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Short-Term River Flow Forecasting Framework and Its Application in Cold Climatic Regions

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Abstract: Catchments located in cold weather regions are highly influenced by the natural seasonality that dictates all hydrological processes. This represents a challenge in the development of river flow forecasting models, which often require complex software that use multiple explanatory variables and a large amount of data to forecast such seasonality. The Athabasca River Basin (ARB) in Alberta, Canada, receives no or very little rainfall and snowmelt during the winter and an abundant rainfall–runoff and snowmelt during the spring/summer. Using the ARB as a case study, this paper proposes a novel simplistic method for short-term (i.e., 6 days) river flow forecasting in cold regions and compares existing hydrological modelling techniques to demonstrate that it is possible to achieve a good level of accuracy using simple modelling. In particular, the performance of a regression model (RM), base difference model (BDM), and the newly developed flow difference model (FDM) were evaluated and compared. The results showed that the FDM could accurately forecast river flow (E_{NS} = 0.95) using limited data inputs and calibration parameters. Moreover, the newly proposed FDM had similar performance to artificial intelligence (AI) techniques, demonstrating the capability of simplistic methods to forecast river flow while bypassing the fundamental processes that govern the natural annual river cycle.

Keywords: Athabasca River; cold weather regions; predictive hydrology; simplistic environmental modelling; water resources

1. Introduction

Hydrological processes are the results of the continuous natural changes of the state of water between the atmosphere and the earth, and several models exist in the literature to simulate and forecast such processes. Within a watershed, the hydrological cycle can be considered as a closed system because there are no external inputs or outputs of water entering or exiting the system [1]. Hydrological modelling for large watersheds, which could include multiple basins, is often challenging due to the complexity of hydroclimatic regimes related to intra- and inter-basin variations in topography, climatic patterns, land cover, basin drainage density, soil drainage capacity, and other similar factors [2,3]. These factors play an important role in hydrological modelling in cold weather regions such as the Athabasca River Basin (ARB) considered in this study. Cold weather regions such as the Taiga, Tundra, and Alpine biomes are characterized by long, very cold winters, and short, cool summers with average temperatures generally in the range 30 °C and −25 °C. In cold regions, climatic conditions greatly influence river flow—while there is no or very little contribution to the river from rainfall and snowmelt during the winter, a large rainfall–runoff and snowmelt lead to considerable flow increases during the spring and summer months, increasing the risk of flooding [4]. Moreover, the basin drainage density is reduced during the colder months as creeks and minor watercourses tend to freeze as well as topsoil, which does not provide any significant drainage capacity. Due to these reasons, accurate forecasting of stream flows in cold climatic regions is highly challenging and often requires a large amount of input data in the form of explanatory variables to capture the large variations in climatic regimes, resulting in long computational times for calibration and, consequently, numerous calibration parameters [5].

Several types of hydrological models have been developed for river flow forecasting in cold regions, among which two distinct classes can be identified: process-driven and data-driven models. Process-driven models are deterministic in nature and aim to recreate the hydrological processes in a physically realistic fashion, considering the internal sub-processes and mechanisms within a watershed [1]. Such modelling approaches are based on elaborate frameworks and require multiple variables depending on the underlying principles upon which they are developed. The cold regions hydrological model (CRHM) is one platform specifically created for hydrological modelling in cold weather regions that is widely adopted for simulation of hydrological processes in numerous catchments in Canada. CRHM considers a comprehensive representation of physical processes including blowing snow, interception and sublimation of snow, energy balance, snowmelt, canopy influence on radiation, and infiltration to frozen soils. Bhuiyan et al. [6] used a similar process-based hydrologic modelling system to forecast spring flooding in the Sturgeon Creek watershed, Manitoba, Canada. This approach estimated runoff by relating weather parameters such as temperature and precipitation with snow depth and soil infiltration capacity. The CRHM demonstrated a good level of performance in the attempt of forecasting stream flow in agricultural areas similar to the ARB. However, the large number of explanatory variables necessary to explain the complex physical processes led to falsifications of snow sublimation, snow transport, and infiltration to frozen soil evaluations that, as consequence, were very influential in stream discharge generation [7]. The snow cover duration (SCD) was found to be a key component in the snowmelt-runoff model (SRM)—with increasing global temperatures, SCD decreases, leading river flow forecasting to inaccuracies when models are overfitted on historical data during calibration. Such data requirement implies that data availability and uncertainty within the multiple explanatory variables pose major limitations to process-driven models [8].

Data-driven models, on the other hand, relate outputs and inputs through a set of mathematical parameters, equations, or time series expressions [9]. Hill et al. [10] developed regression equations from flow data that express discharge as function of the basin's physical and meteorological characteristics. The developed regression model was used for quantifying mean annual values, seasonal variation, and interannual variability of runoff in an ungauged basin in the Gulf of Alaska. A statistical modelling approach was adopted by Tsakiri et al. [11] for the estimation of water discharge in Schoharie Creek, New York. The relationship between water discharge, climatic variables, and groundwater level were evaluated to accurately estimate run-off in a network of interconnected watersheds. These data-driven modelling approaches demonstrate the possibility of overcoming the limitations associated with process-based models for hydrology applications [12–15]. Further, data-driven models could also be location-independent and could be used for climatically similar locations by adjusting the few model calibration parameters through a method called regionalization. This method classifies basins or regions based on geomorphological (e.g., terrain characteristics, land cover, hydrologic response) and climatology information by similarity, through a set of parameters. This method could become challenging when attempting to transfer numerous explanatory variables, often associated with process-driven models, to a new area of interest [16,17]. This is especially important in cases where the area of interest has little or no data available for specific explanatory inputs (i.e., groundwater levels and SCD) to use in the model calibration phase. Despite the advantages, the use of data-driven models has seen very few applications for river flow forecasting in cold regions such as the ARB. Veiga et al. [18] forecasted the flow at the Bow River in the city of Calgary, Alberta, Canada, using the base-difference model that only used the daily river flow values with 3 days advance from three gauging stations located upstream as inputs. Although simplistic in its approach, the model showed superior performance metrics based on the coefficient of determination (r^2 = 0.93) and root mean square error (RMSE = 14 m^3/s). A single-input sequential adaptive neuro-fuzzy inference system (ANFIS) was used by Belvederesi et al. [2] to forecast flows along the Athabasca River in Alberta, Canada. The ANFIS-based model accurately estimated the river flow (r^2 = 0.99, Nash–Sutcliffe coefficient = 0.98) with a lead time of 6 days using a single input. The research work by Veiga et al. [18] and Belvederesi et al. [2] substantiates the possibility of using simple data-driven modelling frameworks for accurately forecasting river flows in cold regions such as the ARB.

Over the past 40 years, the lower reaches of the ARB have been disturbed by an extensive urban and industrial development due to the extraction of energy resources (i.e., oil and gas). The impact of these activities has been a growing concern for the environment and ecology of this area, which has led to many scientific studies pertaining to long-term variations in surface water quality and quantity and climate change impact assessments in this region [19–21]. This industrial development also implies changes in land uses that increase spring runoff and, consequently, the risk of flooding. Because the existing literature is limited in terms of short-term river flow forecasting applications in cold regions, the present study aimed to enhance knowledge in the hydrological modelling field.

The main objective of this study was to develop a simplistic hydrological model that could be used to make short-term river flow forecasting in cold regions. A novel flow difference model (FDM) is proposed that estimates river flow at downstream stations based on daily flow differences observed between stations. Moreover, two existing simplistic methods, the base difference model (BDM), firstly described by Veiga et al. [18], and a regression model (RM), were compared to the performance of the FDM. These models were applied to forecast the Athabasca River flow at Fort McMurray based on the flows measured at three upstream hydrometric stations, namely, Jasper, Hinton, and Athabasca. These methods were evaluated using two different calibration and validation dataset approaches to understand if simplistic data-driven hydrological modelling could be affected by the selection of time-dependent calibration and validation datasets.

2. Materials and Methods

2.1. Study Area

The Athabasca River is located in Alberta, Canada, and it originates from the Columbia Icefield in Jasper National Park, flowing for over 1200 km into Lake Athabasca. The upper reaches of the Athabasca River are characterized by a mountainous topography, including alpine, sub–alpine, and montane ecoregions. The middle portion of the ARB contains industrial developments such as forestry, open pit coal mines, limestone quarries, and agricultural areas. The lower reaches of the Athabasca River range between the town of Fort McMurray and the confluence of the Peace and Athabasca Rivers with Lake Athabasca, which forms a vast wetland called the Peace–Athabasca delta [22,23]. Fort McMurray is located about 1000 km away from the origin of the Athabasca River in the regional municipality of Wood Buffalo, which is considered the focal point of Canada's oil sands industry, being the third largest oil deposit in the world and hosting local and foreign workers from the energy sector. Consequently, there are increasing concerns regarding environmental protection issues, especially related to water quality and quantity. Figure 1 shows the area of interest in this study.

Usually, this region experiences long, cold winters and short, mild summers. In Fort McMurray, January represents the coldest month (−12.2 °C) and July the warmest (23.7 °C). The average rainfall is highest in July (80.7 mm) and lowest in January (0.4 mm). As consequence, these climatic variables lead to a great annual variation in river flow—in January, the average river flow at Fort McMurray is 170 m^3/s, while it measures an average of 1376 m^3/s in July, which is approximately 8 times larger than January [4]. During the colder months (i.e., December to March), there is almost no contribution of rainfall and snowmelt, while large rainfall–runoff and snowmelt are observed in the warmer months (i.e., April to November). In spring, the soil underneath the snow cover is still frozen, causing an enhanced runoff of rainfall and thawing snow. The considerable annual variation of river flow in cold regions poses a challenge to hydrological modelling. For this reason, a modelling technique that can predict such variability and bypass the complex hydrological processes that influence the river flow is preferred.

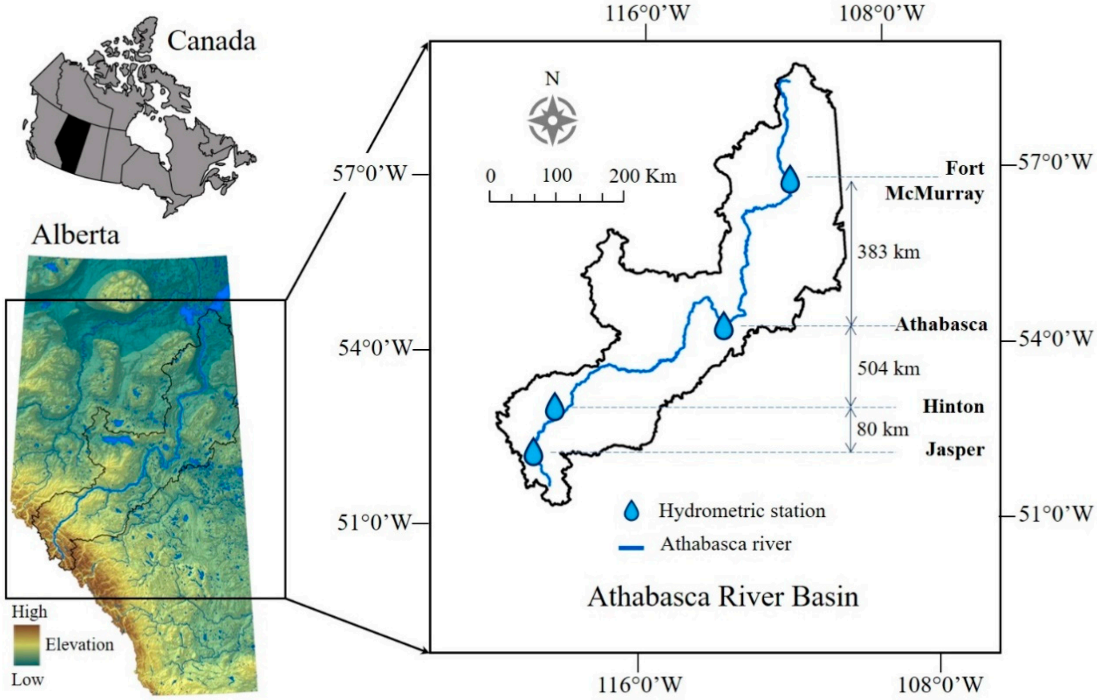

Figure 1. Map of the study area showing the location of the four gauging stations of interest over the Athabasca River.

2.2. Methods

2.2.1. Data Selection Approaches

Historical daily flow records from 1971 to 2014 were acquired from the Water Survey of Canada (WSC) at 4 hydrometric stations: Jasper (07AA002), Hinton (07AD002), Athabasca (07BE001), and Fort McMurray (07DA001) [24]. These locations were selected based on data consistency and completeness of records [2,25]. Two data selection approaches were used to address errors related to time-dependent input variables that might arise during the modelling process [2]; approach 1 uses sequentially-clustered data, and approach 2 uses data in regular intervals (e.g., odd/even years of records). For the sequentially clustered data approach, we selected annual river flow data between 1971 and 2000 for calibration, while data ranging between 2001 and 2014 was used for validation. For the second approach, we used river flow data during odd years between 1971 to 2014 (i.e., 1971, 1973, $\cdots$, 2013) for model calibration, and data pertaining to even years for the same range of time period were used for validation of the models. Subsequently, the performance of the BDM, FDM, and RM was evaluated on data selected through either approach to determine the influence of time-dependent variables.

2.2.2. Estimation of Optimal Lead Time

A correlation analysis of data collected from each gauging station was conducted to estimate the optimal lead time (*OLT*), which indicates the time (in days) taken for the mass of water to move from one station to the other. The flow at Fort McMurray at time "*t*" was correlated to the flow at other gauging stations (i.e., Jasper, Hinton, and Athabasca) for different lag periods ranging between 1 and 10 days (i.e., $t-1$, $t-2$, $\cdots$, $t-10$). Among the coefficient of determination (r^2) values estimated for various lag periods, we identified the lag period corresponding to the highest value of r^2 as the optimal lead time between Fort McMurray and the other stations upstream. Daily flow records acquired at Jasper, Hinton, Athabasca, and Fort McMurray were used for the optimal lead time analysis. The estimated optimal lead time between stations also indicated the forecasting capability of the models. More details regarding the method used in this study for the estimation of the optimal lead time between stations (i.e., Jasper–Fort McMurray, Hinton–Fort McMurray, and Athabasca–Fort McMurray) can be found in [2].

2.2.3. Model Development and Validation

This study adopted simplistic modelling methods for flow forecasting that imply the use of a limited number of input variables and calibration parameters, as well as relatively inexpensive and easy to use computational resources. There are several studies in the literature that have aimed to forecast the Athabasca River flow at Fort McMurray. Sophisticated tools such as the variable infiltration capacity (VIC) or the soil and water assessment tool (SWAT) have shown high performance in hydrological modelling; however, they often require a large amount of input variables (i.e., climate data, runoff estimates, topography layers) for model calibration, which generate a complex set of calibration parameters. These tools are also relatively expensive and require knowledgeable operators. To address these disadvantages, this study proposes three simplistic methods to forecast flow at Fort McMurray: (1) a base difference model (BDM), (2) a novel flow difference model, and (3) linear and nonlinear regression models. The BDM was firstly introduced by Veiga et al. [18] based on the assumption that the difference in flow measured at separate locations along the river was generally constant during the colder months, when the contribution of rainfall and snowmelt was negligible. Hence, the BDM uses a base difference (BD) flow calculated as the average difference in discharge between the upstream and the downstream gauging station during the colder period of the year. The BD is calculated as follows:

$$\overline{Q_{bd}} = \frac{\sum_1^n \left(Q_{ds@t} - Q_{stn@t-OLT_p} \right)}{n} \tag{1}$$

where $\overline{Q_{bd}}$ is the average base difference between the station downstream and the stations upstream, $Q_{ds@t}$ is the flow at a station downstream at time t (i.e., Hinton, Athabasca, or Fort McMurray), $Q_{stn@t-OLT_p}$ is the flow at one station upstream (i.e., Jasper, Hinton, or Athabasca) at time t–OLT, n is the number of observations, and p represents each station pair (i.e., Jasper–Hinton, Jasper–Fort McMurray, Hinton–Athabasca, Athabasca–Fort McMurray).

The flow at the downstream location is then forecasted using

$$\widetilde{Q}_{ds@t} = Q_{stn@t-OLT_p} + \overline{Q_{bd}} \tag{2}$$

where $\widetilde{Q}_{ds@t}$ is the forecasted flow at a station downstream (i.e., Hinton, Athabasca, or Fort McMurray) at time t.

The FDM uses the daily difference (DD) between the upstream and downstream gauging stations as follows:

$$DD_i = Q_{ds@t_i} - Q_{stn@t_i} \tag{3}$$

$$\widetilde{Q}_{ds} = Q_{stn@t-OLT_{p_i}} + DD_i \tag{4}$$

where DD is the daily flow difference between the station located downstream and the stations upstream; i is the day of the year ($i = 1, \cdots, 365$); $Q_{ds@t_i}$ is the flow at a downstream station at time t, on day i; $Q_{stn@t_i}$ is the flow at the upstream station (i.e., Jasper, Hinton, or Athabasca) at time t, on day i; $\widetilde{Q}_{ds}$ is the forecasted flow at a downstream station (i.e., Hinton, Athabasca, or Fort McMurray); and $Q_{stn@t-OLT_{p_i}}i$ is the flow at an upstream station at time t–OLT, on day i.

The equation describing the RM based on simple linear regression is

$$\widetilde{Q}_{ds@t} = a \cdot Q_{stn@t-OLT_p} + \varepsilon \tag{5}$$

where $\widetilde{Q}_{ds@t}$ is the flow at a station downstream at time t, $Q_{stn@t-OLT_p}$ is the flow at one station upstream (i.e., Jasper, Hinton, or Athabasca) at time t–OLT, and a and ε are the regression parameters described in Equation (5). The performance of the BDM and the FDM was compared to both linear and non-linear RM in terms of accuracy in forecasting. For the nonlinear RM, this study considered six polynomial regression degrees, employing the following equations:

$$\widetilde{Q}_{ds@t} = a \cdot Q^{m}{}_{stn@t-OLT_p} + \cdots + b \cdot Q_{stn@t-OLT_p} + \varepsilon \tag{6}$$

where m is the polynomial degree, and a, b, and ε are the regression parameters.

The flow data from three hydrometric stations located upstream were used to forecast the flow downstream at Fort McMurray using different combinations, i.e., (i) Jasper, (ii) Jasper–Hinton, and (iii) Jasper–Hinton–Athabasca. The predictive performance of models was evaluated using quantitative statistical metrics, such as the coefficient of determination (r^2), the root mean square error (RMSE), and the Nash–Sutcliffe coefficient of efficiency (E_{NS}). The r^2 indicates the goodness-of-fit between measured and predicted flow values. Estimated values for r^2 range between 0 to 1 and values closer to 1 indicate higher correlation and vice-versa. The RMSE is the normalized error represented by the distance between the predicted and the measured flows. Higher estimates of RMSE indicate poorer fit of observed values to model forecasts and lower values indicate better fit. The E_{NS} is a widely used parameter for specifically assessing the goodness of fit of hydrologic models. Estimates of E_{NS} range between $-\infty$ to 1, while values closer to one indicate higher correlation between observed and model predicted values; values closer to zero indicate no correlation and highly negative estimates indicate antagonistic relation between model results and observations.

3. Results and Discussion

3.1. Optimal Lead Time

The optimal lead time was estimated by performing a correlation analysis of the flow observed between upstream and downstream stations. This procedure was performed for approaches 1 and 2 to find the influence of time-dependent variability in the flow data. However, calculations using both datasets returned similar optimal lead times, implying that the effect of variability in annual flow patterns is insignificant. The highest r^2 between Athabasca and Fort McMurray was found at $t-2$ (r^2 = 0.923) for both approaches, indicating that the optimal lead time between these stations is 2 days. This implied that flow forecasting for Fort McMurray using data from Athabasca station could be made 2 days in advance. Between Hinton and Fort McMurray, the highest r^2 of 0.58 was estimated at $t-4$, denoting an optimal lead time of 4 days between these stations. In the case of Jasper–Fort McMurray, the optimal lead time corresponded to 5 days (r^2 = 0.494). However, for the Jasper–Hinton and Hinton–Athabasca station pairs, the estimated optimal lead times were 1 (r^2 = 0.961) and 3 (r^2 = 0.633), respectively. The total lead time between Jasper and Fort McMurray estimated by summation of the optimal lead times between the upstream stations and Fort McMurray (i.e., Jasper–Hinton = 1 day, Hinton–Athabasca = 3 days, and Athabasca–Fort McMurray = 2 days) would be equal to 6 days according to Belvederesi et al. [2]. This might be due to the actual optimal lead time between Jasper and Fort McMurray being in between 5 and 6 days. Because the r^2 values for the 5- and 6-day difference were close for the Jasper–Fort McMurray analyses (i.e., 0.494 and 0.491, respectively), this study considered 6 days lead time between Jasper and Fort McMurray.

3.2. Calibration and Validation Datasets

The annual average daily flow for various gauging stations selected for calibration and validation is shown in Figure 2. The plot in Figure 2a shows the annual average flow pattern at Jasper, Hinton, Athabasca, and Fort McMurray for approach 1 over the time period 1971–2000, which was used for model calibration. The corresponding validation dataset was based on the annual average flow at stations over the period 2001–2014 (Figure 2b). Figure 2c,d shows the calibration and validation datasets used for approach 2, which considered flow data at regular intervals (odd/even). Figure 2c shows the annual average flows for the odd years (i.e., 1971, 1973, . . . , 2013) used for the calibration of the models. The validation dataset for the second approach consisted of annual average flows for even years between 1971 and 2014 (Figure 2d). A constant offset among the flow data for various stations could be noted during the colder months, from day 1 to 105 (1 January to 15 April) and from day 335 to 365 (December 1st to December 31st), which denoted the base flows at these locations. This was consistent between calibration and validation datasets considered for both approaches 1 and 2, respectively.

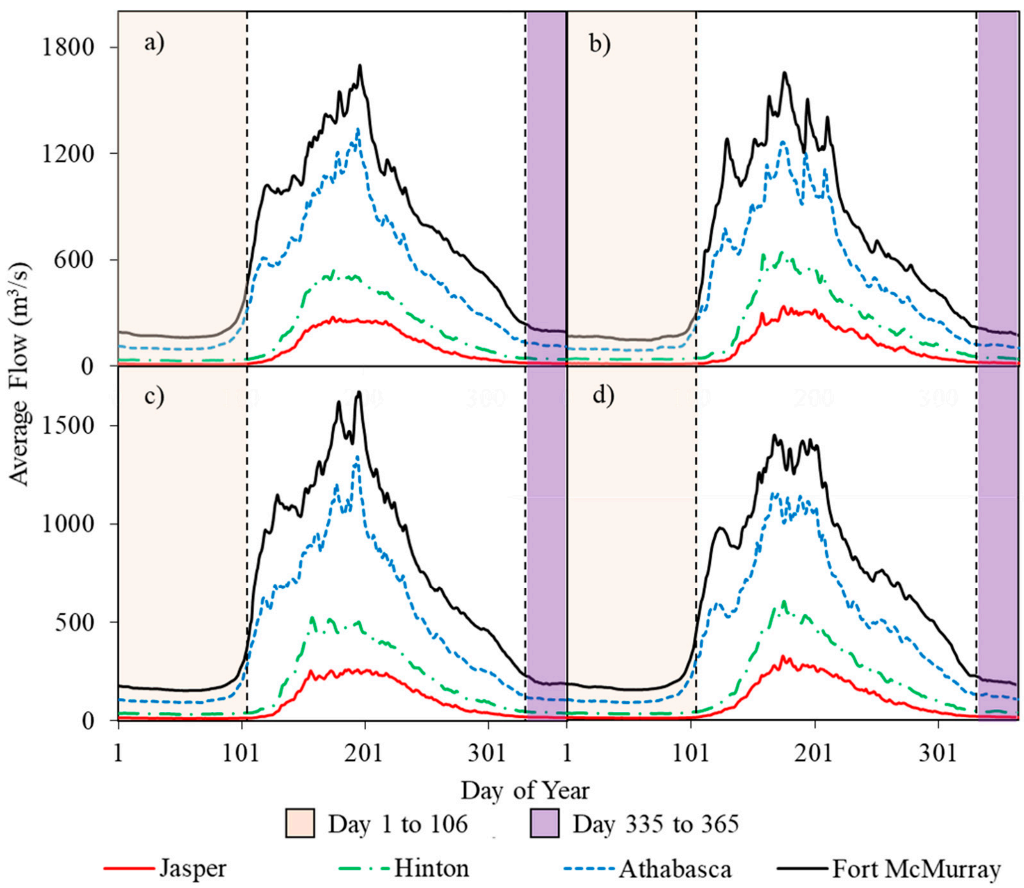

Figure 2. Daily average flow at Jasper, Hinton, Athabasca, and Fort McMurray for (**a**) 1971–2000, (**b**) 2001–2014, (**c**) 1971–2014 (odd years only), and (**d**) 1971–2014 (even years only) (modified after [2]).

3.3. Base Difference

The average BD between gauging stations was calculated between 1st December and 15th April, as a constant offset in flow was observed among stations (Figure 2). This constant offset was considered as the base flow as described by Veiga et al. [18]. The BD estimates between gauging stations were observed to increase with respect to the distance between stations. For approach 1, the BD estimates were 22.72, 83.63, and 75.52 m^3/s for Jasper–Hinton (80 km), Hinton–Athabasca (504 km), and Athabasca–Fort McMurray (383 km), respectively. The BD estimates using approach 2 did not vary to a large extent, signifying the consistency of flow data over the years considered in this study. The BD using approach 2 returned 23.21, 73.84, and 68.62 m^3/s for Jasper–Hinton, Hinton–Athabasca, and Athabasca–Fort McMurray, respectively. The difference in BD between the two approaches was 0.49, 9.79, and 6.9 m^3/s for the respective station pairs mentioned above. The BD estimated difference in flow between Jasper and Fort McMurray (967 km) was 181.87 and 165.67 m^3/s for approaches 1 and 2, respectively, with a difference of 16.2 m^3/s. The difference in BD acquired using different data selection approaches slightly increased with distance between the stations, which would be expected due to the small variation in precipitations over the large region.

3.4. Performance of Models

To evaluate the capability of the models to forecast the river flow at Fort McMurray, we implemented three model techniques, i.e., BDM, RM, and FDM, using daily flow data from Jasper, Jasper–Hinton, and Jasper–Hinton–Athabasca stations in addition to the daily average flow over the validation time-period. These analyses are synthesized in Table 1, Table 2, and Table 3 for the BDM, RM, and BDM, respectively. Additionally, a graphical presentation of the modelled outputs using the daily average flow in relation to the observed flow at Fort McMurray is discussed in Section 3.4.4.

3.4.1. BDM

Table 1 shows the relations between the modelled and observed daily flow at Fort McMurray using the Jasper, Jasper–Hinton, and Jasper–Hinton–Athabasca flows as inputs. In approach 1, regardless the input flow data combinations, similar agreements were found, i.e., the r^2, E_{NS}, and RMSE values were in the ranges of (i) 0.18 to 0.77, −0.45 to 0.45, and 198.64 to 818.15 m^3/s, respectively, using Jasper flow records; (ii) 0.20 to 0.76, −0.49 to 0.43, and 199.94 to 816.07 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.19 to 0.76, −0.37 to 0.62, and 198.27 to 817.40 m^3/s, respectively, using Jasper–Hinton–Athabasca flow. In approach 2, similar agreements were also observed in comparison to approach 1, i.e., the r^2, E_{NS}, and RMSE values were in the ranges of (i) 0.33 to 0.84, −0.55 to 0.39, and 205.06 to 874.04 m^3/s, respectively, using Jasper flow; (ii) 0.29 to 0.83, −0.59 to 0.38, and 207.96 to 879.09 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.28 to 0.84, −0.46 to 0.67, and 206.35 to 880.00 m^3/s, respectively, using Jasper–Hinton–Athabasca flow.

Additionally, the modelling was also performed as a function of daily average flows for the period of interest, and was compared against the observed values at Fort McMurray. It revealed that approach 1 provided similar agreements for each of the input combinations, i.e., the r^2, E_{NS}, and RMSE values were (i) 0.73, −0.12, and 438.93 m^3/s, respectively, using Jasper flow; (ii) 0.67, −0.11, and 438.60 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.72, −0.12, and 439.66 m^3/s, respectively, using Jasper–Hinton–Athabasca flow. In the case of approach 2, the agreements among the input combinations were similar, i.e., the r^2, E_{NS}, and RMSE values were (i) 0.78, −0.34, and 491.71 m^3/s, respectively, using Jasper flow; (ii) 0.71, −0.36, and 495.35 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.77, −0.34, and 492.27 m^3/s, respectively, using Jasper–Hinton–Athabasca flow, which were somewhat worse in comparison to approach 1 outcomes.

The results for approaches 1 and 2 demonstrated that the BDM could not capture the inter-annual variability of the Athabasca River flow. The E_{NS} values estimated for the BDM forecasted flows were negative in approximately 60 and 83% of the cases in approaches 1 and 2, respectively, which demonstrated the poor capability of the model to forecast the intra- and inter-annual variations in river flow. The considerably large RMSE obtained for the BDM analyses suggested that this modelling technique was unsuitable for large basins, independently of the calibration data approaches.

Note that the BDM was successfully implemented to forecast the Bow River flow in Calgary, Alberta; however, it failed to provide reasonable results for the Athabasca River at Fort McMurray. Although the two locations are geographically and climatically close, the Bow River Basin (BRB) and the ARB are topographically different. The catchment area of ARB (i.e., approximately 159,000 km^2) is also much larger than that of BRB (i.e., approximately 26,200 km^2). Due to these reasons, the flow that contributed to each station from their respective catchment area is not proportional and varies to a large extent during certain seasons such as the spring, summer, and fall. These inferences indicate that the BDM would not be suitable for flow forecasting in these types of scenario.

Table 1. Summary of the statistical performance indices estimated for daily flows forecasted at Fort McMurray using the BDM for approaches 1 and 2 for individual validation years. The average row indicates the values produced as a function of daily average flows for the period of interest shown in Figure 2.

Validation Year	Jasper			Jasper–Hinton			Jasper–Hinton–Athabasca		
	r^2	E_{NS}	RMSE (m^3/s)	r^2	E_{NS}	RMSE (m^3/s)	r^2	E_{NS}	RMSE (m^3/s)
Approach 1: Calibration 1971–2000									
2001	0.65	0.13	447.75	0.63	0.12	448.86	0.64	0.17	448.29
2002	0.70	0.45	198.64	0.69	0.43	199.94	0.71	0.62	198.27
2003	0.55	0.03	389.67	0.53	0.01	390.60	0.50	0.04	392.50
2004	0.61	−0.12	473.99	0.61	−0.16	475.21	0.62	−0.19	481.81
2005	0.63	−0.45	609.03	0.61	−0.49	610.26	0.61	−0.37	610.39
2006	0.62	−0.02	293.85	0.61	−0.04	295.13	0.63	0.06	294.09
2007	0.18	−0.25	635.44	0.20	−0.21	632.02	0.19	−0.19	632.64
2008	0.50	−0.08	437.71	0.47	−0.09	439.73	0.46	−0.09	440.28
2009	0.56	0.01	360.44	0.54	−0.01	362.63	0.54	0.05	362.99
2010	0.67	−0.01	303.83	0.66	−0.02	304.79	0.67	0.08	304.12
2011	0.67	−0.07	815.15	0.67	−0.09	816.07	0.65	−0.06	817.40
2012	0.77	0.03	614.94	0.76	0.01	616.78	0.76	0.04	616.85
2013	0.56	−0.15	797.72	0.55	−0.17	799.32	0.52	−0.12	801.22
2014	0.41	−0.17	536.61	0.40	−0.18	537.44	0.40	−0.18	538.03
Average	0.73	−0.12	438.93	0.67	−0.11	438.60	0.72	−0.12	439.66
Approach 2: Calibration 1971–2014 Odd Years									
1972	0.55	−0.25	733.39	0.52	−0.29	733.39	0.51	−0.25	733.79
1974	0.33	−0.50	874.04	0.29	−0.53	879.02	0.28	−0.34	880.00
1976	0.69	−0.41	571.68	0.65	−0.46	578.18	0.66	−0.42	577.66
1978	0.57	−0.55	681.00	0.57	−0.59	686.66	0.58	−0.45	686.37
1980	0.56	−0.50	690.25	0.52	−0.52	694.33	0.51	−0.46	694.52
1982	0.59	−0.15	641.82	0.57	−0.17	646.87	0.58	−0.17	546.21
1984	0.50	−0.36	495.29	0.47	−0.40	498.19	0.47	−0.40	498.73
1986	0.48	−0.26	717.74	0.65	−0.29	478.10	0.47	−0.25	714.37
1988	0.64	−0.05	439.78	0.39	−0.39	743.35	0.68	0.08	429.28
1990	0.54	−0.25	717.41	0.75	0.16	390.92	0.45	−0.24	722.17
1992	0.59	−0.10	330.87	0.64	−0.32	733.92	0.57	0.02	332.00
1994	0.65	−0.16	531.54	0.57	−0.15	331.73	0.65	−0.17	532.33
1996	0.66	−0.50	834.21	0.64	−0.15	527.70	0.65	−0.37	830.58
1998	0.64	−0.24	377.45	0.68	−0.55	839.42	0.64	−0.14	378.95
2000	0.84	0.11	377.91	0.83	0.09	380.63	0.84	0.21	380.20
2002	0.70	0.39	205.06	0.69	0.38	207.96	0.71	0.67	206.35
2004	0.61	−0.23	487.55	0.61	−0.21	485.62	0.62	−0.24	492.15
2006	0.63	−0.10	300.93	0.55	−0.12	305.78	0.63	0.13	304.77
2008	0.50	−0.15	450.40	0.47	−0.14	449.03	0.46	−0.08	449.57
2010	0.65	−0.10	315.97	0.66	−0.09	315.03	0.67	0.15	314.38
2012	0.77	−0.01	624.71	0.76	−0.02	626.37	0.76	−0.01	626.43
2014	0.43	−0.25	541.72	0.40	−0.22	546.85	0.40	−0.22	547.44
Average	0.78	−0.34	491.71	0.71	−0.36	495.35	0.77	−0.34	492.27

Table 2. Summary of the statistical performance indices estimated for daily flows forecasted at Fort McMurray using the RM for approaches 1 and 2 for individual validation years. The average row indicates the values produced as a function of daily average flows for the period of interest shown in Figure 2.

Validation Year	Jasper			Jasper–Hinton			Jasper–Hinton–Athabasca		
	r^2	E_{NS}	RMSE (m^3/s)	r^2	E_{NS}	RMSE (m^3/s)	r^2	E_{NS}	RMSE (m^3/s)
Approach 1: Calibration 1971–2000									
2001	0.58	0.54	282.58	0.63	0.52	332.95	0.61	0.50	337.74
2002	0.73	−0.48	321.38	0.72	0.56	330.16	0.76	−0.75	349.23
2003	0.52	0.25	340.25	0.57	0.46	289.38	0.51	0.22	346.98
2004	0.63	0.56	291.86	0.64	0.63	269.05	0.63	0.57	290.63
2005	0.65	0.64	299.20	0.66	0.65	295.45	0.65	0.64	300.77
2006	0.61	−0.12	305.64	0.58	0.31	239.43	0.62	−0.06	297.88
2007	0.19	0.09	549.71	0.20	0.11	542.72	0.20	0.09	548.31
2008	0.51	0.38	331.34	0.52	0.38	330.42	0.49	0.36	337.84
2009	0.54	0.29	303.89	0.50	0.43	271.95	0.53	0.27	308.34
2010	0.71	0.24	263.40	0.76	0.59	193.33	0.73	0.27	257.11
2011	0.67	0.60	496.65	0.66	0.59	500.53	0.66	0.58	533.80
2012	0.76	0.75	310.37	0.62	0.60	390.17	0.78	0.77	298.78
2013	0.55	0.54	499.00	0.57	0.55	495.93	0.54	0.53	508.34
2014	0.41	0.33	404.73	0.46	0.37	392.85	0.39	0.32	407.20
Average	0.73	0.66	241.46	0.61	0.60	264.09	0.72	0.65	246.11
Approach 2: Calibration 1971–2014 Odd Years									
1972	0.52	0.48	466.37	0.50	0.47	467.30	0.50	0.49	463.04
1974	0.32	0.22	628.63	0.34	0.23	624.31	0.32	0.22	627.27
1976	0.69	0.68	271.33	0.68	0.67	276.16	0.69	0.67	273.60
1978	0.64	0.59	347.51	0.63	0.59	349.21	0.63	0.59	349.06
1980	0.55	0.53	387.80	0.55	0.53	387.29	0.54	0.53	387.85
1982	0.59	0.59	382.23	0.59	0.58	385.22	0.60	0.59	380.85
1984	0.52	0.43	317.47	0.54	0.46	310.19	0.52	0.39	330.25
1986	0.52	0.50	447.43	0.46	0.43	475.66	0.54	0.49	451.54
1988	0.68	0.57	279.71	0.74	0.50	301.00	0.69	0.59	273.01
1990	0.53	0.52	443.84	0.54	0.53	439.59	0.52	0.51	447.28
1992	0.60	0.02	306.60	0.61	0.04	303.08	0.60	−0.05	317.33
1994	0.67	0.66	287.22	0.67	0.66	287.25	0.67	0.65	289.70
1996	0.72	0.57	443.82	0.72	0.56	445.74	0.66	0.62	416.11
1998	0.65	0.39	267.38	0.66	0.40	265.24	0.64	0.34	276.99
2000	0.85	0.75	201.06	0.84	0.74	203.14	0.86	0.74	203.92
2002	0.73	−0.48	321.38	0.72	−0.47	320.66	0.75	−0.86	359.98
2004	0.63	0.56	291.86	0.63	0.57	288.02	0.62	0.54	299.02
2006	0.56	0.45	310.85	0.59	−0.13	307.54	0.62	−0.13	307.17
2008	0.51	0.38	331.34	0.52	0.40	326.50	0.49	0.34	342.97
2010	0.71	0.24	263.40	0.70	0.23	264.10	0.71	0.23	264.36
2012	0.76	0.75	310.37	0.77	0.76	306.77	0.78	0.78	293.81
2014	0.41	0.33	404.73	0.42	0.35	400.31	0.40	0.31	411.77
Average	0.80	0.78	198.99	0.74	0.70	231.82	0.79	0.76	208.17

Table 3. Summary of the statistical performance indices estimated for daily flows forecasted at Fort McMurray using the FDM for approaches 1 and 2 for individual validation years. The average row indicates the values produced as a function of daily average flows for the period of interest shown in Figure 2.

Validation Year	Jasper			Jasper–Hinton			Jasper–Hinton–Athabasca		
	r^2	E_{NS}	RMSE (m^3/s)	r^2	E_{NS}	RMSE (m^3/s)	r^2	E_{NS}	RMSE (m^3/s)
Approach 1: Calibration 1971–2000									
2001	0.92	0.83	180.79	0.92	0.85	159.70	0.96	0.89	155.94
2002	0.90	0.86	173.75	0.89	0.82	174.21	0.90	0.45	195.59
2003	0.93	0.89	156.34	0.92	0.87	147.38	0.94	0.89	131.68
2004	0.90	0.84	160.88	0.93	0.75	190.20	0.93	0.90	139.71
2005	0.91	0.83	172.80	0.94	0.83	180.50	0.94	0.94	117.99
2006	0.91	0.80	179.77	0.91	0.89	149.73	0.88	0.79	133.23
2007	0.92	0.89	157.88	0.85	0.81	193.30	0.92	0.91	171.36
2008	0.92	0.81	173.20	0.89	0.91	166.09	0.93	0.90	130.85
2009	0.95	0.85	161.45	0.91	0.93	156.77	0.95	0.92	104.36
2010	0.94	0.86	167.83	0.93	0.85	184.61	0.94	0.93	80.92
2011	0.92	0.84	165.26	0.91	0.85	186.42	0.98	0.97	138.95
2012	0.90	0.93	138.31	0.83	0.73	232.24	0.96	0.95	139.01
2013	0.92	0.90	141.47	0.89	0.80	183.30	0.89	0.81	323.77
2014	0.93	0.89	155.02	0.92	0.89	161.15	0.92	0.91	146.59
Average	0.94	0.86	156.51	0.95	0.86	153.44	0.94	0.86	157.58
Approach 2: Calibration 1971–2014 Odd Years									
1972	0.88	0.89	117.78	0.92	0.91	124.05	0.94	0.94	153.37
1974	0.90	0.93	112.71	0.86	0.87	144.98	0.97	0.95	151.59
1976	0.95	0.96	90.58	0.92	0.91	125.10	0.85	0.83	194.39
1978	0.92	0.94	107.69	0.95	0.95	105.04	0.91	0.90	168.71
1980	0.91	0.84	118.41	0.96	0.96	95.07	0.92	0.91	173.15
1982	0.96	0.90	104.19	0.88	0.88	142.40	0.96	0.95	128.82
1984	0.95	0.92	103.75	0.92	0.90	122.82	0.88	0.88	147.67
1986	0.85	0.78	124.36	0.91	0.89	118.76	0.97	0.97	111.39
1988	0.92	0.85	114.04	0.95	0.97	97.63	0.95	0.94	105.82
1990	0.97	0.97	88.16	0.90	0.90	130.73	0.93	0.92	181.80
1992	0.87	0.92	113.43	0.94	0.94	108.53	0.92	0.89	102.80
1994	0.95	0.94	98.90	0.92	0.91	125.27	0.97	0.95	105.94
1996	0.95	0.91	102.93	0.95	0.95	105.96	0.93	0.91	203.46
1998	0.94	0.93	105.23	0.93	0.90	122.55	0.87	0.81	150.29
2000	0.91	0.89	110.78	0.90	0.92	113.48	0.94	0.86	150.25
2002	0.93	0.85	115.25	0.88	0.88	137.21	0.91	0.45	195.34
2004	0.90	0.92	103.50	0.86	0.85	145.10	0.93	0.90	138.85
2006	0.88	0.88	113.54	0.95	0.97	98.70	0.88	0.79	133.61
2008	0.92	0.91	106.37	0.93	0.94	109.94	0.93	0.91	128.56
2010	0.86	0.89	114.30	0.92	0.92	127.24	0.93	0.91	88.44
2012	0.95	0.94	97.18	0.91	0.90	119.52	0.96	0.95	135.95
2014	0.93	0.92	102.10	0.90	0.89	118.98	0.93	0.93	133.48
Average	0.97	0.95	90.98	0.97	0.97	83.40	0.97	0.95	99.77

3.4.2. RM

Table 2 shows the relations between the modelled and observed daily flow at Fort McMurray using the Jasper, Jasper–Hinton, and Jasper–Hinton–Athabasca flows as inputs. In approach 1, regardless the input flow data combinations, similar agreements were found, i.e., the r^2, E_{NS}, and RMSE values were in the ranges of (i) 0.19 to 0.76, −0.48 to 0.75, and 263.40 to 549.71 m^3/s, respectively, using Jasper flow records; (ii) 0.20 to 0.76, 0.11 to 0.65, and 193.33 to 542.72 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.20 to 0.78, −0.75 to 0.77, and 257.11 to 548.31 m^3/s, respectively, using Jasper–Hinton–Athabasca flow. In approach 2, slightly better agreements were observed in comparison to approach 1, i.e., the r^2, E_{NS}, and RMSE values were in the ranges of (i) 0.32 to 0.85, −0.48 to 0.75, and 201.06 to 628.63 m^3/s, respectively, using Jasper flow; (ii) 0.34 to 0.84, −0.47 to 0.76, and 203.14 to

624.31 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.32 to 0.86, −0.86 to 0.78, and 203.92 to 627.27 m^3/s, respectively, using Jasper–Hinton–Athabasca flow.

Further, the modelling was also performed as a function of daily average flows for the period of interest and was compared against the observed values at Fort McMurray. This revealed that approach 1 provided similar agreements for each of the input combinations, i.e., the r^2, E_{NS}, and RMSE values were (i) 0.73, 0.66, and 241.46 m^3/s, respectively, using Jasper flow records; (ii) 0.61, 0.60, and 264.09 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.72, 0.65, and 246.11 m^3/s, respectively, using Jasper–Hinton–Athabasca flow. In case of approach 2, the agreements among the input combinations were similar, i.e., the r^2, E_{NS}, and RMSE values were (i) 0.80, 0.78, and 198.99 m^3/s, respectively, using Jasper flow records; (ii) 0.74, 0.70, and 231.82 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.79, 0.76, and 208.17 m^3/s, respectively, using Jasper–Hinton–Athabasca flow, which were better in comparison to approach 1 outcomes.

Generally, the RM showed better performance than the BDM. The RM using approach 2 consistently produced more accurate results than approach 1. The lowest average RMSE was obtained by the model that used Jasper inputs for approaches 1 and 2. Thus, the use of multiple stations as input did not generally improve the models' forecasting capabilities. Similar to the BDM, the RM demonstrated higher forecasting performance when flow inputs from Jasper were employed in the model. The second order regression consistently provided higher r^2 and E_{NS}, and lower RMSE estimates using approach 2.

3.4.3. FDM

Table 3 shows the relations between the modelled and observed daily flow at Fort McMurray using the Jasper, Jasper–Hinton, and Jasper–Hinton–Athabasca flows as inputs. In approach 1, regardless the input flow data combinations, similar agreements were found, i.e., the r^2, E_{NS}, and RMSE values were in the ranges of (i) 0.90 to 0.95, 0.80 to 0.93, and 138.31 to 180.79 m^3/s, respectively, using Jasper flow records; (ii) 0.83 to 0.94, 0.73 to 0.93, and 147.38 to 232.24 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.88 to 0.98, 0.45 to 0.97, and 80.92 to 323.77 m^3/s, respectively, using Jasper–Hinton–Athabasca flow. In approach 2, slightly better agreements were observed in comparison to approach 1, i.e., the r^2, E_{NS}, and RMSE values were in the ranges of (i) 0.85 to 0.97, 0.78 to 0.97, and 88.16 to 124.36 m^3/s, respectively, using Jasper flow; (ii) 0.86 to 0.96, 0.85 to 0.97, and 95.07 to 145.10 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.85 to 0.97, 0.45 to 0.97, and 88.44 to 203.46 m^3/s, respectively, using Jasper–Hinton–Athabasca flow.

In addition, the modelling was also performed as a function of daily average flows for the period of interest and was compared against the observed values at Fort McMurray. This revealed that approach 1 provided similar agreements for each of the input combinations, i.e., the r^2, E_{NS}, and RMSE values were (i) 0.94, 0.86, and 156.51 m^3/s, respectively, using Jasper flow records; (ii) 0.95, 0.86, and 153.44 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.94, 0.86, and 157.58 m^3/s, respectively, using Jasper–Hinton–Athabasca flow. In the case of approach 2, the agreements among the input combinations were similar, i.e., the r^2, E_{NS}, and RMSE values were (i) 0.97, 0.95, and 90.98 m^3/s, respectively, using Jasper flow records; (ii) 0.97, 0.97, and 83.40 m^3/s, respectively, using Jasper–Hinton flow; and (iii) 0.97, 0.95, and 99.77 m^3/s, respectively, using Jasper–Hinton–Athabasca flow, which were better in comparison to approach 1 outcomes.

The FDM demonstrated the best results among the three modelling techniques. The higher forecasting accuracy obtained by the FDM using daily average flows was also validated by the results of the inter-annual analyses. More than 90% of model forecasts for individual years had E_{NS} values higher than 0.80, indicating excellent performance for both approach 1 and approach 2. In all cases, the FDM produced lower RMSE estimates than the BDM and RM. Although the lowest RMSEs were observed for the models using Jasper–Hinton daily average flow in both approach 1 (i.e., 153.44 m^3/s) and approach 2 (i.e., 83.40 m^3/s), the use of only Jasper daily average flow provided similar outcomes (i.e., 156.51.44 and 90.98 m^3/s for approaches 1 and 2, respectively). As a result of these negligible differences, the FDM using the inputs from Jasper could still be considered the highest performing model due to the reduced number of calibration parameters.

3.4.4. Graphical Presentation of the Modelled Outputs Using Daily Average Flow

Figure 3 shows the dynamics of the modelled and observed flow at the Fort McMurray station using daily average flows for the period 2001–2014 (approach 1) and the even years during the period 1971–2014 (approach 2). The agreements between them in terms of r^2, E_{NS}, and RMSE values are shown in the "average" rows in Tables 1–3 for the BDM, RM, and FDM, respectively.

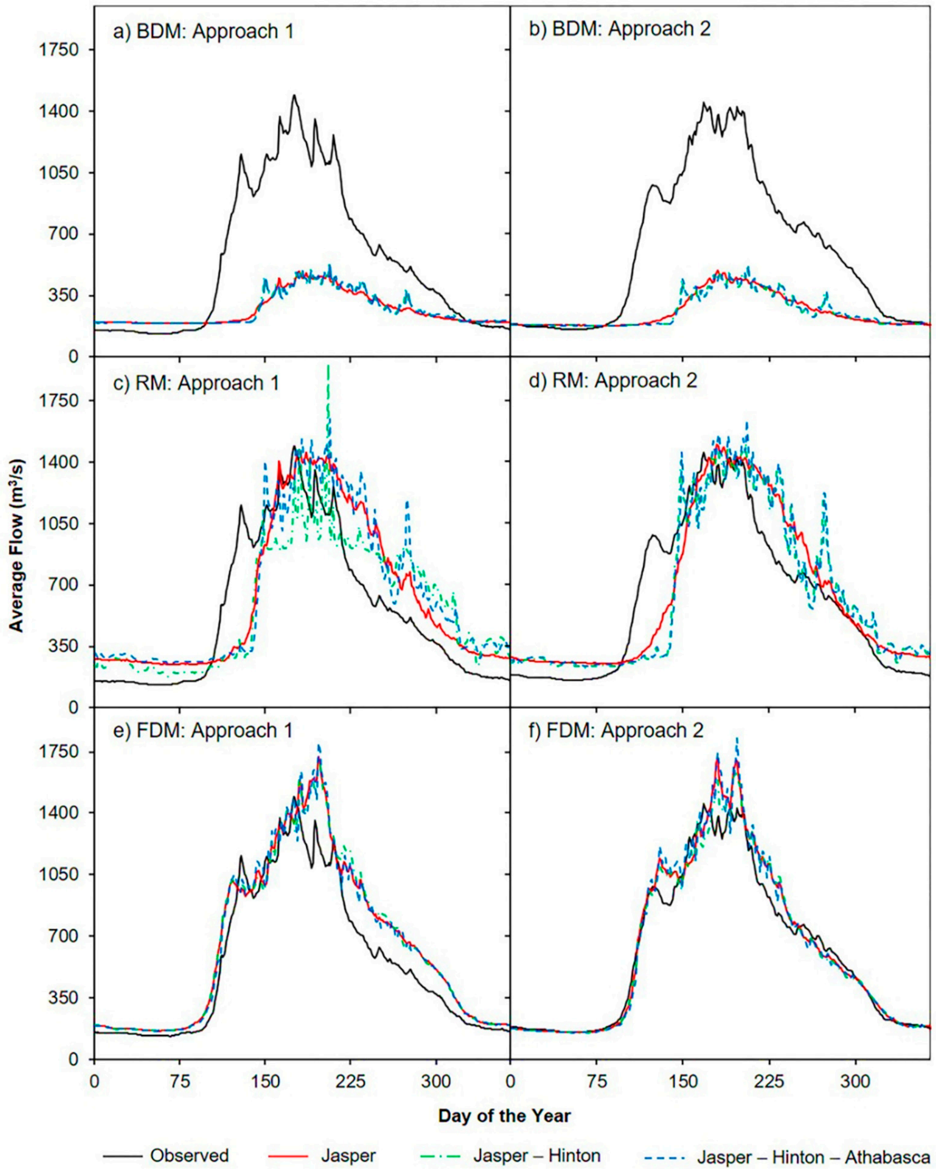

Figure 3. Comparison of the observed and modelled daily average flows at Fort McMurray using base difference model (BDM) (**a**,**b**), regression model (RM) (**c**,**d**), and flow difference model (FDM) (**e**,**f**) techniques for the period 2001–2014 (approach 1) and the even years during the period 1971–2014 (approach 2).

In general, the BDM outputs for approaches 1 and 2 demonstrated good performance in forecasting river flow during the colder months (i.e., December to April). However, poor forecasting ability was detected during spring, summer, and fall, as illustrated in Figure 3a,b for approaches 1 and

2, respectively. The BDM using approach 1 consistently overestimated the winter baseflow (i.e., days 1 to 105 and days 335 to 365) and greatly underestimated river flow between day 106 to 335. The use of approach 2 led to more accurate outputs for the winter baseflow; however, the forecasted flow between day 106 to 334 remained substantially underestimated. The spring freshet, which showed as the increase in observed river flow between day 101 and 140 in Figure 3, represents the contribution of the snowmelt from almost the entire catchment, as Fort McMurray is located towards the lower reaches of the Athabasca River. This contribution could not be captured by the BDM, independent of the approach adopted in the calibration phase. In fact, the modelled output for approaches 1 and 2 detected the first spring increase in flow at day 140, while the observed increase occurred between day 95 and 101. The modelled daily average flow using BDM resulting from the Jasper–Hinton and Jasper–Hinton–Athabasca analyses erroneously identified peaks between day 160 and 280, while the Jasper resulted in a more continuous trend. A similar conclusion could be obtained by observing the results shown in Figure 3c,d for the RM output using approaches 1 and 2, respectively. More continuous outputs were obtained using the inputs from Jasper only, while the Jasper–Hinton and the Jasper–Hinton–Athabasca largely mis-quantified the ranges of the peaks, especially in approach 1. Similar to the BDM in approach 1, the RM failed in forecasting the winter flow, the spring increase, and the late summer/fall decrease. The use of approach 2 did not improve model accuracy for these periods. However, the ranges in the forecasted peaks were greatly reduced in approach 2. Generally, more consistent results were obtained using the FDM, as shown in Figure 3e,f for approaches 1 and 2, respectively. The FDM demonstrated better performance in forecasting the Athabasca River flow between day 101 and 140 in Figure 3, as opposed to the BDM and RM. Better model performance was also observed in the peak flow detection, although the peak estimates were, in most cases, considerably overestimated. This indicated that the FDM could not capture substantially large rainfall and snowmelt events occurring between the Jasper and Fort McMurray stations. The results obtained from approach 1 showed that the FDM overestimated flow for over 90% of the year, and a larger error between modelled and observed values could be noted during the second half of the year. Precisely, the FDM in approach 1 was unsuccessful in accurately forecasting the late summer/fall decrease in flow (i.e., day 215 to 335). However, the use of approach 2 considerably improved the models' performance over this period of the year, and could be considered the best option in this study.

The findings from this present study using simplistic modelling techniques to forecast river flow in the ARB region is highly comparable with estimates produced by more sophisticated process- and data-driven models. The literature offers two studies that aimed at forecasting the Athabasca River flow at Fort McMurray using data-driven models presented by Rood et al. [23] and Belvederesi et al. [2]. While Rood et al. opted for a simple interpolation approach (E_{NS} = 0.79), Belvederesi et al. adopted an adaptive neuro-fuzzy inference system (ANFIS) based on machine learning modelling technique (E_{NS} = 0.98). ANFIS has shown the highest accuracy among the process- and data-driven techniques presented in the literature. In general, artificial intelligence (AI) techniques such as ANFIS have been broadly applied to hydrological modelling for their high performance [26,27]. At the same time, AI models are often complex to calibrate due to numerous calibration parameters, requiring specialized personnel to properly operate the software. In their study, Belvederesi et al. [2] also investigated whether the calibration–validation data selection could affect a model's forecasting accuracy. The authors demonstrated that the performance of a model could be influenced by the selection of calibration and validation datasets due to variability of data over time. As such, the selection of calibration and validation datasets plays a crucial role in the evaluation of the models' performance. Zheng at al. [28] elaborately investigated the influence of datasets used for validation and showed that model accuracy could be affected by the selection of time-dependent datasets. From this present study, results demonstrated that the use of sequentially clustered calibration datasets (i.e., approach 1) over consecutive years might introduce bias in modelling performance due to gradual changes in river flow, which is potentially due to climate change and/or the increasing water uptake for agricultural and industrial uses.

Process–driven models have also been adopted for hydrological purposes in the ARB, mainly for long-term river flow forecasting. Toth et al. [29] investigated the annual variability of the Athabasca River using WATFLOOD, a widely used physical-based hydrological model [30–34]. Historical river flow records along with topography information, rainfall, and temperature were employed to forecast flow regimes at Fort McMurray. The E_{NS} indicated a model accuracy of 0.72 [29]. Eum et al. [35] used a variable infiltration capacity (VIC) model coupled with the global circulation model (GCM) to forecast the Athabasca River flow at Fort McMurray, which employed historical flow, climate, and vegetation–soil–runoff data as inputs in different combinations (E_{NS} = 0.84). Eum et al. [36] and Droppo et al. [37] have also used VIC to forecast flow at Fort McMurray, considering hydrometric and climate data (temperature and rainfall), snow accumulation, snowmelt, potential infiltration into frozen ground, land cover, and three different soil drainages. The VIC performance in these studies are very similar, as an E_{NS} value of 0.74 was reported by both studies. The soil and water assessment tool (SWAT), a physically based model that often requires numerous input variables [38–41], has also been applied for hydrometric modelling in the ARB. Shrestha et al. [42] demonstrated the use of the SWAT to achieve highly accurate estimates of flow at Fort McMurray (E_{NS} = 0.91). However, this required numerous input variables, including snowpack, elevation band, groundwater, soil drainage, soil–vegetation slope, and pond/reservoir hydraulic conductivity data. Because of the successful application of process-driven models for their long-term forecasting capability and the improved performance achieved by data-driven models, further efforts should be dedicated to the investigation of hybrid modelling techniques in order to provide highly reliable river flow and flood forecasting models with prolongated forecasting abilities in cold regions. In summary, the simplistic data-driven FDM proposed in this study shows on-par performance when compared to more complex mechanistic models. However, while mechanistic models could make long-term predictions in river flows capturing the effects of climate change and other influencing factors, the FDM is limited to short-term river flow and flood forecasting.

4. Conclusions

The findings from this study showed that highly accurate river flow estimates in cold regions could be obtained using simple models. The performance of three simple methods, i.e., the BDM, FDM, and RM was investigated over the Athabasca River, Alberta, Canada, as a case study. Three station pairings (i.e., Jasper, Jasper–Hinton, and Jasper–Hinton–Athabasca) and two dataset selection approaches were employed to understand (i) the incremental benefit derived from the inclusion of each hydrometric station, and (ii) the effect of time-dependent calibration–validation inputs on the modelling process. The BDM was found to be unsuitable for river flow forecasting in large basins such as the ARB. Although better estimates were obtained using the RM, this modelling technique could not capture the base flow during the colder months, the spring melt contribution, and the late summer/fall decrease. Finally, the FDM demonstrated the best results consistently for all the different data selection and station pairing approaches. The r^2, E_{NS}, and RMSE values of flow estimates at Fort McMurray using the FDM indicated that this technique would be suitable for river flow forecasting in cold regions. However, it could be subject to bias when time-dependent inputs would be employed in the model calibration phase, as demonstrated by approach 2 over approach 1. The use of multiple hydrometric stations for model calibration did not lead to considerable enhancements in the model forecasting capability. Thus, the flow data from one single upstream hydrometric station at Jasper was sufficient to achieve adequate model performance. This study also demonstrated that the predictive performance obtained from the newly developed FDM was on par with AI-based models such as ANFIS. The simplistic modelling techniques here proposed would require fewer calibration parameters and lower computational effort and time when compared to more sophisticated AI approaches. However, further efforts should be dedicated to increase the forecasting time capability of such simplistic modelling techniques. Moreover, the models should be improved to better capture substantially large rainfall and snowmelt events occurring between the Jasper and Fort McMurray stations as they demonstrated low performance to predict extreme peaks in annual flow. A combination of different simplistic approaches and seasonal analysis would also provide insight in this direction. As such, the FDM model proposed in this study showed promise for short-term river flow and flood forecasting in cold regions based on the observed flow at upstream stations.

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