text{if } CPI_t \geq Th_Q \\ (CPI_t + Th_Q) * L_f & \text{if } CPI_t < Th_Q \end{cases} \right) & \text{for summer – autumn period} \end{cases} \quad (7)$$

The converted CPI_t ($Q_{sim(t)}$) was then passed through a transformation function $Maxbas$ [-] (Seibert, 2005) (equation 8) which transforms the runoff generated to get the proper shape of the hydrograph at the outlet of the catchment. The $Maxbas$, which is the time base of a triangular weighting function defined by equation (9), accounts for delays in response as a result of storage in the catchment. The output from the $Maxbas$ transformation stage was then passed as the model's runoff output Q_t [mm/d].

$$Q_t = \sum_{i=1}^{Maxbas} c_{(i)} * Q_{sim(t-1+1)} \quad (8)$$

190 Where

191 $c_{(i)} =$

$$192 \int_{i-1}^i \frac{2}{Maxbas} - \left| u - \frac{Maxbas}{2} \right| \frac{4}{Maxbas^2} du =$$

$$193 - \frac{(|Maxbas - ((i-1)*2)| - |Maxbas - (i*2)| - 4)Maxbas - ((i-1)*2)|Maxbas - ((i-1)*2)| + (i*2)|Maxbas - (i*2)|}{2*Maxbas^2} \quad (9)$$

194 2.3 Model calibration and optimization procedure

195 The model was calibrated using the routine snow parameters (T_{crit} , DDf , cfr , S_{corr} , TSF , f), the recession
 196 coefficient K_r , the precipitation correction factor P_{corr} , the threshold flow factor Th_Q , the runoff
 197 conversion factors C_T and L_f , and the transformation function $Maxbas$. Default values of the P_{calt} (0.1),
 198 and T_{calt} (0.6) (Seibert, 2005; Akhtar et al. 2009) were used. Long-term average daily precipitation was
 199 used as the initial current precipitation value CPI_0 , as recommended by Smakhtin and Masse (2000).
 200 The initial values of the snow water equivalent SWE_1 , snowpack water-holding capacity WHC_1 and
 201 snow temperature T_{s1} were assumed to be 0. The first year of the catchments' data records was used as
 202 the initialization period, while the remaining years were used for the calibration. Depending on the
 203 duration of runoff records available from each of the catchments, a minimum of six years' records was
 204 used for model calibration while the remaining years were used for model validation (Table 2).

205 In order to reduce calibrated parameters, a sensitivity analysis of the model parameters was performed
 206 to determine the insensitive parameters that can be kept constant during the optimization procedure.
 207 The sensitivity analysis was undertaken using the generalized likelihood uncertainty estimation
 208 (GLUE) approach (Beven and Binley, 1992; Krebs et al., 2016), while parameter optimization was
 209 performed using the Monte Carlo procedure. The GLUE procedure was performed in two stages. The

first stage evaluated parameter sensitivity when all the model performance criteria (Both runoff and *SWE* performance criteria) were considered together, while the second stage evaluated parameter sensitivity when each of the model performance criteria were considered separately. The prior parameter spaces (Table 3) were selected based on previous studies on snow hydrology (Anderson, 1973; Kuusisto, 1980; Marks et al., 1992; DeWalle and Rango, 2008), studies on the HBV conceptual hydrological model (Seibert, 1999; Seibert and Vis, 2012) and studies on recession coefficient (Linsley et al., 1975; Fedora and Beschta, 1989). Uniform distribution of the parameters within the prior parameter space was assumed and 10,000 runs of the Monte Carlo procedure were performed after which parameter sets with acceptable objective functions values were selected as the posterior parameter space. The objective functions for best model performance were defined, for both the simulated runoff and simulated *SWE*, based on a set of model performance criteria (the Nash-Sutcliffe model efficiency eff , the natural logarithm of the Nash-Sutcliffe model efficiency $eff_{\log}$, the relative Nash-Sutcliffe model efficiency eff_{rel} , the coefficient of determination r^2 and mean difference D_{mean}) (Krause et al., 2005; Seibert, 2005). The cumulative distribution of the posterior parameter space was plotted against the cumulative distribution of the prior parameter space to determine the sensitivity of each of the parameters. The Kolmogorov-Smirnov test (*KS*-test) was used to establish the statistical difference between the prior parameter space and the posterior parameter space cumulative distributions in order to address the lack of statistical validity of the GLUE approach (Krebs et al., 2016). Parameters that showed no sensitivity were fixed and the remaining ones used for the model calibration. The optimized parameter set from the model calibration procedure was thereafter validated using the validation periods (Table 2).

The use of the selected performance criteria to evaluate the model's performance was based on the need to account for model performance on different aspects of the hydrograph, such as low flows and

high flows (Krause et al., 2005). The model parameters' sensitivity to each of the performance criteria was evaluated by plotting each of the performance criteria against the prior parameter space distribution. In order to remove the effects of area in this evaluation, standardized values of observed runoff (standardized with catchment areas) were used from each catchment in the study.

3 Results and discussion

3.1 Parameter sensitivity analysis

The GLUE procedure with combined performance criteria (eff , eff_{log} , eff_{rel} and r^2) showed that the CPI_{snow} model was sensitive in all parameters with the exception of the refreezing factor cfr , and the snowpack water-holding capacity factor f , where the model showed less sensitivity to their deviations (Fig. 3). However, the CPI_{snow} model showed varying degrees of sensitivity to each of the parameters when the GLUE procedure was performed separately with each of the performance criteria. For runoff performance criteria, all the parameters, with the exception of cfr , f , Tsf , and $Maxbas$, showed varying degrees of sensitivity to the Nash-Sutcliffe model efficiency eff criterion and the natural logarithm of the Nash-Sutcliffe model efficiency eff_{log} . The eff_{rel} criterion was only influenced by Th_Q , P_{corr} , K_r , and to some extent, C_T while the r^2 criterion was highly influenced by K_r and DDf parameters. Only K_r was highly sensitive to all the runoff performance criteria (Table 4). The SWE performance criteria were only influenced by P_{corr} , S_{corr} , DDf , and T_{crit} parameters. This confirmed that model parameter sensitivity is largely dependent upon the performance criteria used, as observed by Ouyang et al. (2014). The most sensitive parameters from the GLUE procedure were the threshold flow factor Th_Q , the recession coefficient K_r , the degree day factor DDf , the critical temperature T_{crit} , the precipitation correction factor P_{corr} , the snow correction factor S_{corr} and the runoff conversion factors: C_T and L_f .

In the CPI_{snow} model, the threshold flow parameter took into account the base flows in the watershed as a result of groundwater table position. Owing to this, Th_Q played a key role in maintaining the minimum daily outflow from the catchments. This made Th_Q the main parameter for controlling the saturation condition in the catchment and thus its high sensitivity. A lower Th_Q indicates a catchment with low base flow while a higher Th_Q indicates catchments with high base flow. On other hand, the recession coefficient K_r controlled the recession limbs of the simulated runoff hydrographs. This made it the primary parameter for controlling similarity between the observed and simulated runoff variation patterns. The high sensitivity of the degree day factor DDf and the critical temperature factor T_{crit} was expected since these parameters control snow-melting processes and spring runoff depends on them. Similar results have been observed by Seibert (1997). Given that the degree day factor DDf depends on the extent of forest cover in the catchment (Kuusisto, 1980), a small alteration in its value affects the water equivalent of the snowpack (Seibert, 1999). This results in significant changes in the spring runoff, which will affect model performance. High sensitivity in the precipitation and snow correction factors (P_{corr} and S_{corr}) and the runoff conversion factors (C_T and L_f) was also expected since the precipitation and snow correction factors corrects the uncertainty in precipitation measurements while the conversion factors controls the proportion of precipitation that becomes runoff. These four factors controlled the volume difference between the observed and the simulated runoff. The transformation function $Maxbas$ controls the shape of the hydrograph hence its sensitivity to the $eff_{\log}$ performance criterion.

Furthermore, the model was mildly sensitive to the snow surface temperature factor T_{sf} . This is because the snow surface temperature factor plays a role in the snowmelt processes. From the sensitivity analysis, the T_{sf} factor was highly sensitive when the prior parameter space was defined to be between 0.02 and 1.5. However, when the parameter space was defined to be between the values of

0.12 and 0.5, the Tsf factor was less sensitive. This range is in conformity with the values used by Marks et al. (1992) and Anderson (1973). The less sensitivity of the cfr and f factor conformed to the results obtained by Seibert (1997), which is why these parameters are normally kept constant during model calibrations. The results of the KS -test and cumulative prior and posterior parameter distribution plots for each parameter are shown in Figure 3.

3.2 Parameter calibration, validation and model performance

Based on the results obtained from the parameter sensitivity analysis, the less sensitive parameters cfr , f and Tsf were kept at constant values. The other parameters were used to calibrate the model for each of the study catchments. The optimal parameter sets obtained for each of the study catchments (Table 5) produced a Nash-Sutcliffe model efficiency eff greater than 0.60 on average in both the calibration and validation periods (Table 6). The optimal recession coefficient K_r realized in the study areas fell within the range (0.85 to 0.98) proposed by Linsley et al. (1975), Fedora and Beschta (1989), and Smakhtin and Masse (2000). However, applying the regression relationship between catchment area and recession coefficient, as observed by Fedora and Beschta (1989), in the present study areas produced K_r values with poor model performance. This could be an indication that K_r is more dependent on region than on catchment size. The optimal degree day factor DDf and threshold temperature T_{crit} were in line with the range recommended for catchments located in boreal regions (Seibert, 2005). The threshold flow factor Th_Q and the conversion factors: C_T and L_f differed considerably among the study catchments. The reason for such a difference might be related to topography, vegetation and soil characteristics since these parameters accounts for base flows and peak flows, which are dependent on these catchment characteristics. Lower and similar values of the transformation function $Maxbas$ were realized in the smaller catchments with less storage while higher values were realized in the bigger

catchments with higher storage characteristics. Furthermore, lower values of C_T and L_f were realized in the bigger catchments while higher values were realized in the smaller catchments. Further studies with a greater number of catchments will be needed in order to establish a possible relationship between these parameters and catchment topology, vegetation patterns, and soil and geological characteristics in boreal sub-arctic conditions.

In general, the CPI_{snow} model produced a satisfactory performance in the study catchments, with average model efficiencies (eff , eff_{log} , eff_{rel} and r^2) greater than 0.5 (Table 6 and 7, Figs. 5, 6, 7 and 8). Poor model performance in peak flows (up to a 5 % decrease in model efficiency) was observed in catchments where interpolated grid precipitation and temperature data were used compared to the catchments located near a meteorological station. The reason for this observation could be underestimation or overestimation during the interpolation procedure. As noted by Venäläinen et al. (2005), the Finnish Meteorological Institute's 10 km x 10 km interpolated grid data works well with daily temperature but not with daily precipitation. The large spatial variation, especially in the case of rain events, results in a remarkable difference between the interpolated values and measured values. The interpolation tends to cut the peak values away, especially when the measured precipitation values are above 10 mm/day. This results in the interpolated values being systematically lower than the measured values. This difference will result in poor model performance, especially with regard to an accurate representation of peak flows, as seen in the Myllypuro, Kuusivaaranpuro, Vähä-Askanjoki, Kotioja and Kuoliojoki catchments (Figs. 5, 6 and 7). Underestimation or overestimation of precipitation values will also have a profound influence on model calibration, affecting the values of precipitation-dependent parameters (S_{corr} , P_{corr} , C_T , and L_f).

By including SWE in the model calibration procedure, the posterior parameter space of most of the model parameter space was reduced considerable when the objective functions were set for both the

runoff and *SWE* performance criteria, than when they were set for runoff performance criteria only (Fig. 4). This helped to minimize the problem of badly defined parameters experienced in most conceptual models (Seibert, 1977; Beven and Binley, 1992; Jakeman and Hornberger, 1993). Also, given that snowmelt is the major contributor to runoff processes in the sub-arctic regions, including *SWE* calibration in the CPI_{snow} model ensured that snow accumulation and runoff from the catchments are predicted accurately.

3.3. Application of the CPI_{snow} model in practice

Unlike most physically-based and conceptual models, the CPI_{snow} model offers a less parameterized and less expensive method for estimating runoff from ungauged catchments where there is an extensive shortage of data. The novelty of the approach is that the model accounts for the snowmelt process by coupling the *CPI* formulation developed by Smakhtin and Masse (2000) with the point snowmelt-runoff model of DeWalle and Rango (2008) to generate daily runoff hydrographs from ungauged boreal catchments. The model application starts with inputting average daily precipitation and air temperature records into the model's data input and calculation section (Fig. 9). Where available, observed daily runoff and snow line are also an input. The values for the state parameters are assigned, including the mean elevation of the catchment and the mean elevations of the precipitation and temperature stations used. In cases where mean elevations of the precipitation and temperature stations are not known, their values can be assumed to be the same as the mean elevation of the catchment. The initial value of the catchments' current precipitation index CPI_0 and the elevation difference between the catchments' mean elevations and the weather stations' mean elevations are calculated automatically from the input data.

343 The model is calibrated by manually changing the values of the calibration parameters (T_{crit} , DDf , cfr ,
344 Tsf , f , S_{corr} , K_r , Th_Q , C_T , L_f , $Maxbas$, and P_{corr}). Additionally, automatic calibration of the model can be
345 achieved by using the version of the model that includes the Monte Carlo procedure. In this case, a
346 prior parameter space is defined by the user and the Monte Carlo procedure generates random values
347 within the defined prior parameter space using a uniform distribution method. By defining an objective
348 function or set of objective functions with respect to the model performance criteria, parameter sets that
349 meet the objective functions are generated from the Monte Carlo procedure as the posterior parameter
350 space. By comparing the cumulative distribution of the prior parameter sets and posterior parameter
351 sets from the Monte Carlo run using the GLUE procedure (Beven and Binley, 1992; Krebs et al.,
352 2016), the less sensitive or insensitive parameters can be identified. The insensitive parameters can then
353 be kept constant using their average values from the posterior parameter sets. With the posterior
354 parameter space as the new prior parameter space, the sensitive parameters are then used to calibrate
355 the model. The optimal parameter sets can be derived by taking the ensemble average of the parameter
356 sets that meet the defined objective functions from the Monte Carlo procedure.

357 In cases where observed runoff records are not available, optimal parameter sets for the model can be
358 derived through model parameter regionalization procedure (Wagener et al., 2007; Blöschl et al.,
359 2013). In this case, similar catchments (with runoff records) in close proximity to the ungauged
360 catchment are used to generate optimal model parameter sets that are applicable to the ungauged
361 catchments' hydrological conditions. The process hinges on the ability to establish hydrological
362 similarity between the gauged catchments and the ungauged catchment (Blöschl et al., 2013).

363 The developed CPI_{snow} model is a lumped approach using three parameters Th_Q and C_T , and L_f to
364 account for losses and saturation condition in the catchment, so it cannot assess the different
365 hydrological processes contributing to runoff generation. Despite this limitation, it is a viable tool for

daily runoff modeling. It can also be used in studies on climate change impacts on runoff. Given that it can be calibrated with only nine parameters (K_r , S_{corr} , P_{corr} , Th_Q , T_{crit} , DDf , C_T , L_f , and $Maxbas$), while keeping other less sensitive parameters constant, makes it easy to use. Additionally, it requires little to no site investigation of the catchment properties before it can be applied. This makes it an ideal choice when the budget is small and a rapid estimate of runoff is required, as in boreal and arctic areas with poor data coverage and a sparse monitoring network (Gusev et al., 2007; Lique et al., 2015).

4 Conclusions

This study presented a current precipitation-based hydrological model (CPI_{snow}) for predicting continuous daily runoff from ungauged catchments. It described a method of coupling a snowmelt model with a current precipitation index formulation to generate daily runoff time series from snow-dominated catchments. The CPI formulation was improved by introducing four factors, Th_Q , C_T , L_f , and $Maxbas$ into the formulation, which account for base flow, converts the simulated daily current precipitation index into runoff, and transforms the runoff into daily runoff hydrograph. The results presented above show that it is possible to model daily runoff from snow-dominated sub-arctic catchments using only daily precipitation and temperature data.

The CPI_{snow} model gave a satisfactory performance in all the studied catchments. The model was observed to be highly sensitive to nine out of its twelve parameters, making it easier to calibrate compared to most models with extensive parameterization. Furthermore, inclusion of SWE in the model calibration procedure ensured accurate prediction of runoff hydrology in the sub-arctic regions. It also reduced the likelihood parameter space during model calibration. The model can be used directly to simulate daily runoff time series from ungauged catchments with seasonal snow cover. The model is a valuable tool for runoff prediction in catchments where there is a considerable shortage of data.

388 Additional material

389 Excel-based CPI_{snow} model (manual calibration and Monte Carlo automatic calibration versions).

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 396 references.

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Table 1. Study catchments and their physical characteristics.

Catchment		Physical characteristics								
ID	Name	Area [km ²]	Avg. slope [%]	Min. elev. [m]	Max. elev. [m]	Artificial areas [%]	Agric. areas [%]	Forest [%]	Wetland [%]	Lake [%]
C1	Vääräjoki ¹	19.3	5.70	167	319	0.00	0.00	84.36	0.00	0.00
C2	Myllypuro*	9.9	6.00	175	258	0.28	0.57	96.60	14.20	0.00
C3	Kuusivaaranpuro*	27.6	4.20	232	375	1.75	1.02	90.46	34.60	0.00
C4	Vähä-Askanjoki*	16.4	10.40	152	383	0.00	0.00	89.36	0.00	0.00
C5	Myllyoja ²	28.5	7.70	171	406	0.53	0.08	93.85	9.90	0.00
C6	Kotioja*	18.1	2.70	162	241	0.68	2.72	67.92	43.90	0.00
C7	Laanioja ³	13.6	7.10	269	453	3.69	0.22	92.60	0.00	0.00
C8	Kuoliojoki*	105	3.70	263	353	0.00	2.00	78.01	26.70	10.00
C9	Oulankajoki ⁴	1986	4.00	141	469	0.79	1.24	68.18	18.00	4.80
C10	Nellimjoki ⁵	314	7.60	195	507	0.03	0.00	91.50	2.02	9.60
C11	Kajoonjärvi ⁶	125	6.70	167	293	0.00	2.26	85.00	1.14	13.50
C12	Jongunjoki ⁷	932	5.70	114	285	0.00	0.09	94.05	11.29	4.90

* 10 km x 10 km grid interpolated data

¹ 101886 Kuusamo Lentoasema weather station

² 101952 Savukoski weather station

³ 102005 Inari Saariselkä tourist centre weather station

⁴ 101887 Kuusamo Kiutaköngäs weather station

⁵ 102033 Inari Ivalo Lentoasema weather station

⁶ 101609 Juuka Niemelä weather station

⁷ 101636 Lieksa Lampela weather station

Table 2. Periods of daily runoff records used for model calibration and validation for each of the study catchments.

ID	Catchment name	Runoff Data period	SWE Data Period	Calibration period	Validation period
C1	Vääräjoki	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C2	Myllypuro	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C3	Kuusivaaranpuro	1990 – 1998	1990 – 1998	1990 – 1995	1996 – 1998
C4	Vähä-Askanjoki	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C5	Myllyoja ^P	1990 – 2009	1990 – 2009	1990 – 1996	2003 – 2009
C6	Kotioja*	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C7	Laanioja	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C8	Kuoliojoki	1977 – 1990	-	1977 – 1984	1985 – 1990
C9	Oulankajoki ^P	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C10	Nellimjoki	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C11	Kajoonjärvi	1990 – 2003	1990 – 2003	1990 – 1996	1997 – 2003
C12	Jongunjoki	1997 – 2010	1997 – 2010	1997 – 2003	2004 – 2010

* Used for parameter sensitivity and uncertainty analysis

^P Gap between calibration and validation period is due to lack of SWE data in those years

Table 3. Prior and posterior parameter space used for Kotioja catchment model calibration and parameter sensitivity analysis.

Parameters	Prior parameter space			
	Prior parameter space		Posterior parameter space	
	Max.	Min.	Max.	Min.
Snow routine				
T_{crit}	-0.01	-1.00	-0.04	-0.75
DDf	5.00	2.00	4.81	2.02
cfr	0.07	0.02	0.07	0.02
f	0.045	0.02	0.045	0.02
Tsf	0.50	0.12	0.50	0.13
S_{corr}	1.10	0.85	1.10	0.90
CPI routine				
K_r	0.90	0.85	0.89	0.85
Th_Q	5.00	0.50	3.08	0.70
C_T	0.15	0.05	0.13	0.07
L_f	0.12	0.02	0.08	0.02
$Maxbas$	5	1	5	1
Precipitation correction				
P_{corr}	1.05	0.50	1.04	0.62

Table 4. Degree of parameter sensitivity to each of the model performance criteria based on the *KS*-test.

Runoff Parameter Sensitivity Matrix												
Performance criterion	T_{crit}	DDf	cfr	f	Tsf	S_{corr}	P_{corr}	K_r	Th_Q	C_T	L_f	$Maxbas$
eff	++	++	-	-	-	++	++	++++	--	++++	+	-
eff_{log}	--	+++	--	-	--	+	+	++	++++	++	++++	+
eff_{rel}	-	-	-	-	-	-	+	+	++++	--	--	-
r^2	-	+	-	-	-	--	--	++	-	-	-	-
SWE Parameter Sensitivity Matrix												
eff	+	++	-	-	-	++	++++	-	-	-	-	-
eff_{log}	+	++	-	-	-	+	++++	-	-	-	-	-
r^2	+	++	-	-	-	+	++	-	-	-	-	-
++++ $D > 0.27$, +++ $D = 0.22$ to 0.27 , ++ $D = 0.17$ to 0.22 , + $D = 0.11$ to 0.17 , -- $D = 0.06$ to 0.11 , - $D = 0.01$ to 0.06												

Table 5. Ensemble average of optimal parameter sets generated for each of the study catchments.

Catchment	Parameter											
	T_{crit}	DDf	cfr	f	Tsf	S_{corr}	K_r	Th_Q	C_T	L_f	$Maxbas$	P_{corr}
Vääräjoki	-0.25	4.30	0.05	0.03	0.50	1.05	0.85	5.20	0.08	0.075	2	1.01
Myllypuro	0.01	3.56	0.05	0.03	0.50	1.02	0.86	1.50	0.09	0.05	2	1.02
Kuusivaaranpuro	-0.26	3.87	0.05	0.03	0.50	1.08	0.85	1.90	0.08	0.07	2	0.92
Vähä-Askanjoki	-0.21	2.98	0.05	0.03	0.50	1.08	0.85	4.10	0.08	0.075	2	0.90

Myllyoja	-0.15	3.20	0.05	0.03	0.50	1.01	0.85	3.50	0.08	0.075	3	0.85
Kotioja	-0.25	3.86	0.05	0.03	0.50	1.02	0.85	1.53	0.09	0.05	3	0.99
Laanioja	-0.25	3.80	0.05	0.03	0.50	0.98	0.88	6.60	0.06	0.05	3	0.90
Kuoliojoki	-0.22	4.15	0.05	0.03	0.50	1.01	0.91	4.50	0.05	0.04	8	0.90
Oulankajoki	-0.23	4.20	0.05	0.03	0.50	1.05	0.89	4.00	0.06	0.05	6	0.98
Nellimjoki	-0.21	3.20	0.05	0.03	0.50	1.02	0.95	10.50	0.03	0.025	15	1.20
Kajoonjärvi	-0.20	3.20	0.05	0.03	0.50	1.02	0.95	14.00	0.03	0.02	15	0.80
Jongunjoki	-0.18	3.15	0.05	0.03	0.50	1.05	0.92	5.05	0.05	0.025	8	1.05

558

559 **Table 6.** Runoff Performance evaluation of the generated optimal parameter sets for each catchment.

Catchment	Runoff Performance criterion									
	<i>eff</i>		<i>eff</i> _{log}		<i>eff</i> _{rel}		<i>r</i> ²		<i>D</i> _{mean}	
	Cali	Vali	Cali	Vali	Cali	Vali	Cali	Vali	Cali	Vali
Vääräjoki	0.62	0.60	0.56	0.59	0.74	0.79	0.62	0.67	7.37	-12.51
Myllypuro	0.70	0.72	0.52	0.53	0.64	0.51	0.70	0.73	-4.08	-11.01
Kuusivaaranpuro	0.72	0.65	0.57	0.55	0.84	0.72	0.75	0.65	-7.04	1.00
Vähä-Askanjoki	0.70	0.73	0.65	0.58	0.76	0.73	0.71	0.73	3.42	-1.63
Myllyoja	0.58	0.67	0.54	0.54	0.67	0.73	0.60	0.68	-0.04	-6.92
Kotioja	0.72	0.56	0.53	0.57	0.82	0.75	0.72	0.56	-6.81	6.80
Laanioja	0.70	0.77	0.53	0.50	0.85	0.84	0.73	0.77	1.42	-3.37
Kuoliojoki	0.61	0.68	0.62	0.58	0.58	0.54	0.66	0.73	9.21	1.11
Oulankajoki	0.59	0.61	0.55	0.51	0.74	0.89	0.59	0.62	-4.21	-7.22
Nellimjoki	0.74	0.63	0.56	0.51	0.72	0.74	0.80	0.66	-1.05	2.74
Kajoonjärvi	0.72	0.76	0.50	0.51	0.73	0.75	0.74	0.77	6.11	-7.75
Jongunjoki	0.76	0.61	0.53	0.54	0.86	0.68	0.79	0.64	-8.77	-3.59

Cali. = calibration period, and Vali. = validation period

560

561

Table 7. SWE Performance evaluation of the generated optimal parameter sets for each catchment.

Catchment	SWE Performance criterion					
	eff		eff_{log}		r^2	
	Cali	Vali	Cali	Vali	Cali	Vali
Vääräjoki	0.91	0.94	0.80	0.87	0.95	0.94
Myllypuro	0.89	0.90	0.64	0.81	0.95	0.94
Kuusivaaranpuro	0.96	0.86	0.90	0.67	0.96	0.97
Vähä-Askanjoki	0.91	0.92	0.79	0.88	0.93	0.95
Myllyoja	0.89	0.70	0.79	0.70	0.91	0.87
Kotioja	0.94	0.94	0.82	0.84	0.96	0.95
Laanioja	0.52	0.85	0.90	0.67	0.67	0.94
Kuoliojoki	-	-	-	-	-	-
Oulankajoki	0.92	0.62	0.75	0.73	0.92	0.64
Nellimjoki	0.65	0.85	0.88	0.76	0.67	0.88
Kajoonjärvi	0.64	0.93	0.55	0.74	0.82	0.94
Jongunjoki	0.87	0.73	0.71	0.50	0.93	0.81

Cali. = calibration period, and Vali. = validation period

Figure 1. Spatial location of catchments used in the study.

Figure 2. Flow diagram of the CPI_{snow} model (modified from the point snowmelt-runoff model flow diagram by DeWalle and Rango (2008)). Snowmelt-runoff model in blue and CPI model in red.

Figure 3. Cumulative frequency distribution of the prior and posterior parameter space produced during the parameter sensitivity analysis. D is the KS -test. Sensitive parameters are indicated by bold font while less sensitive parameters are indicated by normal font.

Figure 4. Plots of model parameter spaces from the Monte Carlo procedure for two cases of when objective functions were set for runoff performance criteria only and when objective functions were set for both runoff and SWE performance criteria.

Figure 5. Plots of CPI_{snow} model performance in the study catchments (1) Vääräjoki, (2) Myllypuro and (3) Kuusivaaranpuro for (a) calibration and (b) validation periods.

Figure 6. Plots of CPI_{snow} model performance in the study catchments (4) Vähä-Askanjoki, (5) Myllyoja and (6) Kotioja for (a) calibration and (b) validation periods.

588 Figure 7. Plots of CPI_{snow} model performance in the study catchments (7) Laanioja, (8) Kuoliojoki and
589 (9) Oulankajoki for (a) calibration and (b) validation periods.

590

591 Figure 8. Plots of CPI_{snow} model performance in the study catchments (7) Nellimjoki, (8) Kajoönjärvi
592 and (9) Jongunjoki for (a) calibration and (b) validation periods.

593

594 Figure 9. CPI_{snow} model application steps (automatic calibration procedure). * Manual calibration
595 procedure stops at this step with manual manipulation of the calibration parameters to arrive at optimal
596 parameter sets with desired performance results.

597

1 Input daily precipitation and air temperature data

2 Input daily runoff and snow line data if available

3 Assign values to the state parameters SWE_1 , WHC_1 , T_{s1} , P_{calt} and T_{calt}

4 Input mean elevations of the catchment and weather stations

*5 Define prior parameter space and objective functions

6 Run the Monte Carlo procedure

7 Compare cumulative distribution of the prior parameter sets to that of the posterior parameter sets from the Monte Carlo run using GLUE method

8 Identify insensitive/less sensitive parameters. These parameters can be kept constant using their average value from the posterior parameter sets

9 Use the posterior parameter space as the new prior parameter space and run the Monte Carlo procedure keeping the insensitive parameters at constant values

10 Take ensemble average of the new posterior parameter sets from the Monte Carlo run as the optimal parameter set

11 Validate the optimal parameter set using an independent period

12 If satisfactory performance is not achieved, repeat steps 5-11 with different prior parameter space

1 **Highlights**

- 2 • A precipitation index-based model with a snow component was developed and tested.
- 3 • The model can be used where underlying physical conditions of a basin are not known.
- 4 • The model can simulate daily runoff from basins with seasonal snow cover.
- 5 • The model performed best in small basins with less storage attributes.
- 6 • An open-access Excel-based model is provided for runoff simulations.