Supplement of

5

Assessing the adequacy of traditional hydrological models for climate change impact studies: A case for long-short-term memory (LSTM) neural networks

Jean-Luc Martel¹, François Brissette¹, Richard Arsenault¹, Richard Turcotte², Mariana Castañeda-Gonzalez¹, William Armstrong¹, Edouard Mailhot², Jasmine Pelletier-Dumont², Gabriel Rondeau-Genesse³, Louis-Philippe Caron³

¹Hydrology, Climate and Climate Change (HC3) laboratory, École de technologie supérieure, Montreal, Canada, H3C 1K3
²Direction principale de l'expertise hydrique (DPEH), Ministère de l'Environnement et de la Lutte contre les changements climatiques, de la Faune et des Parcs (MELCCFP), Quebec, Canada, G1R 5V7
³Ouranos, Montreal, Canada, H3A 1B9

Correspondence to: Jean-Luc Martel (jean-luc.martel@etsmtl.ca)



Figure S1: Catchment descriptors for the 148 catchments of this study and for the 1,000 extra donors catchments for the extended LSTM-based model.



Figure S2: LSTM-based model structure developed and implemented in this study.



Figure S3: Kling-Gupta Efficiency (KGE; a), Nash-Sutcliffe Efficiency (NSE; b), relative bias (β ; c), correlation coefficient (r; d), variance ratio (y; e), and normalized root mean square error (NRSME; f) metrics over the independent 5-year training period (1983-2002).



Figure S4: Projected mean winter streamflow (QMDJF) changes for the 4 sensitivity scenarios: temperature increase of +3 $^{\circ}$ C (a) and +6 $^{\circ}$ C (b) and precipitation relative change of -20% (c) and +20% (d).



Figure S5: Same as Figure S4, but for mean spring streamflow (QMMAM).



Figure S6: Same as Figure S4, but for mean annual maximum streamflow (QMM).



Figure S7: Same as Figure 11, but on a seasonal basis.



40 Figure S8: Same as Figure 11, but the 20% increase in precipitation scenario.



Figure S9: Same as Figure S8, but on a seasonal basis.



Figure S10: Same as Figure 11, but the 20% increase in precipitation scenario.