Can post-processed meteorological ensemble forecasts outperform a sophisticated analogog model for operational streamfloow forecasting?

Marie-Amélie Boucher[1], Fabian-Tito Arandia-Martinez[2] and Jocelyn Gaudet[3]
[1]Université du Québec à Chicoutimi, Saguenay, Canada
[2]Hydro-Québec Operations, Montréal, Canada
[3]Institut de Recherche d'Hydro-Québec, Varennes, Canada

Context and Objectives

An analog approach was developed by Hydro-Québec to produce ensembles of streamflow forecasts. This approach has been used operationally since the 70's. The goal of this study are to:

- Compare different bias correction and post-processing strategies to improve ensemble streamflow forecasts;
- Re-evaluate (c.f. Evora et al., 2005) the possibility of using meteorological ensemble forecasts instead of analogs to obtain ensembles of streamflow forecasts;
- Assess the importance of human expertise in the forecasting process.

Methodology

1. **Modeling**
- Meteorological forecasts from three different atmospheric models (only ECMWF's are shown on this poster)
  - Precip and temperature, 2011-2013
  - 50 members
  - 1- to 9-day horizon, 6-hour time step aggregated to daily time step.
- Lumped conceptual model HSAMI (Fortin, 2000)

2. **Post-processing**
- Bias correction
  - Separately for each forecasting horizon *OR* averaged
  - Separately for different streamflow magnitude (deciles) *OR* averaged
- Weighted Kernel Dressing (WKD, Fortin et al., 2006)

3. **Performance assessment using a leave-one-out cross validation**
  - Skill score (CRPS) and Ignorance
  - Reliability diagram

4. **Test bed**
  - 3 watersheds used for hydro-power production

Figure 1. Geographical location of Baskatong, La-Grande 4 and Outardes-4 in the province of Quebec, Canada.

Results – Importance of the human expertize

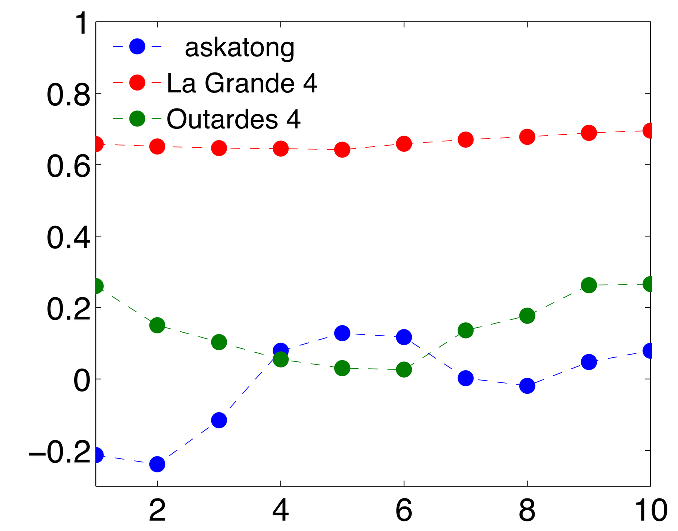

Figure 2. CRPS Skill Score (left) and difference in ignorance score (right) for analog forecasts, as a function of lead-time. The reference is the non-Expertized analog forecast. CRPS skill score: the higher, the better, A negative delta ignorance score represents a loss of information between Expertized and Non-Expertized forecasts.

Results – Post-processing

Figure 3. CRPS Skill Scores for streamflow forecasts based on meteorological ensembles from the ECMWF as a function of lead-time for the three watersheds shown in Figure 1 and for different bias-correction and post-processing strategies.

Figure 4. Information gain between hydrological ensembles based on meteorological forecasts from ECMWF and non-Expertized analog forecasts as a function of lead-time for the three watersheds under study. A positive delta ignorance score implies that analogs are more informative than forecasts based on meteorological ensembles.

Results – Reliability

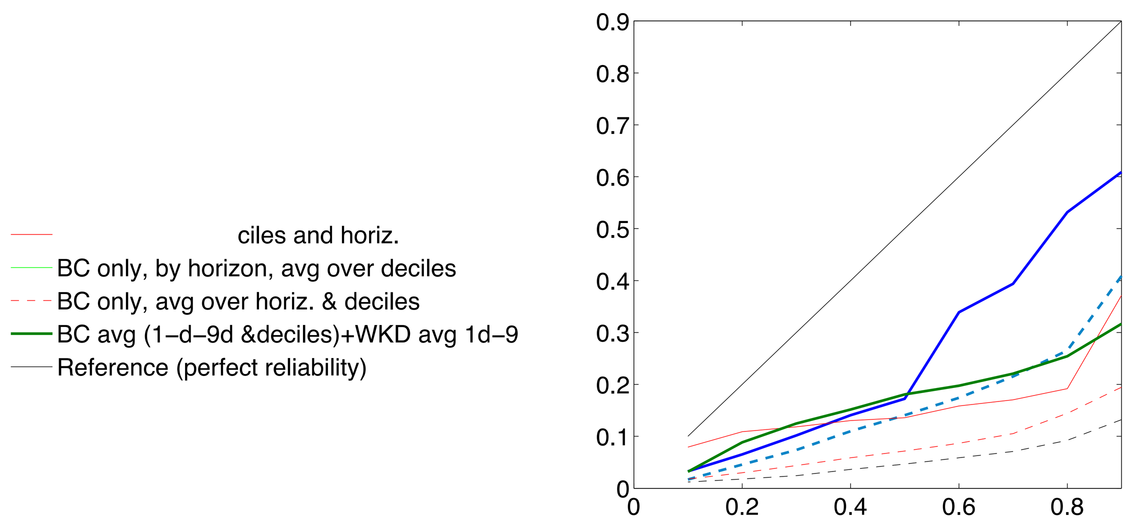

Figure 5. An example of reliability diagram at 9-day lead time for La Grande 4 and Outardes-4 after post-processing (various methods).

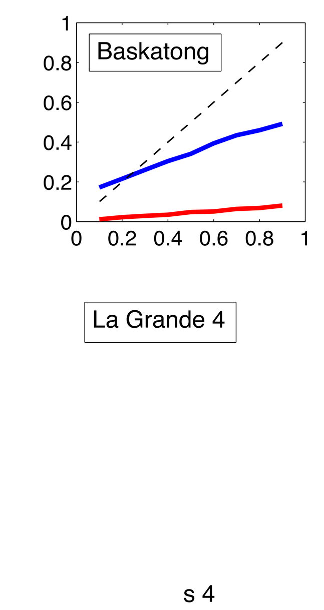

Figure 6. Reliability diagrams for Raw and Expertized analog forecasts

Conclusions

- Post-processing (WKD) successfully improves over raw streamflow forecasts based on meteorological forecasts…
- …but analog forecasts are superior in terms of both CRPS and ignorance scores, at least for short lead-times.
- WKD can handle bias correction on its own. Additional separate bias correction is risky.
- None of the forecasting systems tested herein is reliable
  - Structural uncertainty (hydrol. model) and initial condition uncertainty not accounted for.
- Ensembles based on raw meteorological forecasts are (a little bit) more reliable than raw analogs

Future work:

- Comparison with raw Grand Ensemble and with Bayesian Model Averaging
  - Precip and temperature forecasts from three agencies: ECMWF, NCEP and MSC.

Contact

Marie-Amélie Boucher
Université du Québec à Chicoutimi
Marie-amelie_boucher@uqac.ca

Acknowledgements

This work was funded in part by NSERC and Hydro-Québec. The authors wish to thank the ECMWF for maintaining the TIGGE portal that provides free access to ensemble meteorological forecasts for research purposes.

References

Evora N. 2005. Valorisation des prévisions météorologiques d'ensemble. Technical Report IREQ-2005-065. Hydro-Québec, Institut de Recherche.

Fortin V., Favre A.C., and Saïd M., 2006. Probabilistic forecasting from ensemble prediction systems: improving upon the best-member method by using a different weight and dressing kernel for each member. Quart. J. Roy. Meteorol. Soc. 132, 1349–1369.

Fortin V., 2000. Le modèle météo-apport HSAMI: historique, théorie et application. Institut de recherche d'Hydro-Québec, Varennes.

Ensemble water temperature forecasting: accounting for uncertainty associated with meteorological inputs

Sébastien Ouellet-Proulx[1]; André St-Hilaire[1]; Marie-Amélie Boucher[2]
[1]Institut National de la Recherche Scientifique; [2]Université du Québec à Chicoutimi

Introduction

High temperature episodes are known to increase stress on aquatic organisms such as salmonids [1]. In some hydrological systems where dams have altered natural flows, thermal management strategies have been implemented to protect aquatic communities while maintaining socio-economic benefits delivered by freshwater resources. One such strategy is the release of cool water from an upstream reservoir to protect local fish populations from high water temperatures. These releases are often based on short term water temperature forecasts [2]. These forecasts are subject to various sources of uncertainty known to affect the precision of thermal models. Despite having some knowledge about these uncertainties, there individual impact on water temperature forecasts remains poorly understood [3,4].

Objectives

1. Produce daily ensemble water temperature forecasts for a 5 day lead-time.
2. Characterize uncertainty induced to the water temperature forecasts by meteorological inputs.
3. Compare the performances of the ensemble water temperature forecasts to archived deterministic water temperature forecasts.

Methodology

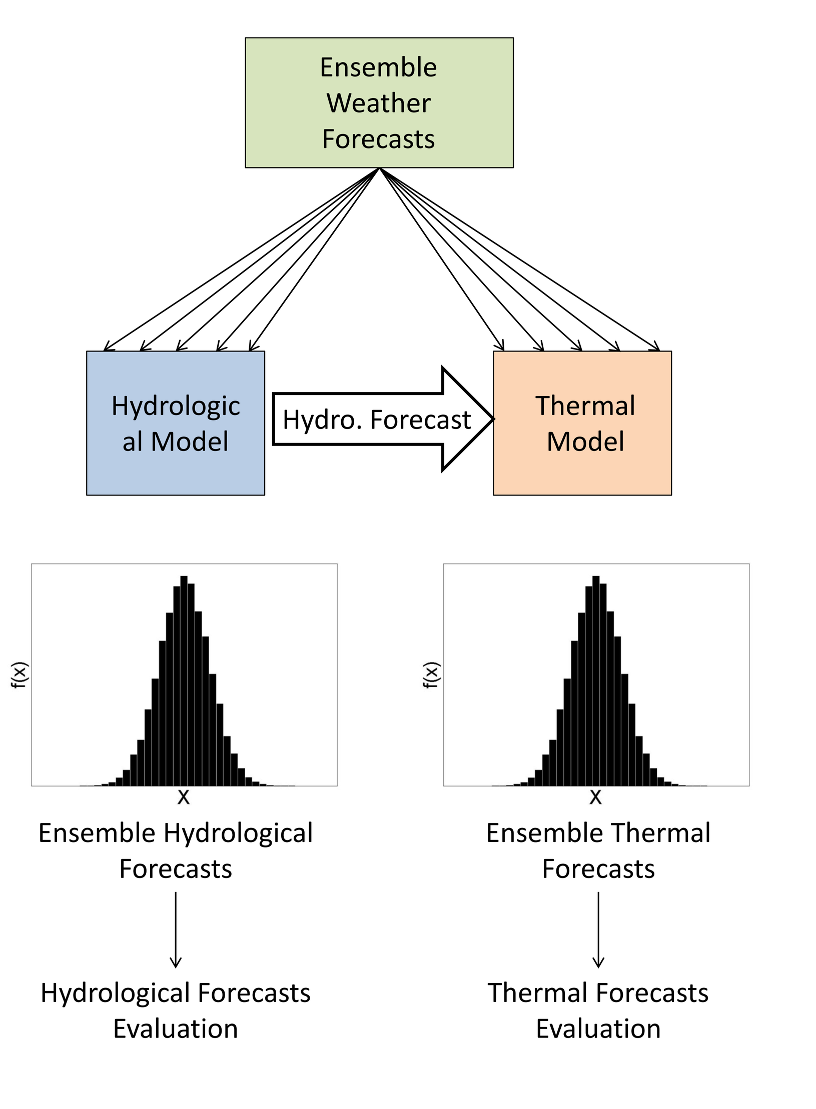

Figure 1. Forecasting framework of discharge and water temperature.

CEQUEAU

Semi-distributed Model

Hydrological Model Inputs:
- Physiographic data
- Air temperature
- Total precipitation

Thermal Model Inputs:
- Net solar radiation
- Wind speed
- Air vapour pressure
- Cloud cover
- Air Temperature

Weather Forecasts:
- Canadian Meteorological Center
- 20 members
- Extracted from TIGGE portal

Performance criteria:
- CRPS/MAE [5]
- Brier score [6]
- Reliability plot [7]

Study Site

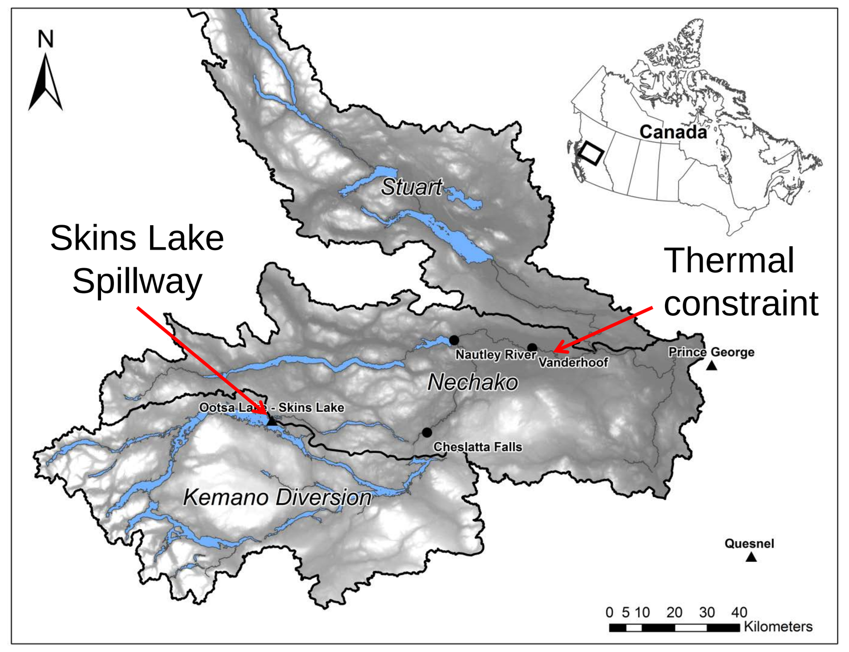

Figure 2. Nechako drainage basin

Operational Thermal Constraint
- July 20th – August 20th
- Sockeye salmon run
- Temperature threshold: 20°C
- Travel time of 5 days

Important Dimensions
- Sub-basin: 15000 km²
- Distance between spillway and constraint : 260 km

Results

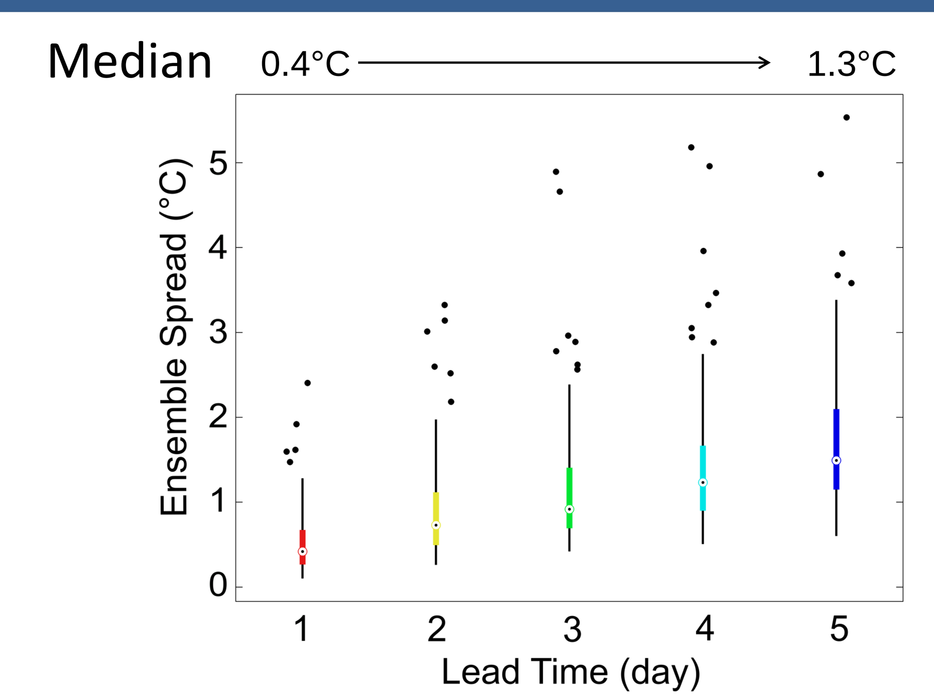

Figure 3. Box plots of the ensemble spreads for lead times of 1 to 5 days (all years)

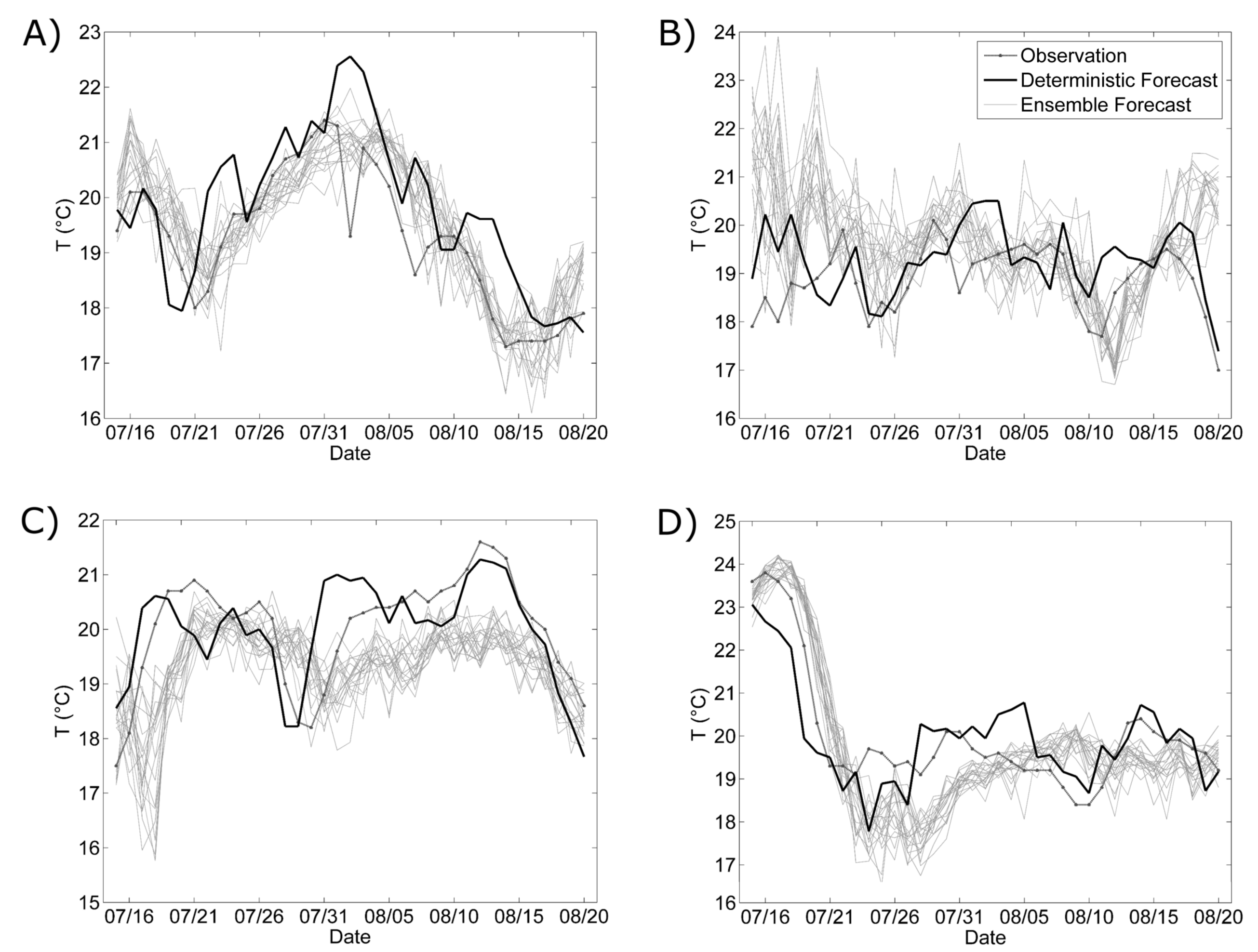

Figure 4. Ensemble and deterministic water temperature forecasts for a five day lead time A) 2009, B) 2010, C) 2013 and D) 2014.

Table 1. MCRPS, MAE and Brier scores for both sets of forecasts

Hz	Ens. Brier (Tw>20)	Det. Brier (Tw>20)	Ens. MCRPS (°C)	Det. MAE (°C)
1	0.33	0.15	0.91	0.47
2	0.30	0.20	0.76	0.66
3	0.28	0.26	0.72	0.78
4	0.28	0.34	0.70	0.93
5	0.29	0.36	0.70	1.04

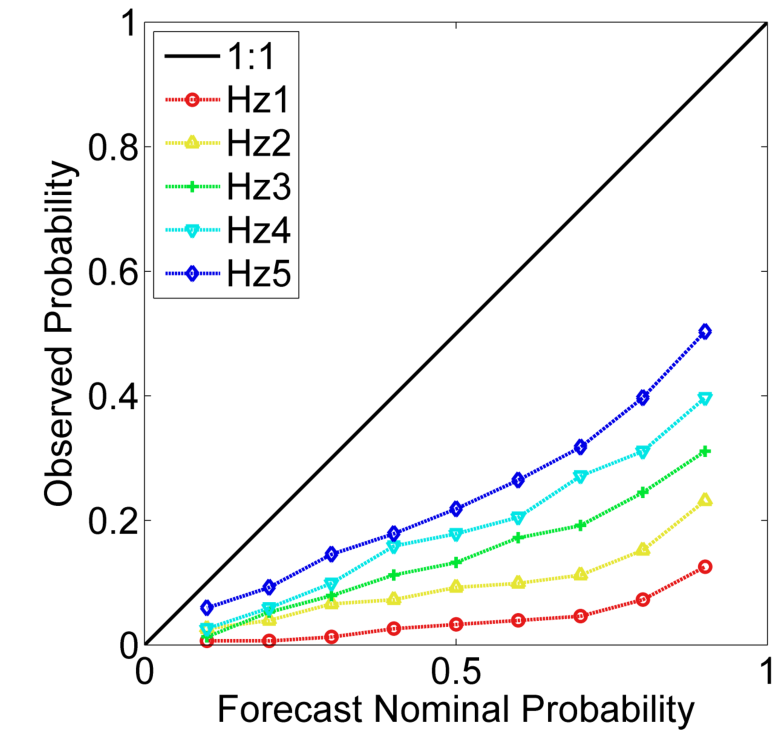

Figure 5. Reliability plots for all five forecasting horizons of water temperature.

Conclusions

- First step towards building a simple framework to include uncertainty in water temperature forecasting
- Uncertainty of meteorological inputs propagated within the forecasting framework
- Better performances of the ensemble forecasts for longer lead-times
- Reliability improved with lead-time

Future work:
Uncertain initial conditions: data assimilation
Structural uncertainty: multi-module

Acknowledgements

This work was funded in part by NSERC and Rio Tinto. The authors wish to thank J. Benckhuysen B. Larouche and M. Latraverse for their assistance in the realization of this project. They also wish to thank the ECMWF for maintaining the TIGGE portal that provides free access to ensemble meteorological forecasts for research purposes.

Contact

Sébastien Ouellet-Proulx
Institut national de la recherche scientifique
Email: sebastien.ouellet-proulx@ete.inrs.ca

References

1. Ward, J. and Stanford, J. 1982. Thermal response in the evolutionary ecology of aquatic insects. Ann. Rev Entomol. 27, 97-117.
2. Huang, B., Langpap, C. and Adams, R. M. 2011. Using instream water temperature forecasts for fisheries management: an application in the Pacific Northwest, J. Am. Water Resour. Assoc., 47, 861–876.
3. Bartholow, J.M.: Modeling Uncertainty. 2003. Quicksand for Water Temperature Modeling. in Hydrological Science and Technology. Proceedings of American Institute of Hydrology conference on Hydrologic Extremes: Challenges for Science and Management. 19, 221-232.
4. Hague, J. M. and Patterson, D. A. 2014. Evaluation of statistical river temperature forecast models for fisheries management. North American Journal of Fisheries Management. 34, 132-146
5. Gneiting, T., and Raftery, A. E. 2007. Strictly Proper Scoring Rules, Prediction, and Estimation. Journal of the American Statistical Association, 102, 359–378.
6. Brier, G.W. 1950.Verification of forecasts expressed in terms of probability. Monthly weather review 78: 1–3.
7. Stanski, H. R., Wilson, L. J., and Burrows, W. R. 1989. Survey of common verification methods in meteorology, WMO World Weather Watch Tech Report 8, WMO, Downsview, Ontario, 7189