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Efficacy of a hydrologic model in simulating discharge from a large mountainous catchment

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Summary Three sets of climatic input data from weather station observations and reanalysis products were compared for use in the simulation of streamflow for a large mountainous basin in subarctic Canada. These data sets are statistically different or show biases for most months. Yet, when they were used in conjunction with specific suites of parameters optimized for individual data sets, the hydrological model (SLURP) was able to simulate flows from these data sets which compare satisfactorily with measured discharge of the 275,000 km^2 Liard catchment. The progressive downstream change in simulated discharge was scrutinized to reveal how and why, despite using inputs that are different, the model can simulate comparable basin outflows. It was found that through the effects of overestimating or under-adjusting the flow for various sub-basins, the model can simulate discharge that matches the measured Liard flow. This compensating mechanism enhances the flexibility of the model in producing acceptable outflow for a large catchment.

Introduction

The performance of a macro-scale hydrological model is influenced by how the basin is divided into sub-units, the scale of investigation, process representation in the model, parameterization, and input data considerations. In a previous study, van der Linden and Woo (2003a) compared several models of increasing complexity to investigate the role of major hydrological processes in streamflow simulation. In another study, Van der Linden and Woo (2003b) applied a distributed model to a mountainous catchment in subarctic Canada, to examine the transferability of parameters derived for the overall basin, to simulate flows for its sub-basins. These studies used a common data set and the effects of input data have not been considered (Arnell, 1999). The role of different data sets, available at various scales, requires further investigation. Furthermore, hydrological simulations tend to optimize only for the flow at the basin outlet (Kuchment et al., 2000), but the manner in which flows are generated in its sub-units is rarely revealed. It is important to understand how distributed models derive the final outlet flow through aggregation of runoff from the sub-units in a basin.

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Mountainous basins consist of complex landscape and land cover, and experience large variations in climate, rendering them suitable candidates to test the influence of data sources on flow simulation by macro-hydrological models. The Liard Basin in the Mackenzie drainage, Canada, is one such catchment that benefits from having temperature and precipitation data from different data sources. For this study, we make use of three climatic data sets as inputs to SLURP (Semi-distributed Land Use based Runoff Processes), a well-tested hydrological model for mountain basins (Kite et al., 1994), to simulate streamflow for the Liard Basin; and to examine how the simulated flow for different parts of the basin compare with the measured discharge available for several sub-basins within the Liard catchment. The purposes are to study the effects of data on flow simulation of a large mountainous basin, and to understand how a macro-scale model is able to produce an aggregation of sub-basin discharge to match the flow at the basin outlet.

Study area, data source and the SLURP model

The Liard basin is used as the test catchment (Fig. 1). The Liard, a major tributary of the Mackenzie, drains an area of 275,000 km^2 in the mountainous Western Cordillera (Woo and Thorne, 2003). Three northwest-southeast trending mountain chains (Stikine Ranges, Selwyn and Rocky Mountains) occupy most of the basin, with elevation exceeding 3200 m. Plateaus and lowlands occur in the southeast with elevations of 170–800 m. The Cordillera is effective in blocking most moisture bearing winds from the Pacific Ocean and orographic precipitation is most notable in the western sector. Snow is a major form of precipitation, but rainfall is common in the summer and autumn. Located at high latitudes (57–63°N), the basin has a cold temperate to subarctic setting. There is also strong vertical zonation in the mountain climate, but most of weather stations are found only in the valleys. The basin is largely covered by tundra, deciduous and evergreen forests. The river is gauged at its mouth, at Fort Simpson above the confluence with the Mackenzie, at three other locations along its main trunk as well as at several tributary basins. Discharge data from these gauging stations were used to calibrate and to compare with the values simulated by the hydrological model.

This study uses SLURP version 12.2 for hydrological simulation. The model is well tested and has been applied successfully to basins of various sizes including those in a mountainous environment (Kite et al., 1994). The model divides a large catchment into aggregated simulated areas (ASAs) each encompassing a number of land cover types characterized by a set of parameters. Simulation by SLURP is based on: (1) a vertical component consisting of surface water balance and flow generation from several storages at daily time intervals, and (2) a horizontal component of flow delivery within each ASA and channel routing to the basin outlet. The present study subdivides the Liard basin into 35 ASAs (Fig. 2) which partitions the basin into sufficiently distinctive sub-basins. The mean elevation, area and areal percentages occupied by various cover types are obtained by SLURP using input digital elevation data combined with a land cover map.

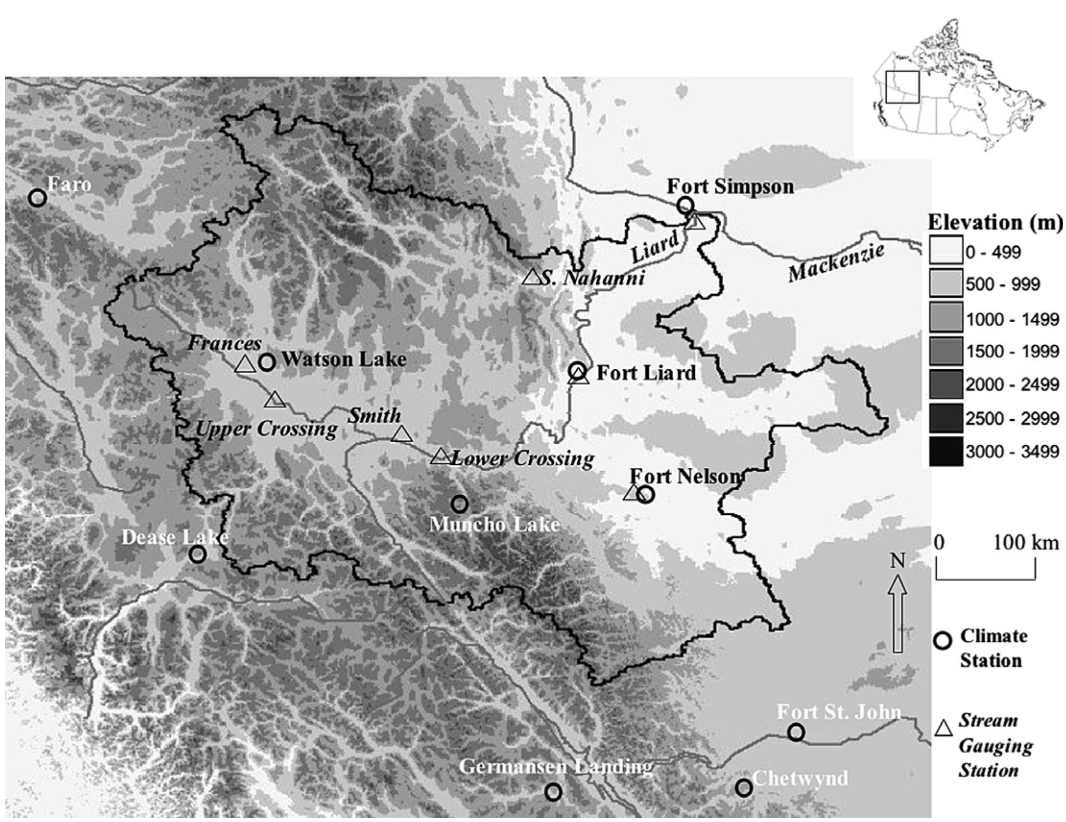

Figure 1 Topography of the Liard Basin (outlined in black) and location of weather stations that provide data for this study.

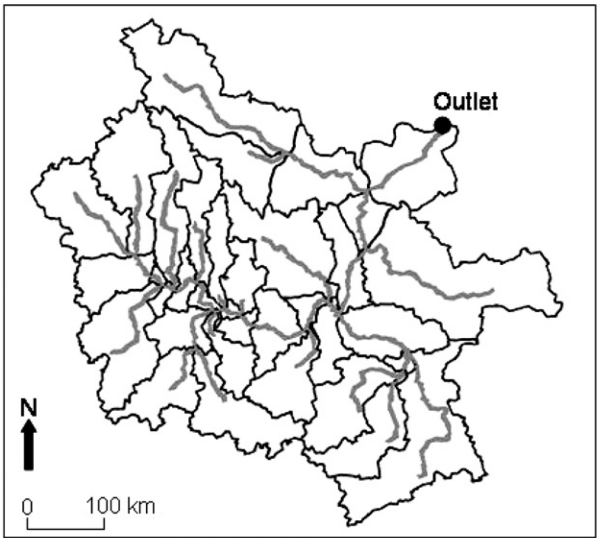

Figure 2 Delineation of the Liard Basin into 35 ASAs, with the outlet of the basin occupying the 35th sub-basin.

Streamflow was simulated for the basin using three sets of climatic data: (1) in situ data from weather stations, (2) NCEP/NCAR (National Centers for Environmental Prediction) Global Reanalysis Data, and (3) weather forecast data produced by the Canadian Meteorological Centre (CMC). The nature of these data sets is described in the next section. We use the data from the 1998–1999 water year for model calibration, and the 1999–2001 data for the validation of simulated discharge.

Only five land cover types are distinguished for the Liard basin: (1) deciduous, (2) evergreen, (3) mixed forests, (4) water and (5) tundra. We limited the number of land cover classes to match the level of reliability in land use mapping and to reduce the number of parameters that need to be estimated. SLURP parameters were optimized for each land cover and climatic data set (Table 1). All of these parameters were allowed to vary within a specified range to enable some physical credibility to be retained (Kuchment et al., 2000). Optimization procedures produce specific suites of specific parameter values for different sets of climatic data. This is necessary because the parameter values have to compensate for the differences of various climatic data sets on streamflow estimation. A comparison of the eight SLURP parameters reveal that the CMC and NCEP parameter values are similar, while the in situ have much lower values. The parameters not optimized by SLURP are listed in Table 2, and are constant between the data sets (excluding lapse rates used for the in situ data).

Ground level observations from 10 weather stations within and around the Liard basin (Fig. 1) provide daily measurements of temperature and precipitation. These were considered to be in situ data for this study. The NCEP/NCAR

Table 2 Designated parameter values used in SLURP for all climatic input data sets, except the lapse rates that apply only to the in situ data

Parameters	Land cover type	Value
Temperature lapse rate (°C/ 100 m), (in situ data only)		0.75
Precipitation lapse rate (%/ 100 m), (in situ data only)		5
Albedo	Deciduous	0.15
	Evergreen	0.13
	Mixed forest	0.14
	Water	0.075
	Tundra	0.25
Snowmelt factor (mm/°C/day), (parabolic function between January and July)	January	1
	July	2
Field capacity (as fraction of soil water)		0.25
Wilting point (as fraction of soil water)		0.05
Priestley/Taylor α_{water}		0.3
Priestley/Taylor α_{soil}	Deciduous	0.95
	Evergreen	0.95
	Mixed forest	0.95
	Water	1.26
	Tundra	1.26
Spittlehouse β	Deciduous	10
	Evergreen	10
	Mixed Forest	10
	Water	16
	Tundra	16

Table 1 Maximum and minimum range in which eight parameters are allowed to be optimized along with the ranges of values obtained for each data set through optimization

Parameter	Minimum value	In situ	CMC	NCEP	Maximum value
Initial contents of slow store (% of maximum)	0	13–63	27–70	20–82	100
Maximum infiltration rate (mm/day)	0	1–76	0–82	0–73	100
Manning's roughness, *n*	0.001	0.001	0.001–0.2	0.02–0.2	0.2
Retention constant for fast store (days)	1	17–91	59–78	14–100	100
Maximum capacity for fast store (mm)	0	686–1700	922–1666	129–1770	2000
Retention constant for slow store (days)	1	1769–5033	17,080–47,700	12,150–41,160	50,000
Maximum capacity for slow store (mm)	0	502–2268	5565–8047	263–8771	10,000
Time of travel (days)	0.25	1–2	1–2	1–2	10

reanalysis data (hereafter denoted as NCEP data) include six-hourly temperature and daily precipitation from 1948 onward, gridded at a spatial resolution of 250 km. The Canadian Meteorological Centre (CMC) currently uses the Global Environmental Multiscale model for weather forecasting. The forecast data are saved twice daily based on the 0000 and 1200 UTC model runs. CMC began archiving data for the Mackenzie GEWEX Study on 1 October 1995 with a horizontal scale of 24 km for the study period. Archiving is done at three hourly intervals from the beginning of the integration up to 24:00 h. The surface temperature and precipitation fields are extracted for this study.

Comparison of climate data sets

There is no means to identify which of the data sets most closely represents 'reality' since 'true' climatic information is impossible to obtain for this mountainous region. Each type of data has its special attributes. The in situ observations are point measurements that are biased by station locations since most of them are found in the valleys. They are subject to measurement error, especially for snowfall, which can be a major form of precipitation in the subarctic mountainous environment. The performance of NCEP data depends largely on the physics incorporated in the climate model, though it represents the atmospheric dynamics, energy and moisture fluxes in a three-dimensional space. Between the two gridded data sets, the CMC product shows considerably more spatial variability with a finer resolution than NCEP. The pattern of precipitation in 1998—1999 showed a prevalence of high values in the southwestern corner of the basin, being the windward side of the Cordillera with heavy precipitation from the Pacific, noticeable in the late fall. The winter and spring was a period of low precipitation, while in the summer, the high precipitation zone expanded into the centre of the Basin (Fig. 3). The in situ station values generally showed a poor match with the values for the corresponding grids in the reanalysis products. There was a tendency for the stations with low precipitation to record values much lower than those from the grids, suggesting the possibility of undercatch by the gauges (Goodison, 1978) or poor siting of the station with respect to precipitation deposition, or an overestimation of precipitation by the reanalysis products.

Monthly temperature values alternated between a north—south gradient during the colder months and an east—west gradient during the warm season (Fig. 4). They reflect the latitudinal temperature differences in the winter and the altitudinal influence in the summer. In general, NCEP yielded colder conditions than CMC , both of which were cooler than the in situ values at the weather station sites.

SLURP calculates weighted average climatic inputs for each of the 35 ASAs from any number of climate stations or gridded data using a weighted Thiessen polygon technique. Temperature is needed for the calculation of snowmelt using the degree-day method, and for evaporation computation using the Spittlehouse method, a modified form of the Priestley and Taylor approach, which has been found to yield reasonable results (Barr et al., 1997). For in situ data, the temperature field is adjusted to account for differences in elevation between the climate stations and the average elevation of the ASA using a specified lapse rate, while precipitation is adjusted for elevation changes using a specified rate of change of precipitation with elevation for each ASA (Table 2) (Kite, 2002). From the CMC and NCEP data, SLURP computes the ASA temperature and precipitation by averaging the values of all the grid points that

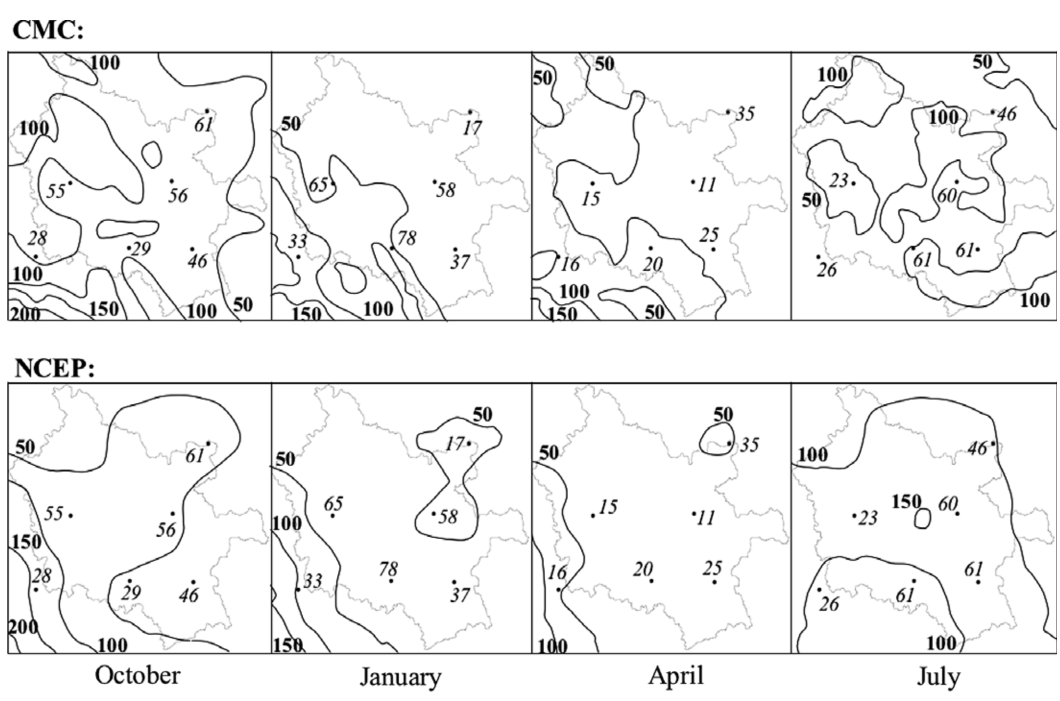

Figure 3 Isohyets showing distribution of monthly precipitation according to the NCEP and CMC data, for the 1998—1999 water year. The Liard Basin is outlined in grey, precipitation for weather stations are in italics and isohyets are labelled in bold numbers.

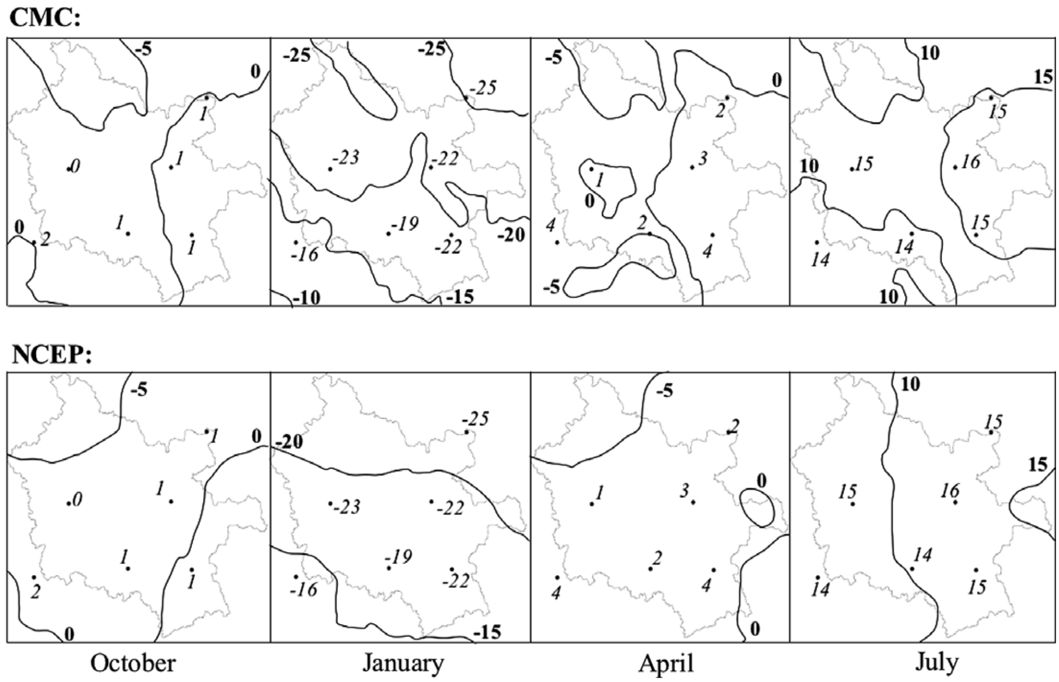

Figure 4 Isotherms showing distribution of monthly mean temperature according to the NCEP and CMC data, for the 1998–1999 water year. The Liard Basin is outlined in grey, temperature for weather stations are in italics and isotherms are labelled in bold numbers.

lie within an ASA. Fig. 5 summarizes the monthly temperature and precipitation generated by SLURP for the entire Liard Basin based on the three data sets. Pairwise statistical comparisons are made of the in situ, NCEP and CMC derived monthly temperature and precipitation values for the 35 ASAs, using the following indicators:

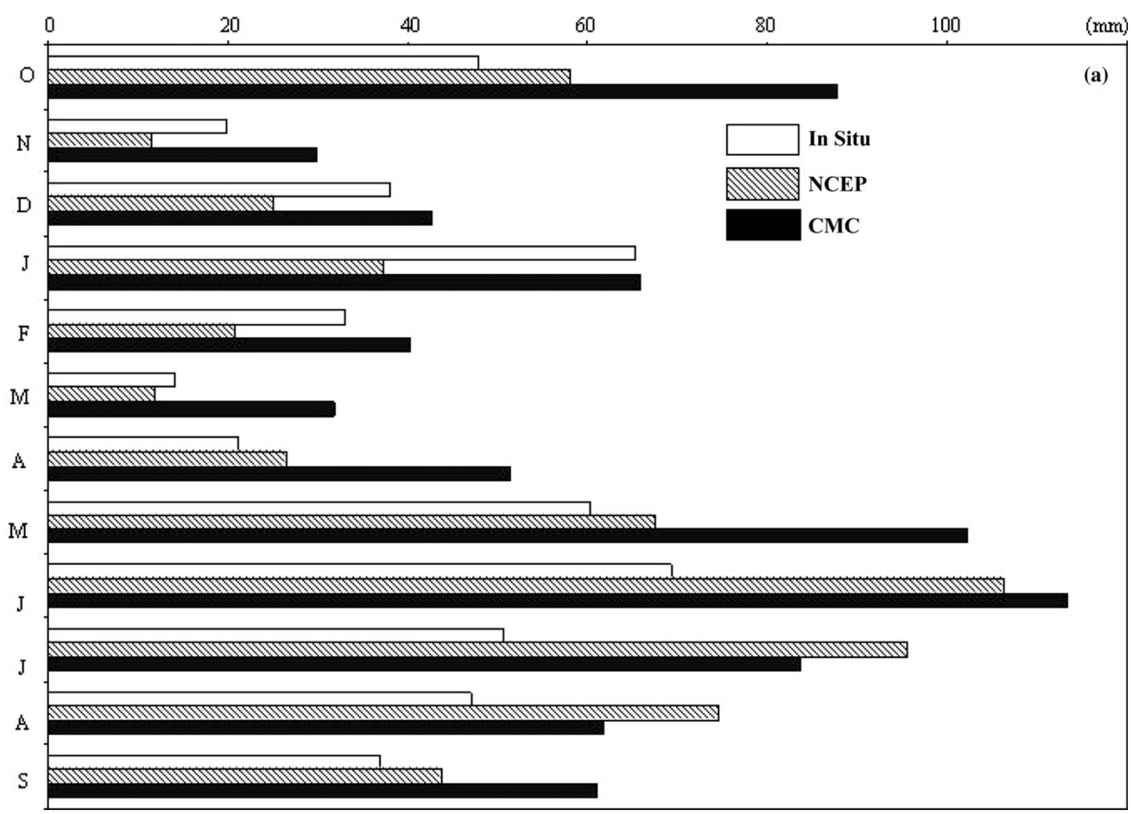

Figure 5 Comparison of: (a) monthly precipitation and (b) monthly temperature for the 1998–1999 water year, according to the in situ station records, NCEP and CMC data.

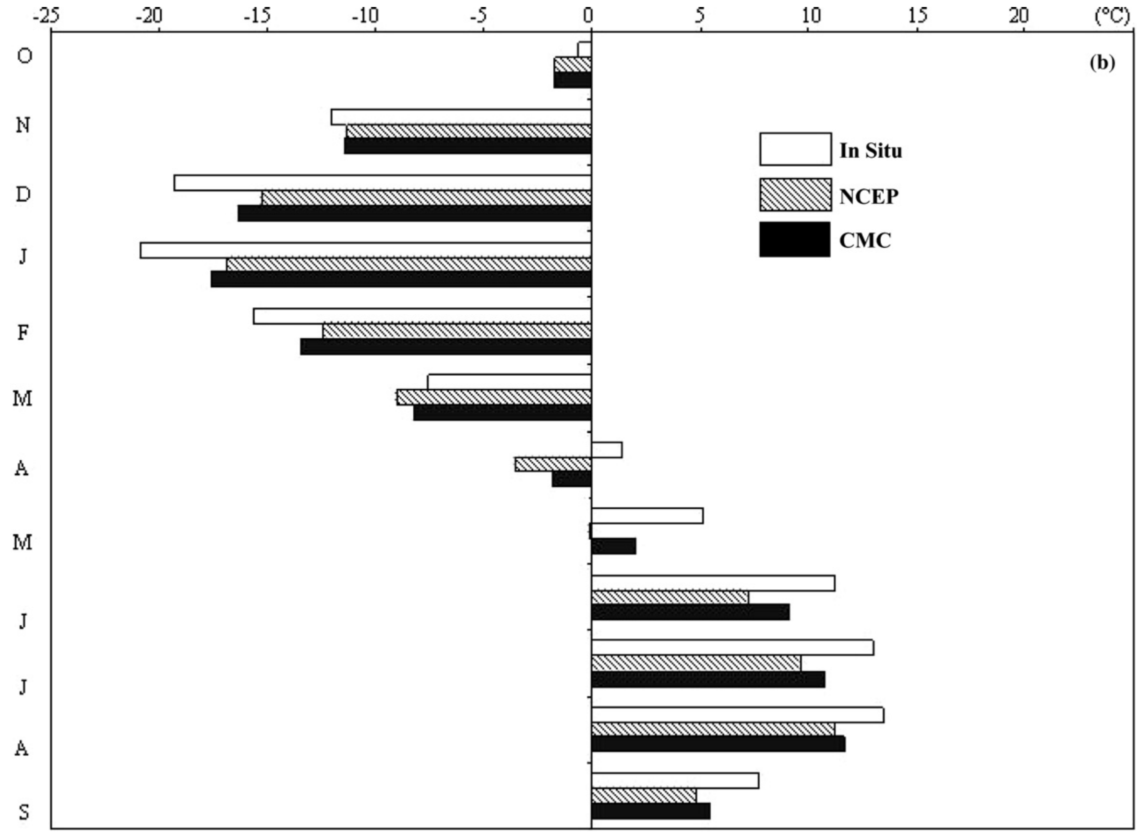

Figure 5 (*continued*)

(a) Spatial correlation (Taylor, 2001), with the correlation coefficient:

$$r = \left\{ 1/n \sum_{i=1}^{n} [x_1(i) - \overline{x_1}][x_2(i) - \overline{x_2}] \right\} \Big/ (s_1 s_2),$$
$$r = \left\{ 1/n \sum_{i=1}^{n} [x_1(i) - \overline{x_1}][x_2(i) - \overline{x_2}] \right\} \Big/ (s_1 s_2). \quad (1)$$

(b) Root-mean-square error (RMSE),

$$\text{RMSE} = \left\{ 1/n \sum_{i=1}^{n} [x_1(i) - x_2(i)]^2 \right\}^{0.5}. \quad (2)$$

(c) Mean bias (MB),

$$\text{MB} = \overline{x_1} - \overline{x_2}. \quad (3)$$

Here, x_1 and x_2 are the data sets derived from two different sources, the over-bars indicate the mean values for the $n = 35$ ASAs, and s_1 and s_2 are their corresponding standard deviations. Table 3 lists the monthly values of r, RMSE and MB.

In terms of precipitation, CMC and NCEP values were poorly correlated during most months, except in the late summer and fall. The pattern of in situ precipitation correlated poorly with both gridded data results during the winter and early summer months. SLURP adjustments (Fig. 5a) yielded lower monthly precipitation from the derived in situ data set than both gridded data sets, except against the NCEP data during the winter months. Compared with NCEP, the CMC basin-values were generally higher, except for the months of July and August. For temperature, the CMC and NCEP showed similar spatial tendencies, hence high correlation, but their correlation with the in situ data was significant only in the winter months (Fig. 5b). With regard to magnitude, the in situ data were consistently warmer than the NCEP and CMC data, except during the months of November to February. The warmer in situ temperatures gave rise to positive values 1 month earlier than the gridded data sets. There was a cold (warm) bias in the NCEP during the summer (winter) months, which resulted in a 1 °C difference between the CMC data, and up to a 5 °C difference against the ASA-averaged in situ values.

It is to be noted that SLURP uses these derived data, and not the original raw inputs, to simulate streamflow. Thus, the noted differences among the three derived data sets should have a bearing on SLURP performance in the flow simulation.

Streamflow simulation for basin outlet

Streamflow simulations were performed by pairing each of the three sets of data with its individually optimized parameters. In this paper, when referring to a simulation run using a particular data set, we imply the combined usage of the climatic data and its associated suite of optimized parameters.

The Nash—Sutcliffe (1970) statistic was used to compare the 'goodness of fit' between the observed discharge and the flows simulated by the various data sets:

$$R_N^2 = (F_0^2 - F^2)/F_0^2 \quad (4)$$

Table 3 Pairwise comparisons of in situ, CMC and NCEP data: (a) monthly precipitation, and (b) monthly temperature for 1998–1999 water year

	CMC vs in situ			NCEP vs in situ			CMC vs NCEP		
	r (%)	RMSE (mm)	MB (mm)	*r* (%)	RMSE (mm)	MB (mm)	*r* (%)	RMSE (mm)	MB (mm)
(a) Precipitation (1998–1999)									
October	28	44	40	4	27	7	35*	33	32
November	25	15	10	27	48	−8	20	60	18
December	30	20	4.8	40*	31	−13	21	38	18
January	−1	30	0.5	−50**	37	−28	34*	31	28
February	31	24	7.2	68**	32	−12	21	48	19
March	53**	20	17.8	38*	50	−2	−5	51	20
April	49**	32	30	−16	47	5	−18	46	25
May	−4	51	42	5	25	7	−30	31	35
June	−21	53	44	56**	32	37	−50**	24	7
July	50**	39	33	23	38	45	28	23	−12
August	42**	23	15	43**	41	28	42*	25	−13
September	37*	32	24	60**	29	7	56**	24	17
	CMC vs in situ			NCEP vs in situ			CMC vs NCEP		
	r (%)	RMSE (°C)	MB (°C)	*r* (%)	RMSE (°C)	MB (°C)	*r* (%)	RMSE (°C)	MB (°C)
(b) Temperature (1998–1999)									
October	39*	2.5	−1.1	54**	2.3	−3.6	59**	1.5	0
November	85**	2.1	0.7	75**	2.5	−0.4	85**	1.1	−0.1
December	78**	4.4	3	58**	5.6	1.6	71**	1.8	−1.1
January	88**	3.8	3.2	79**	4.7	0.1	84**	1.7	−0.8
February	87**	3.1	2.1	78**	4.2	−2.9	84**	1.7	−1.1
March	58**	2.9	−0.6	78**	2.9	−4	66**	1.4	0.8
April	9	4.6	−3.2	35*	5.5	−7.3	76**	2.3	1.7
May	17	4.6	−3.1	30	5.8	−6.1	81**	2.7	2.1
June	1	3.9	−2.1	16	4.8	−6.7	79**	2.5	1.9
July	4	3.6	−2.2	31	4.0	−6.4	74**	1.8	1.1
August	13	3.4	−1.8	34*	3.3	−4.3	79**	1.5	0.5
September	9	3.7	−2.3	38*	3.8	−5.3	74**	1.6	0.6

r is correlation coefficient, RMSE is root-mean-square error, and MB is mean bias.
* Correlation significant at 95% probability.
** Correlation significant at 99% probability.

with F_0 being the initial variance and F being the residual variance. The best fit is at $R_N^2 = 1.0$, becoming worse as R_N^2 departs from 1.0. The root-mean-square error is also computed using the simulated and measured daily discharges.

Fig. 6 indicates that all simulation runs overestimate the winter low flow. This may be attributed to the effect of the storage parameter which controls the release of baseflow. By early April, initial hydrograph rise is simulated using both the in situ and CMC data but the NCEP data yields a late rise as it still gives low temperatures for most parts of the basin. The measured flow does not record a hydrograph rise until late-April, likely due to the presence of river ice on the Liard that always delays the rise until breakup reaches the river mouth. A hydraulic routing algorithm (e.g. Blackburn and Hicks, 2002) is needed to properly simulate the spring hydrograph rise. The timing and magnitude of the observed spring peak is well matched by the in situ data run. The peaks produced by both the NCEP and CMC data are lower, and their simulated recessions are more gradual than the observed data. The NCEP-generated peak lags behind the observed peak by about two weeks, due to its low spring temperatures. The in situ data underestimates the low flows in the summer, possibly due to the high temperatures that produce large evaporation loss at the expense of streamflow. Although the NCEP and CMC data produce more summer low flows than the in situ data, all data sets perform poorly in simulating the summer peaks.

In spite of the considerable differences amongst the three sets of input data, all of them give daily flows that agree well with the discharge measured at the Liard basin outlet near Fort Simpson. The Nash–Sutcliffe R_N^2 is 0.85 using both CMC and NCEP input, and is 0.87 for the in situ data. The RMSE lies between 926 and 996 m^3/s (Table 4).

To validate the model performance beyond the calibration period, outflow was simulated for three water years, 1998–1999 to 2000–2001, using the parameters optimized for 1998–1999 (Fig. 7). Beyond the calibrating period, the R_N^2 for 1999–2000 is 0.80, 0.90, 0.84 for the situ, CMC and NCEP data, and for 2000–2001, the corresponding R_N^2 are 0.89, 0.87, 0.78 (Table 4). The RMSE for 1999–2000 (and 2000–2001) are 913, 661, 835 (961, 1045, 1388) m^3/s for the in situ, CMC and NCEP data. For particular flow attributes, the secondary peak for 2000–2001 tends to be underestimated by the simulations. Otherwise, the flows are well

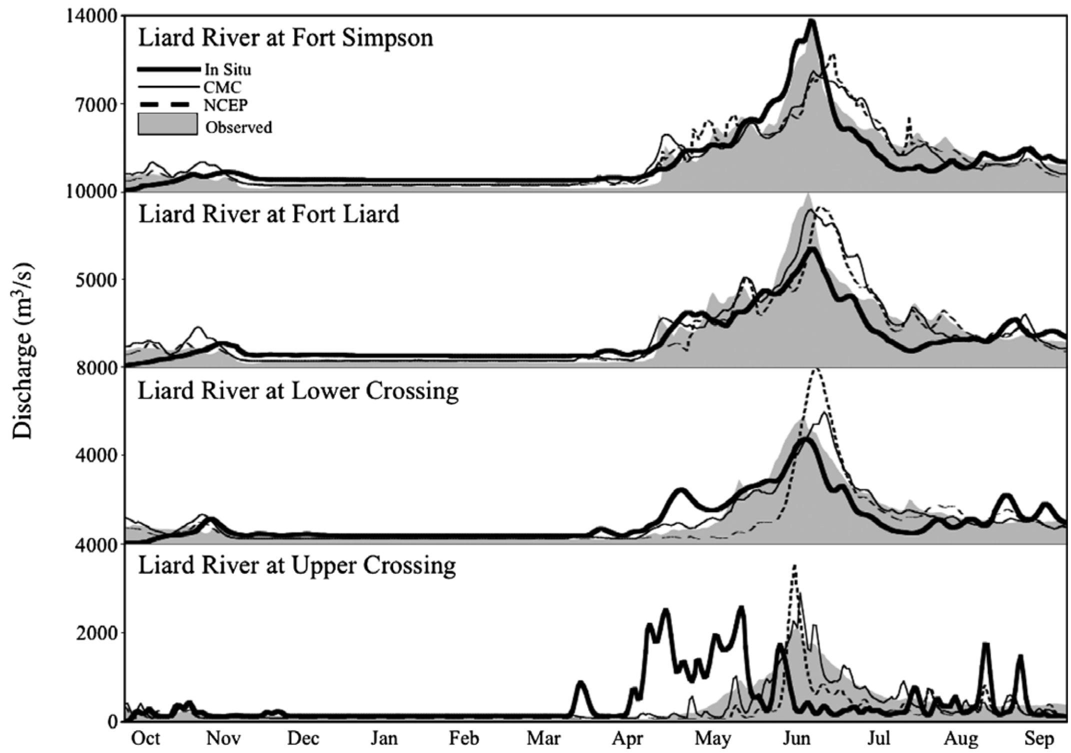

Figure 6 Comparison of measured and simulated streamflow for the Liard River at its outlet near Fort Simpson, at Fort Liard, Lower Crossing and Upper Crossing for the 1998—1999 water year for the three climatic input data sets.

Table 4 Comparison of measured and simulated discharges of Liard River at Mouth, using three sets of climatic input data

	Statistical parameter	In situ	CMC	NCEP
1998—1999	R_N^2	0.87	0.85	0.85
	RMSE (m^3/s)	926	975	996
1999—2000	R_N^2	0.80	0.90	0.84
	RMSE (m^3/s)	913	661	835
2000—2001	R_N^2	0.89	0.87	0.78
	RMSE (m^3/s)	961	1045	1388
Overall period	R_N^2	0.86	0.87	0.81
	RMSE (m^3/s)	925	904	1096

simulated, with the exception that the in situ data yield higher winter discharges than observed. In general, the flows simulated with the three sets of input data are in good overall agreement with the observed daily discharges. These outcomes point to the capability of the optimized parameters in accommodating the disparities amongst the data sets used in streamflow simulation. To understand how the model, in combination with its parameter sets, can override the data differences, we have to examine the ways in which flow is generated for, and aggregated from, different sections of the basin.

Evolution of simulated flows

Several gauged sub-basins in the Liard system correspond with a number of ASAs in the simulation. Their discharge records, together with those from three gauging stations along the main trunk of the Liard River (at the Upper Crossing, Lower Crossing and at Fort Liard, with drainage areas of 33,400, 104,000 and 222,000 km^2), permit comparison with the simulated flows.

Tracing the flows down the Liard River, Fig. 6 compares the measured discharge with the flows simulated using the in situ, NCEP and CMC data. The simulation using in situ data grossly overestimates the flow at the Upper Crossing, with $R_N^2 = -1.1$ (Table 5). This is mainly due to the erroneous flows generated at the headwater ASAs, an example of which is the Frances River (Fig. 8) for which the simulated snowmelt runoff is too early, the peaks too spiky, and the summer flows too erratic. Moving downstream, the simulated Liard discharge is much subdued and better matches the observed flow at the Lower Crossing ($R_N^2 = 0.76$). This is related to the underestimation of tributary contributions from such rivers as the Smith (Fig. 8) that reduce the flow variations along the Liard main trunk. Minor fluctuations in autumnal flow, present at the Upper Crossing simulation, are eliminated, possibly by channel routing along the river. At Fort Liard, the simulated flow exceeds that of the Lower Crossing site, as it loses its false early-melt peak. This is due to flow modification by rivers on the Interior Plains, such as the Fort Nelson River whose flow is much underestimated by SLURP (Fig. 8). Overall, the flow at Fort Liard is underestimated, even though the R_N^2 is 0.78. Downstream from Fort Liard, the main river receives large runoff from the mountainous South Nahanni River for which SLURP overestimates (Fig. 8). This compensates for the underestimation at Fort Liard so that at the river outlet near Fort Simpson, the fit with observed flow is improved ($R_N^2 = 0.87$).

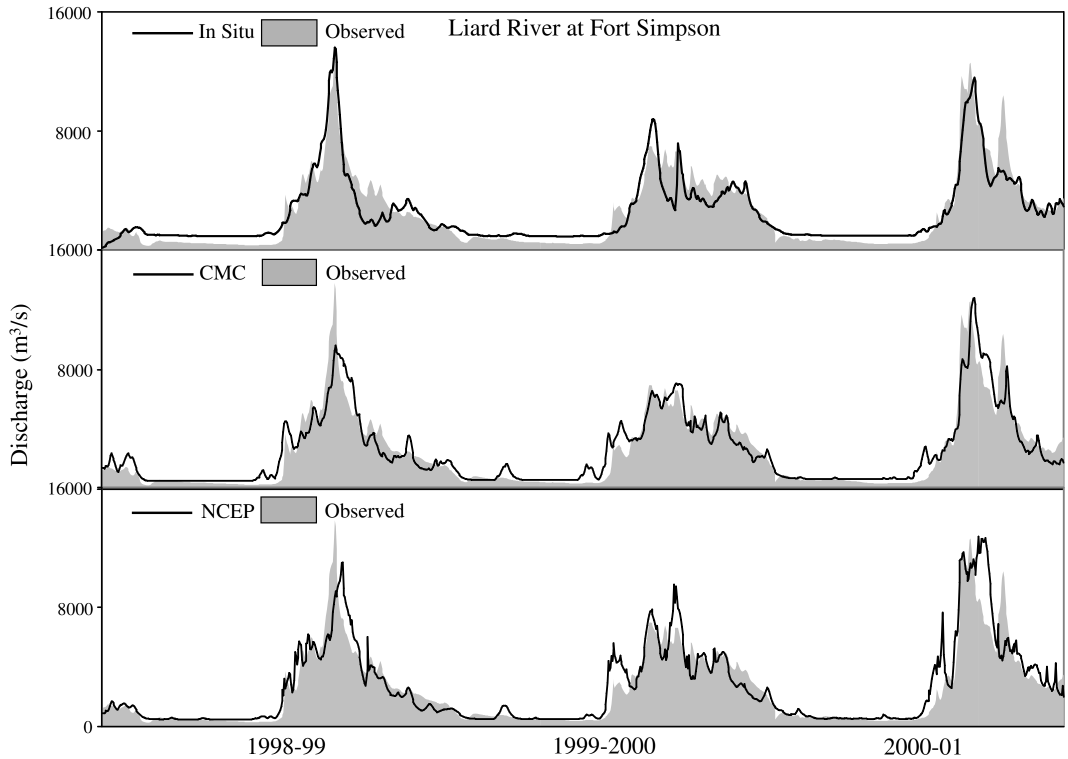

Figure 7 Comparison of measured and simulated streamflow for the Liard River at its outlet near Fort Simpson for the water years 1998–1999, 1999–2000 and 2000–2001 using the three climatic input data sets.

Table 5 Comparison of discharges measured at selected hydrometric stations along the Liard River, with flows simulated using three sets of climatic input data, for various periods

Hydrometric station	Statistical parameter	In situ	CMC	NCEP
Liard River at Mouth, 1998–1999	R_N^2	0.87	0.85	0.85
	RMSE (m^3/s)	926	974	996
Liard River at Fort Liard, 1998–1999	R_N^2	0.78	0.88	0.81
	RMSE (m^3/s)	925	703	874
Liard River at Lower Crossing, 1998–1999	R_N^2	0.76	0.91	0.61
	RMSE (m^3/s)	590	367	757
Liard River at Upper Crossing, 1998–1999	R_N^2	−1.1	0.86	0.51
	RMSE (m^3/s)	630	162	305
Frances River, 1998–1999	R_N^2	−2.1	−0.08	0.4
	RMSE (m^3/s)	297	176	131
Smith River, 1998–1999	R_N^2	−1.9	−380	−180
	RMSE (m^3/s)	15	175	121
Fort Nelson River, 1998–1999	R_N^2	−0.2	−1.2	−2.2
	RMSE (m^3/s)	233	317	380
South Nahanni River, 1998–1999	R_N^2	−7.1	−0.01	−0.31
	RMSE (m^3/s)	736	260	296

R_N^2 is the Nash–Sutcliffe coefficient and RMSE is the root-mean-square error.

The NCEP data generally underestimates the measured discharge, except for the peak, at the Upper Crossing (Fig. 6), yielding an R_N^2 of 0.51. The initiation of snowmelt runoff is delayed; although the timing of the peak is accurate, the magnitude is overestimated. The simulated pattern of discharge for the Upper Crossing is similar to

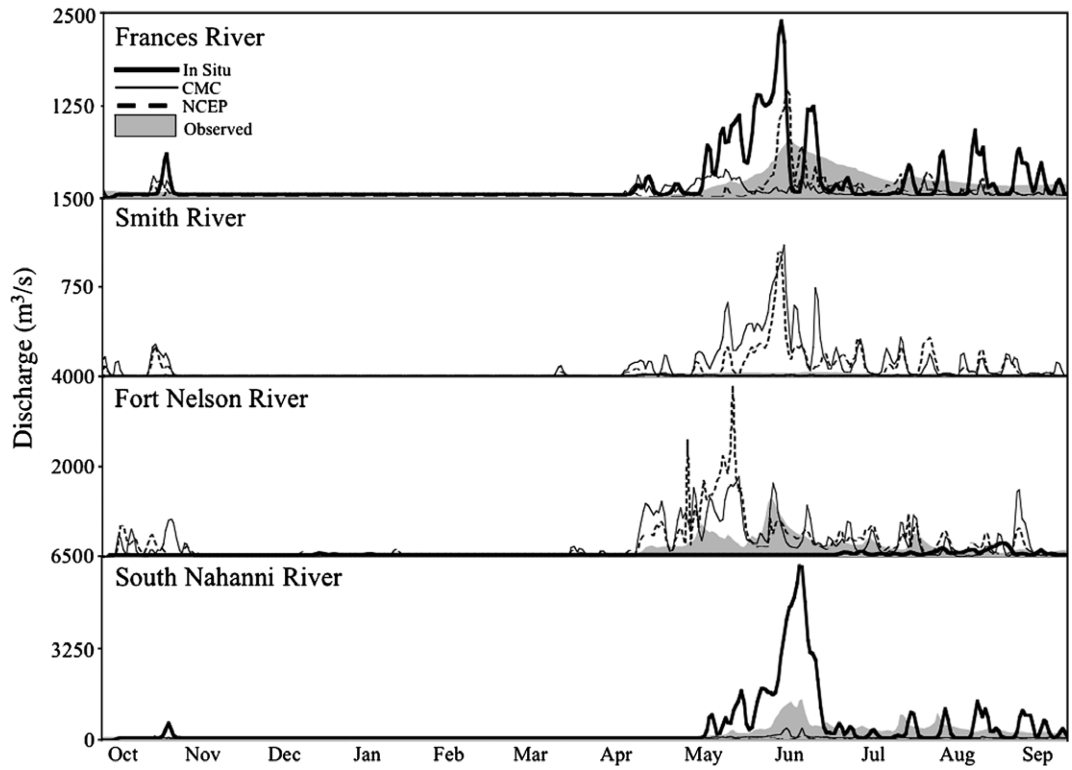

Figure 8 Comparison of measured and simulated streamflow using in situ, NCEP and CMC data for several sub-basins in the Liard system: Francis River, Smith River, Fort Nelson River and South Nahanni River.

that of the Frances River, suggesting that the flow of the Frances strongly influences the flow at this Liard site. At the Lower Crossing, the snowmelt runoff is delayed along with the peak, which is also overestimated. The overestimated peak can be explained by Smith River inputs, but the delay in its arrival may be caused by other tributary inflows or by incorrect routing from the Upper Crossing. The summer flow at the Lower Crossing matches the observed, giving an R_N^2 of 0.61. The simulated flow at Fort Liard is increased to agree better with the measured discharge ($R_N^2 = 0.81$), though the time delay in the peak remains. The simulated snowmelt runoff increases to better match the observed, due to flow modification by rivers on the Interior Plains (e.g. Fort Nelson). At the lower Liard basin, the simulated flow from the South Nahanni River is greatly underestimated but it provides early melt runoff that adjusts the timing of spring flow initiation. The final fit with the observed Liard discharge at its outlet is $R_N^2 = 0.85$.

Streamflow simulated using the CMC data shows a reasonable fit with measured discharge at the Upper Crossing ($R_N^2 = 0.86$) even though there are many spiky peaks and some excessive late autumn high flows (Fig. 6). The simulations for the mountainous headwater basins yields mixed results (e.g. Smith River flow is overestimated and the simulated peak is delayed) but channel routing apparently smooths the hydrograph at the Lower Crossing where the simulated and measured data give $R_N^2 = 0.91$. Down river at Fort Liard, the delayed peak is translated into a bulge on the recession limb from the annual peak while rivers on the Interior Plain contribute to a secondary rise in late summer. The R_N^2 is reduced to 0.87. The CMC data underestimates the flows of large tributaries like the South Nahanni River and this lowers the total Liard flow at its outlet ($R_N^2 = 0.85$). Overall, however, the CMC data performs the most creditably among the three data sets because it produces flows from various sections of the Liard Basin that agree most closely with the measured discharge available at a number of stations (which offer the only available information that permits the simulated results to be checked).

These three examples reveal the different ways in which the flow of the Liard is modified downstream where more ASAs are included in the computational domain. The trajectories along which adjustments are made differ among the data sets, yet the final results give comparable matches (i.e. similar R_N^2 and RMSE) with the observed hydrograph at the basin outlet. The implication here is that as more ASAs are aggregated downstream, more samples become available for averaging out the errors attributed to the flow simulation from individual ASAs.

Discussion and conclusions

Mountainous areas, with complex topography and diverse surface covers, are subject to large variations in climatic conditions over short distances. Without a good coverage of weather stations or an accurate spatial representation of the climatic fields, hydrological models have to resort to interpolations of input values and optimization of model parameters for streamflow simulation. This is an approach adopted by many water resource projects, yet the influence of input data on the simulated flow should be clarified.

This study makes use of three different sets of climatic data as inputs to a macro-hydrological model (SLURP) to simulate daily flow for a large mountainous catchment. The in situ data suffers from a paucity and poor representation of weather stations, even though SLURP interpolates and adjusts the precipitation and temperature values for all ASAs, taking account of the topography. For the simulation periods, both the CMC and NCEP temperatures showed a south—north gradient in winter which shifted to west-east in the summer. Precipitation was highest in the southwest near the continental divide, and had low values on the eastern plains. These patterns were consistent with the regional climate of the Cordillera. In detail, CMC data differ from NCEP data, and the former have a resolution that is an order of magnitude finer than the NCEP. The model accommodates discrepancies among the three input data sources mainly through the parameters, particularly with the storage coefficients. This accounts for the large differences in the optimized retention and maximum storage capacity values for the three data sets (Table 1).

Despite the differences amongst the three data sets, they are all able to generate streamflow that fits satisfactorily (high Nash—Sutcliffe coefficient) with the measure discharge at the basin outlet. This does not imply a capability of the model to correctly simulate the runoff contributions from various sub-basins. Rather, the model makes use of the compensatory effect of over-estimation and under-adjustments in flow calculation at various sub-units, to yield an aggregate discharge that agrees well with the final outflow. Indeed, the model is prone to simulating spatial distribution patterns for other hydrologic variables that depart from reality. For example, a comparison of the simulated snow cover for the Liard Basin with satellite-derived snow areas indicates that while their overall distributions are compatible, there are parts of the Basin where the simulated snow cover do not match the observed (Woo and Thorne, 2006).

Two interesting conclusions may be drawn from the present study: (1) The pattern of streamflow contribution from within the basin is not reliable even where there is a good overall fit between observed and simulated streamflow at the basin mouth. (2) The optimization capability of a macro-scale hydrologic model can compensate for the differences amongst several climate input data sets; and this testifies to the flexibility of the model. Most studies do not report how their distributed models aggregate flows from the basin sub-units to achieve an overall good fit. We compare simulated with measured discharge at several gauging sites within the Liard basin. It becomes apparent that some ASAs overestimate while others underestimate the measured flow. As we approach the basin outlet, there are more ASA discharges available to average out these errors and this process usually improves the performance of the simulation for the entire basin.

At a macro-scale level, there is no certainty as to what the 'true' values of the parameters should be, even for the coefficients of many supposedly physics based equations. Optimization is the only feasible way to obtain their numerical values. However, the values derived from such fitting procedures are data-specific. Thus, a combination of the climatic data with their specific suite of optimized parameters would perform well in the simulation of streamflow. This has the implication that we may be getting the correct answer for the wrong reasons. Possibly, it is the optimized parameter values and not the model representation of physical processes, that are mainly responsible for overcoming the data deficiencies to generate acceptable streamflow at the basin outlet. On the other hand, if prediction is the primary goal for the complex mountainous catchment where reliable climatic data are limited, this study has shown that within limits, well chosen parameters can compensate for data inadequacies to simulate streamflow that are acceptable by such measures as the Nash—Sutcliffe coefficient or the root-mean-square error.

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