Seasonal Prediction of Dam Inflows or Droughts in Manitoba Using Large-Scale Climate Drivers (Case Study: Long Spruce & Kettle Station)

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1. Initial Background

Hydropower is the backbone of Manitoba's energy system, supplying electricity through Manitoba Hydro's network of hydroelectric stations. The performance of these systems directly depends on both the amount and timing of water flowing into reservoirs, as fluctuations in river discharge directly affect energy production and operations. Climate factors such as precipitation, temperature, and long-term weather patterns can significantly influence runoff, creating challenges for water resource management and hydropower reliability (Manitoba Hydro, 2023; Dibike et al., 2020).

The goal of this research is to develop a scientific and practical framework for seasonal inflow forecasting for Manitoba's hydroelectric reservoirs, based on large-scale climate indices. This study will collect and analyze historical data on hydrological and climate variables. Hydrological data will be gathered from Government of Canada Website. Prior to analysis, all datasets will be cleaned, checked for completeness, and normalized to remove outliers and ensure consistency (Hannah et al., 2011).

The expected results of this research will be limited to the time, but it may include an understanding of how large-scale climate drivers affect seasonal inflows to Manitoba's reservoirs. This study aims to connect climate science and hydrological modelling. By combining global climate information with local hydrological processes, it contributes to the broader goal of improving energy security, environmental resilience, and sustainable hydropower development in Manitoba and across Canada (IPCC, 2021).

2. Literature Review

Anis and Sauchyn (2022) studied how climate change affects the hydrology of the Assiniboine River Basin in Canada. Using a *multi-model ensemble* of climate and hydrological models, they simulated both current and future conditions. The results showed that warmer temperatures under future climate scenarios will shift the peak river flows earlier to spring and increase uncertainty in summer flows. This highlights how snowmelt-driven basins are sensitive to climate shifts, and why seasonal climate indicators should be used in forecasting inflows for hydropower dams.

Brimelow et al. (2014) analyzed the major 2011 flood in the Assiniboine River Basin to understand what caused it. They used data on rainfall, snow storage, temperature, and soil moisture to recreate the flood events. The study found that heavy pre-season rainfall, quick snowmelt due to rising temperatures, and already saturated soils together led to severe flooding. The results showed that complex interactions between weather and hydrological factors played a key role, and that improved seasonal models are needed to forecast such floods accurately.

Bajracharya et al. (2025) used the HYPE model to study climate change impacts on streamflow in the Nelson–Churchill River Basin in northern Manitoba. After calibrating the model with long-term data, they ran future warming scenarios. The findings showed that higher temperatures will reduce winter runoff and move the flow peaks to early spring, mainly due to earlier snowmelt and changes in permafrost. This means northern basins respond to climate change more through timing shifts than through total water volume, and dam inflow models must include snow, temperature, and permafrost effects.

St. George (2006) analyzed long-term streamflow data in the Winnipeg River Basin to study links between large-scale climate indices and runoff variability. He found that during El Niño winters, lower precipitation and cooler temperatures delay snowmelt and reduce winter flows, while La Niña brings wetter winters and higher spring runoff. This provided early evidence that teleconnections like ENSO and the Arctic Oscillation (AO) affect seasonal river flows and should be used in forecasting models.

Muhammad et al. (2018) developed a combined Ensemble Streamflow Prediction (ESP) system for the Canadian Prairies using both statistical (MLR, ARIMA, SVR) and physical models. With statistical post-processing for bias correction, they reduced forecast errors by 20–30% compared to single models. This shows that multi-model and bias-correction methods can greatly improve seasonal streamflow forecasting, which is especially valuable for hydropower operations in Manitoba.

Muhammad et al. (2020) studied the Prairie Pothole Region, a semi-arid area highly sensitive to seasonal rain and snowmelt. Their calibrated model showed that under warming scenarios, summer flows will drop and peak runoff will shift earlier to spring, raising risks of low reservoir levels and reduced hydropower generation. They emphasized the need for reliable seasonal forecasting systems to better manage dam operations during droughts.

Chandra et al. (2022) created a new Ensemble Quantile-based Deep Learning Framework to predict streamflow and floods in Australia. It used deep neural networks combined with quantile regression to produce probabilistic forecasts, showing uncertainty ranges instead of single values. The model achieved higher accuracy and reliability than traditional methods and effectively captured complex nonlinear relations among climate, rainfall, and runoff. This approach can help manage uncertainty and improve dam inflow forecasting in places like Manitoba.

Majumder and Reich (2023) introduced a Synthetic Likelihood Approximation method with deep neural networks to model extreme and non-stationary flow events. It dynamically estimated time-dependent probability distributions, improving accuracy for floods and very low flows. The method captured spatial-temporal dependencies and complex nonlinear relations between climate and hydrology.

Lee et al. (2022) examined the economic value of seasonal climate forecast skill for hydropower in 22 large global plants. Using performance indices (like NSE, BSS) and economic models, they found that improving forecast accuracy by just 10–15% can greatly boost power planning efficiency and profitability while reducing drought and overflow risks.

Islam et al. (2024) reviewed studies on the climate resilience of dams and water infrastructure across Canada. They found that increasing floods, droughts, and temperature extremes threaten hydropower performance and safety because most existing dams were designed for past climate conditions. They recommended integrating seasonal forecast and early warning systems directly into dam operation and management.

Dibike et al. (2021) proposed a Dynamic Contributing Area model for the Assiniboine River Basin that allows the active runoff-producing area to change over time depending on rainfall, temperature, soil moisture, slope, and land use. This improved the ability to simulate variable and nonlinear runoff patterns under climate change, enhancing seasonal inflow predictions for hydropower systems, including those in Manitoba.

Kim et al. (2020) analyzed climate impacts on runoff and hydropower potential in northern Manitoba. Using long-term data and regional climate models, they found that rising average temperatures cause less winter runoff and earlier spring peaks, increasing seasonal inflow variability and reducing hydropower stability during warm periods.

Zhang et al. (2022) used an Explainable Convolutional Neural Network (CNN) with Grad-CAM to predict floods in China. The method made deep learning models more interpretable by showing which weather patterns influenced the predictions most. It improved accuracy and revealed spatial-temporal factors driving extreme hydrological events, highlighting the value of explainable AI for trustworthy seasonal inflow forecasts.

Shabbar (2006) studied how the Arctic Oscillation (AO) affects temperature and precipitation in Canada. Positive AO phases bring warmer winters and more rain, while negative phases bring colder, snowier winters. These changes alter the snowmelt and runoff timing. Including AO (alongside ENSO and PDO) as *lagged predictors* in forecasting models can improve seasonal streamflow predictions in cold-region basins.

The list of studies mentioned above grouped and summarized under the two main categories based on their focus, methods, and temporal scope in Table-1 & Table-2.

(a) Seasonal-Scale Prediction

These studies emphasize short-term (months to seasons) variability and prediction skill often linking large-scale climate drivers to basin hydrology or testing machine-learning and ensemble models for operational forecasting.

Table-1: Research background abstract (a)

Author(s) & Year	Study Area	Methodology	Main Findings
St. George (2006)	Winnipeg River Basin	Statistical correlation of ENSO phases and flows	El Niño → reduced winter flows La Niña → wetter springs shows seasonal teleconnection.
Shabbar (2006)	Canada (national)	Statistical analysis of Arctic Oscillation	Positive AO → mild, rainy winters Negative AO → cold, snowy useful for seasonal inflow outlooks.
Brimelow et al. (2014)	Assiniboine Flood	Multi-source (rain, snow, soil, temp)	Seasonal hydrometeorological compounding drove flood event.
Muhammad et al. (2018)	Canadian Prairie Region	Combined statistical & physical models	Multi-model blending improved seasonal streamflow forecast skill by 20–30 %.
Chandra et al. (2022)	Australia	Deep-Learning Quantile Regression	Probabilistic forecasts lowered RMSE and captured non-linear rainfall–runoff patterns better.
Majumder & Reich (2023)	Global (surface-flow extremes)	Deep Neural Networks	Enhanced modeling of seasonal extremes reproduced spatial–temporal patterns.
Lee et al. (2022)	Global hydropower	Economic statistical linkage	Seasonal forecast accuracy ↑ 10–15 % → significant operational/economic gains.
Islam et al. (2024)	Canada	Systematic review	Seasonal early-warning systems essential as climate extremes threaten dam safety.

Seasonal-scale studies aim to predict variability within existing climate bounds, critical for operational decisions (hydropower scheduling, flood preparedness).

(b) Climate-Change-Scale Projection of Inflow, Streamflow, and Other Indicators

These studies evaluate long-term (multi-decadal) changes in runoff regimes, snowmelt timing, and water availability under warming scenarios, typically through climate–hydrology coupled models or downscaled RCM projections.

Table-2: Research background abstract, (b)

Author(s) & Year	Study Area	Methodology	Main Findings
Anis & Sauchyn (2022)	Assiniboine River Basin	Multi-model ensemble (climate + hydrology)	Warming advances spring peaks and heightens summer flow uncertainty.
Bajracharya et al. (2025)	Nelson–Churchill River Basin, MB	HYPE hydrological model under warming	Higher temps → less winter runoff, earlier spring peaks permafrost thaw alters flow timing.
Muhammad et al. (2020)	Prairie Pothole Region	Basin hydrologic model future climate scenarios	Warming reduces summer flows; peak shifts to spring; elevated drought/low-storage risks.
Dibike et al. (2021)	Assiniboine River Basin	Dynamic Contributing Area model	Better represents non-linear runoff response under projected climate variability.
Kim et al. (2020)	Northern Manitoba	Observations & Regional Climate Models	Rising temps → reduced winter flows, earlier spring peaks, more unstable inflows.
Zhang et al. (2022)	China	Explainable CNN (Grad-CAM)	Improved flood projection accuracy; identified key climate drivers.

Climate-change-scale studies aim to project long-term trends and shifts, guiding strategic planning and infrastructure adaptation.

3. Objectives

This study aims to design and develop a scientific, data-driven, and generalizable framework for seasonal prediction of inflows to hydropower reservoirs in Manitoba.

To achieve this main goal, the following objectives are defined:

- To gather and combine historical climate and hydrological data
- To examine seasonal climate–streamflow relationships by evaluating how precipitation, temperature, and snowpack influence discharge across different seasons.
- To compare lagged and non-lagged climate predictors and assess which type provides more reliable relationships with seasonal streamflow.
- To evaluate the predictive skill of empirical seasonal models using the Climate Predictability Tool (CPT) for both stations and identify which climate variables offer meaningful forecasting value.
- To determine the role of winter and spring snow accumulation in shaping spring and summer flows and quantify the basin's hydrologic memory.
- To develop a consistent methodological framework for seasonal streamflow analysis that can be applied to other snow-dominated basins in northern Manitoba.
- To support hydropower management and climate-risk assessment by providing insights that can improve seasonal operational planning and water-resource

4. Research Questions & Hypotheses

Given the importance of accurate inflow forecasting for Manitoba's hydropower system and the role of large-scale climate variability, this research seeks to answer the following questions.

- How do long-term streamflow patterns behave at the Kettle and Long Spruce stations, and do they show any significant trends over the 2000–2023 period?
- What are the seasonal relationships between precipitation, temperature, snowpack, and streamflow in snow-dominated basins of northern Manitoba?
- Do lagged climate variables explain seasonal streamflow more effectively than same-season climate inputs?
- How well can seasonal streamflow be predicted using empirical models such as the Climate Predictability Tool (CPT)?
- Which climate factors provide the strongest predictive signals for high-flow and low-flow seasons?

The answers will guide hypothesis testing and framework development:

- Seasonal streamflow at both Kettle and Long Spruce is strongly controlled by winter and spring snow accumulation.
- Lagged climate variables will show stronger correlations with streamflow than non-lagged.
- Same-season climate conditions, especially precipitation, will have weak predictive value for streamflow.
- The hydrologic mechanisms controlling streamflow will be similar at both stations due to close location of the stations

Study Area

The province of Manitoba, located in central Canada, is one of the main centers of hydropower generation in North America. (Fig.1)

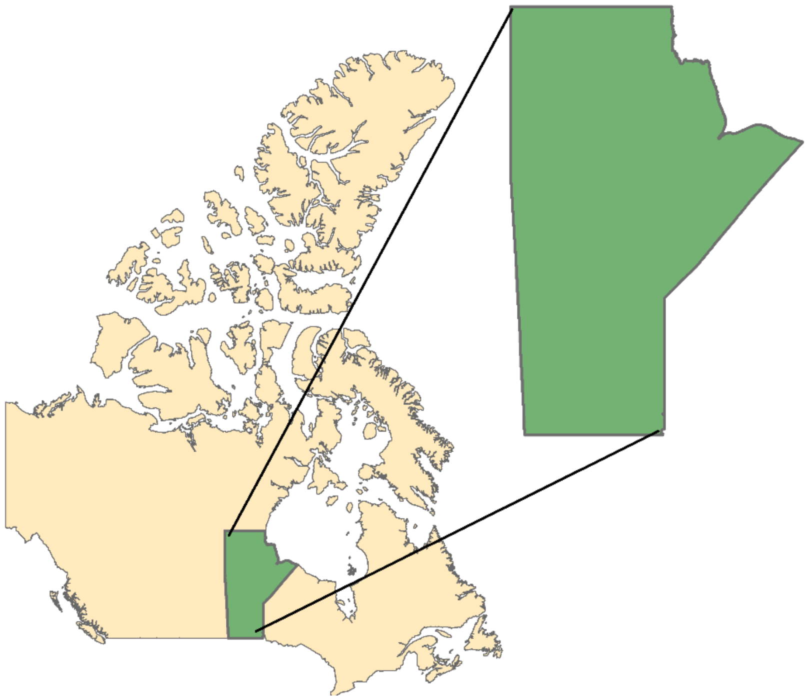


Fig.1 Manitoba Location

The study area in this research includes the Nelson-Churchill River Basin and the Assiniboine River Basin, the main sources of water for Manitoba's major hydroelectric stations, including Limestone, Kettle, Long Spruce, Jenpeg, and Grand Rapids. These river systems play a crucial role in maintaining the province's energy network and managing its water resources.

Geographically, the central area of the study is located at approximately 53.7609° N latitude and 98.8139° W longitude. According to Canada's climate classification, the region has a cold, semi-humid climate, characterized by long, extremely cold winters with average temperatures below zero, and short, humid summers. In northern Manitoba, the climate is influenced by heavy winter snow accumulation, while the southern regions are more affected by atmospheric systems originating from the Pacific Ocean and the North Atlantic.

These climatic and topographic variations create a complex and diverse hydrological pattern across Manitoba's watersheds. Understanding the relationships between large-scale climate indices and seasonal runoff fluctuations in this region is essential for accurate reservoir inflow forecasting, effective water resource management, and the long-term stability of hydropower production.

The fig.2 shows the hydrological and hydroelectric system of Manitoba, highlighting the major rivers, lakes, and dams within the Nelson–Churchill River Basin. The red outline marks the basin boundary inside Manitoba, while the grey area shows the rest of the province. Blue areas represent lakes, and the cyan lines show the river network, with the two main rivers, Rivière Nelson and Rivière Churchill, shown in dark blue. Yellow stars indicate key hydropower stations along the Nelson River, including major facilities such as Kelsey, Kettle Rapids and Long Spruce. Red dots mark additional dam locations from the GRanD database, numbered 1 to 14 and listed in the legend.

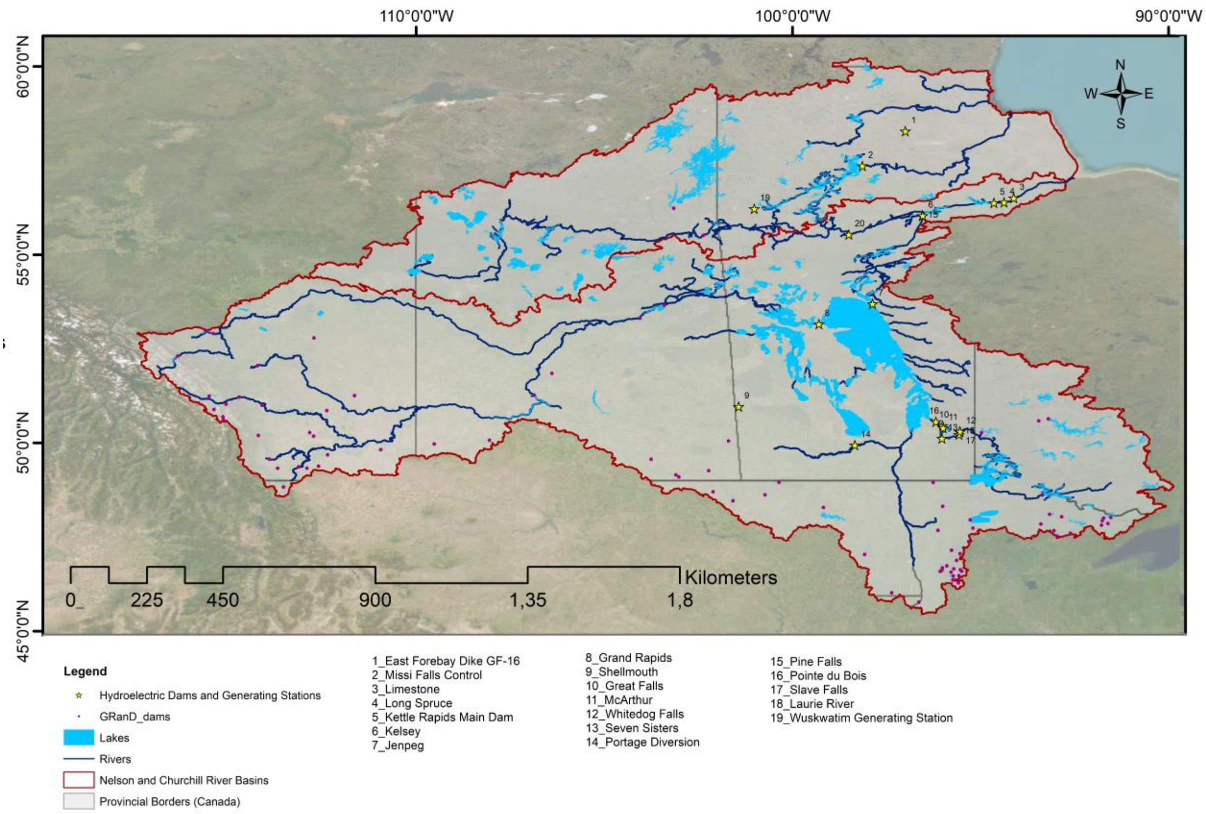


Fig2. Map of the Churchill and Nelson River Basins in Manitoba, Hydroelectric Dams

5. Research Methodology and Data and Information Sources

In this study, the same overall analytical framework was applied to both the Kettle and Long Spruce stations, while all steps were reprocessed separately to account for each station's unique data characteristics. For both sites, several years of climate and hydrologic records including precipitation, snow, temperature, and river discharge were collected, quality-checked, corrected for possible errors, and time-standardized.

To evaluate how climate conditions influence seasonal streamflow, two groups of predictor variables were created: lagged (lag-1) variables and no-lag variables. In the lag-1 models, precipitation and snow from the previous winter or spring were used as predictors for the following season's discharge. This approach reflects well-documented behavior in northern, snow-dominated systems, where much of the warm-season flow originates from the previous year's cold-season accumulation rather than from same-season precipitation (Pomeroy & Gray, 1995). In contrast, the no-lag predictors tested the immediate, same-season relationships between climate conditions and discharge. Using both approaches made it possible to compare short-term climate responses with longer-term storage-driven processes at each station.

Model development and evaluation for both stations were completed using the Climate Predictability Tool (CPT), a widely used tool for empirical climate modelling, regression, correlation analysis, and skill assessment (IRI, 2023; Mekis & Vincent, 2011). Seasonal predictor and predictand datasets for each station were imported into CPT, and outputs such as scatterplots, regression lines, and correlation scores were generated for both lagged and no-lag cases. Evaluation metrics, including correlation coefficients, R^2 values, and the ability of each model to distinguish between high-flow and low-flow seasons, were calculated to confirm statistical validity.

7. Expected Outcomes and Impacts

We expect this study to show how large-scale climate patterns affect streamflow in Manitoba's northern basins. By linking climate data with hydrologic records, the research should explain seasonal inflow changes more clearly and identify which climate indices provide the strongest forecasting signals. The results will likely show that lagged climate variables improve seasonal inflow predictions, especially for detecting low-flow or dry periods.

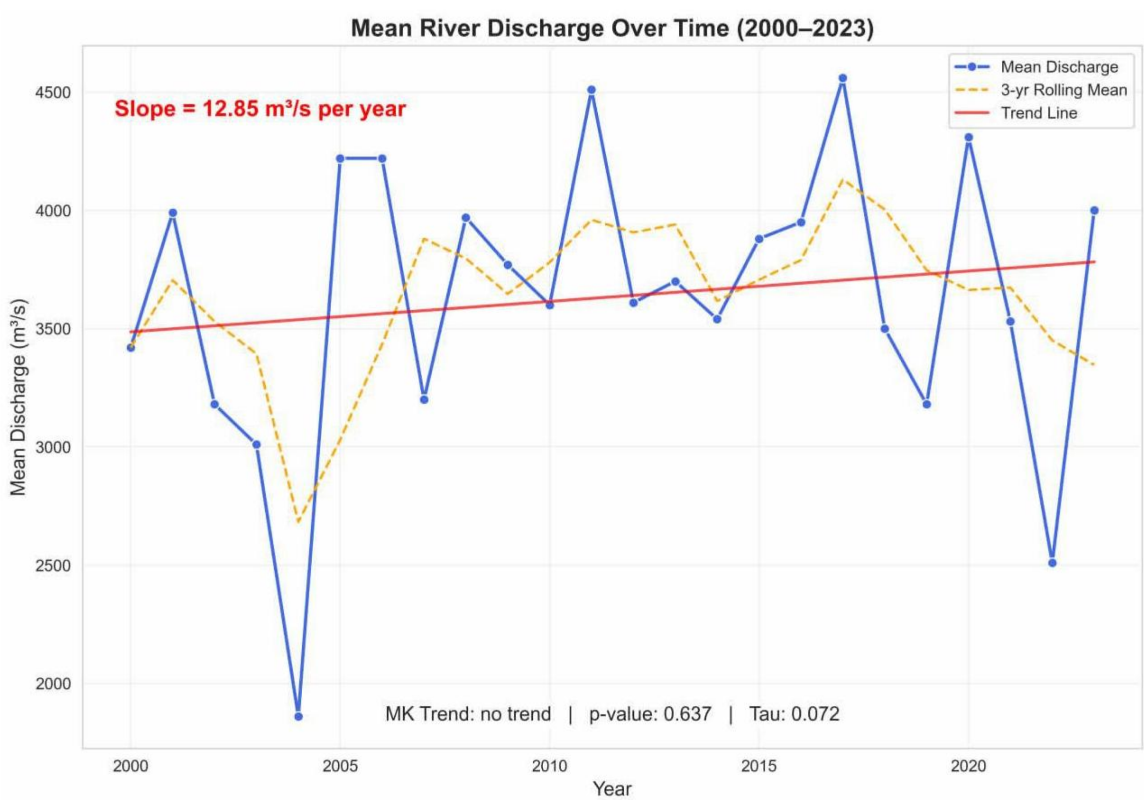
These insights will help Manitoba Hydro improve reservoir operations, scheduling, and early-warning decisions for droughts or floods. The study will also support long-term climate adaptation planning and offer a framework that can be used in other cold, snow-dominated watersheds. Overall, the findings will guide better risk management and make hydropower operations more reliable and efficient.

Discussion-1: Long Spruce Station

Time-Series Analysis of Annual Discharge (2000–2023):

The annual discharge trend from 2000 to 2023 shows noticeable year-to-year fluctuations, but the overall system remains stable with no clear long-term increase. Although the linear trend line indicates a small positive slope of about 12.85 cubic metres per second per year, the Mann–Kendall test (p = 0.637) confirms that this trend is not statistically significant. In other words, the variability from one year to the next is mainly driven by natural climate conditions rather than any long-term shift in the river system.

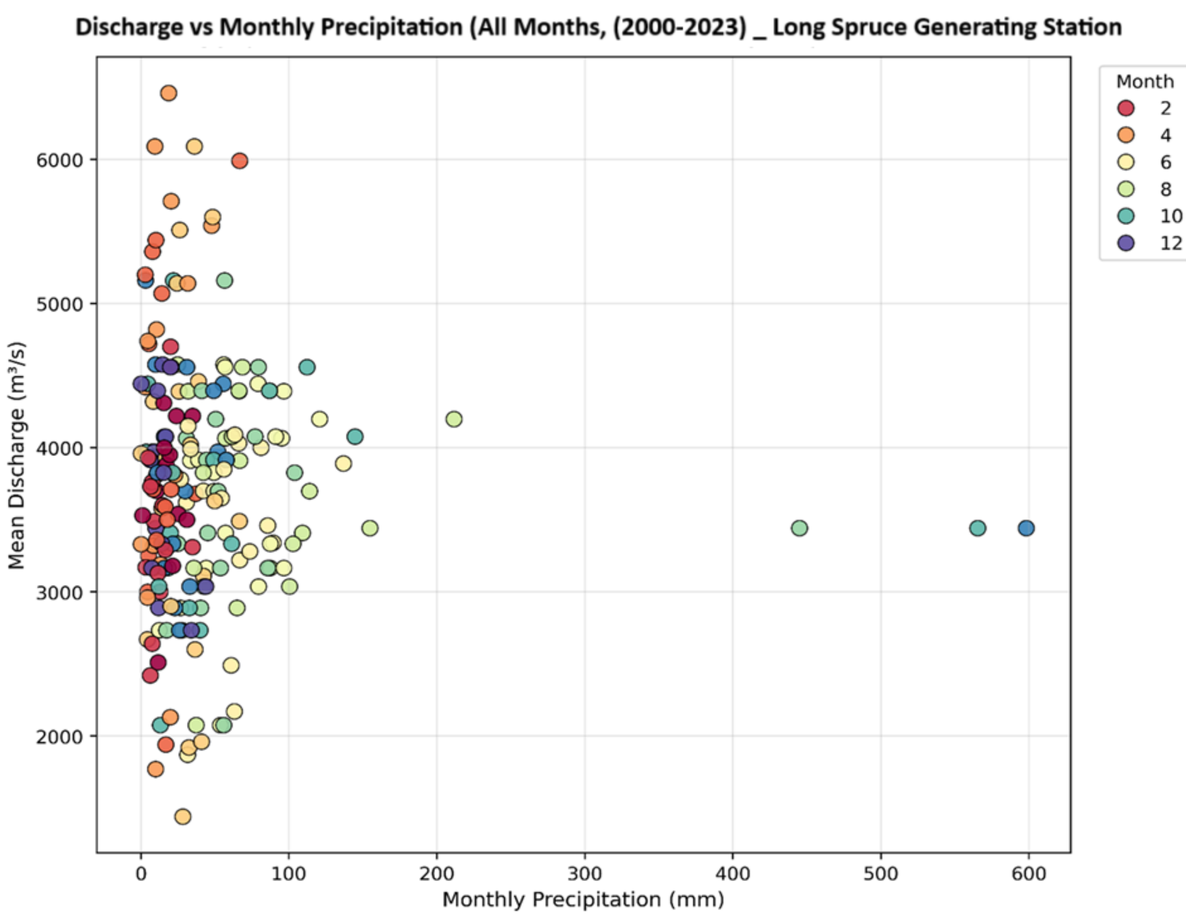
The sharp decreases in flow observed in certain years (around 2005 and 2020) are likely linked to specific climate events in those periods rather than structural changes in the watershed. The three-year moving average also shows that short-term variations remain relatively stable when compared with the long-term mean.



Analysis of the Relationship Between Monthly Precipitation and River Discharge (All Months, 2000–2023):

The scatterplot showing the relationship between monthly precipitation and river discharge across all months indicates that there is no clear or direct connection between same-month rainfall and discharge. The points are widely scattered without forming a recognizable pattern or linear trend. This suggests that monthly discharge in this basin is influenced more by accumulated snow, snowmelt processes, and pre-season moisture conditions than by immediate, month-to-month precipitation.

The distribution of points by month also shows that even during periods with higher precipitation, the river does not necessarily respond right away. This behaviour is consistent with the characteristics of Manitoba's snow-dominated basins, where the influence of cold-season precipitation or the previous year's snowpack is typically much stronger than the effect of short-term rainfall.

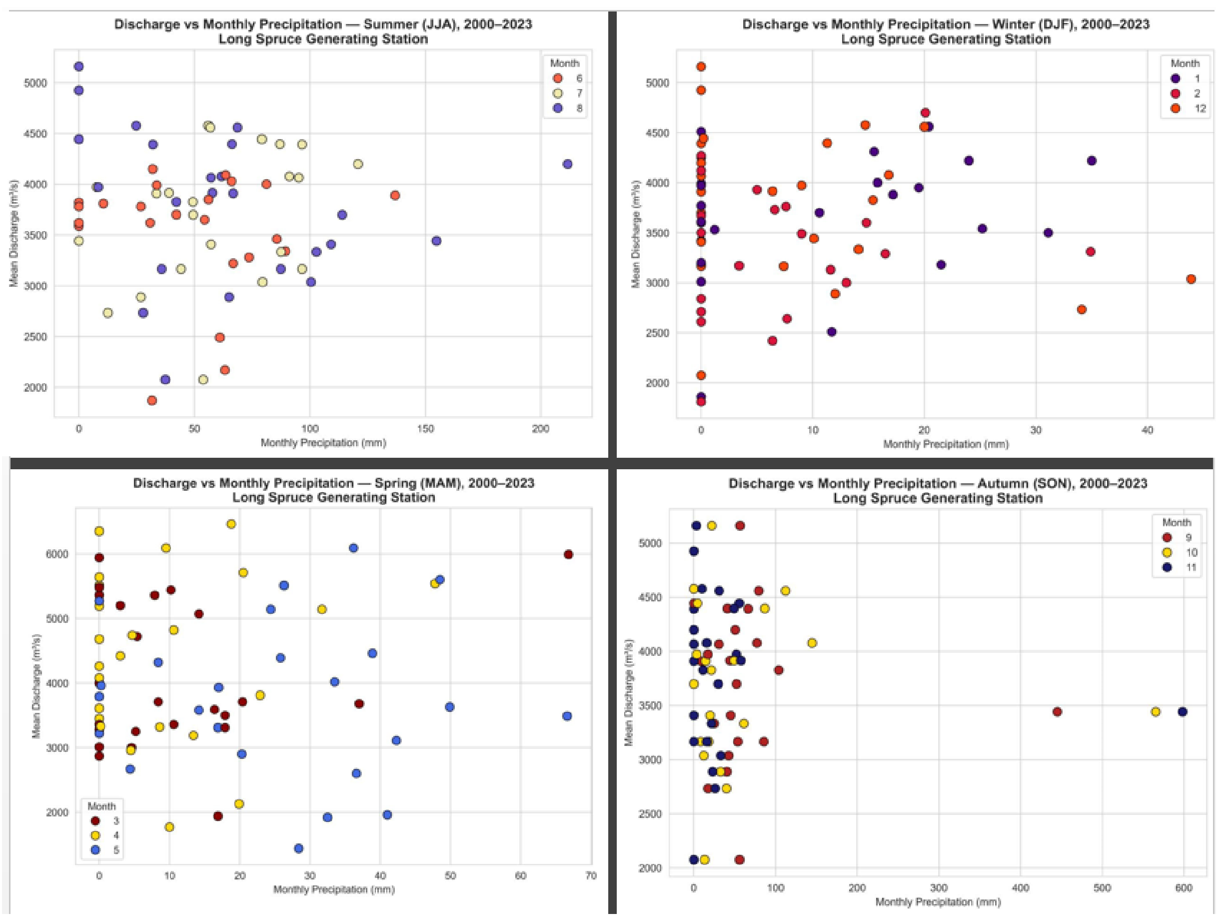


Integrated Analysis of the Four Seasonal Precipitation–Discharge Plots: (JJA, DJF, MAM, SON)

A review of the four seasonal plots shows that there is no clear or reliable relationship between seasonal precipitation and discharge within the same season. In all four cases, the scatter of points is wide and irregular, indicating that seasonal precipitation does not directly control the seasonal flow.

During summer (JJA), precipitation varies across the season, yet discharge largely follows its own pattern, reflecting the stronger influence of winter conditions and the remaining snowpack from the previous year. In winter (DJF), even though precipitation is very low, discharge stays within a relatively narrow range. This is expected because most winter precipitation is stored as snow and does not immediately contribute to river flow.

In spring (MAM), discharge rises sharply while spring precipitation remains relatively low. This pattern is consistent with the natural effect of snowmelt, which drives the seasonal increase in flow rather than same-season rainfall. Autumn (SON) shows a similar behaviour: even when precipitation increases, there is no notable or immediate change in discharge.



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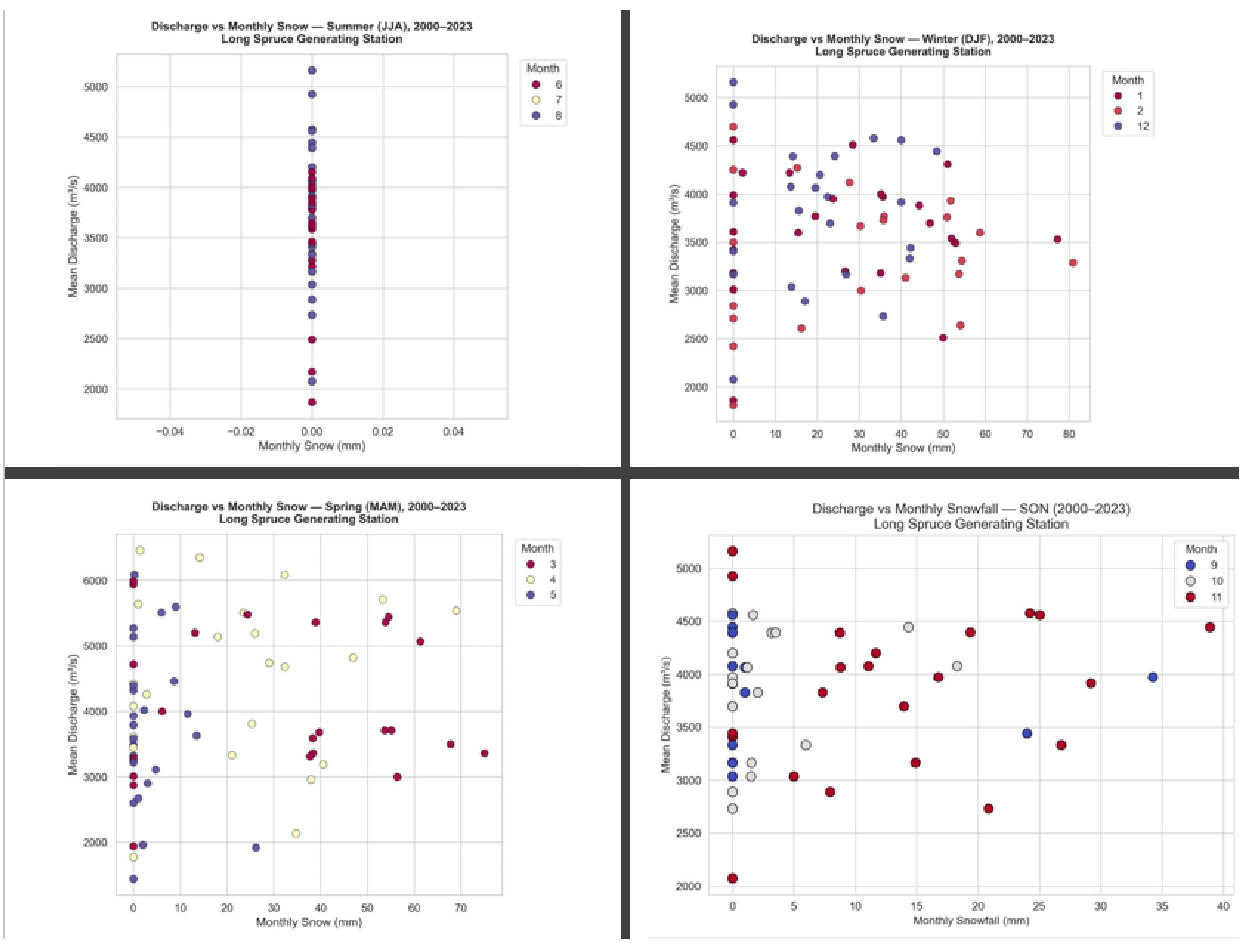
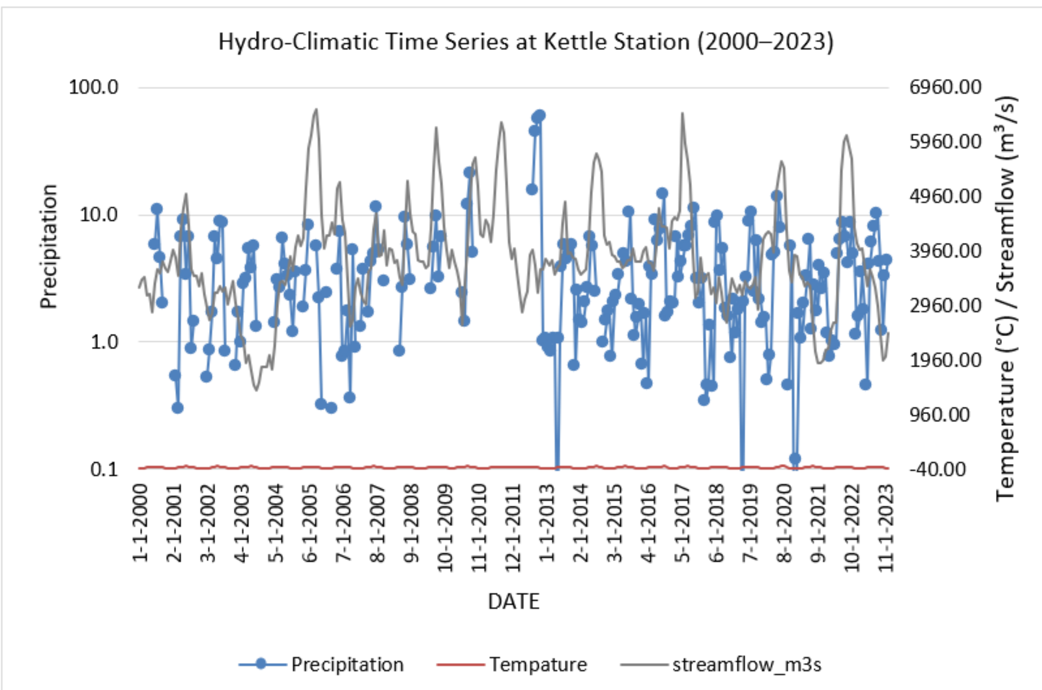


Discussion-1: Long Spruce Station

Time-Series Analysis of Precipitation, Temperature, and Discharge:

These two plots clearly show that changes in river discharge are influenced more by temperature and the amount of stored winter snow than by short-term precipitation. In the first plot, despite large fluctuations in rainfall, the river flow follows a smoother pattern and aligns more closely with temperature variations. This indicates that the system does not respond quickly to immediate rainfall.

The second plot reinforces this interpretation: when temperatures rise and snow begins to melt, discharge increases even if rainfall remains low. Together, these plots demonstrate that river behaviour in this region is primarily driven by snowmelt and seasonal conditions rather than same-month precipitation.



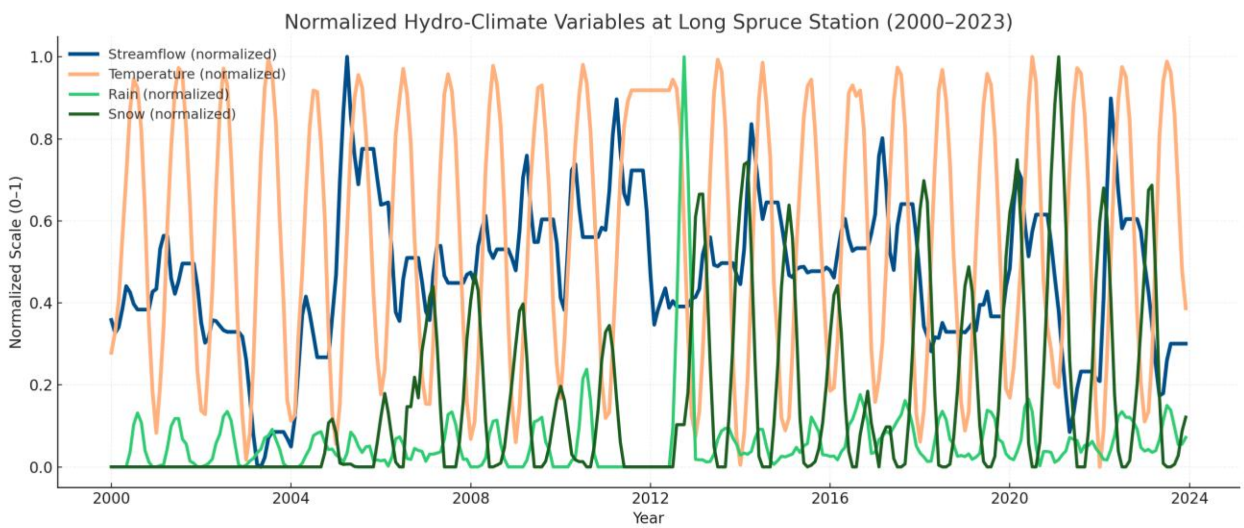
Discussion-1: Long Spruce Station

Analysis of the Normalized Variable Plot:

This plot illustrates the annual cycle of temperature, precipitation, snow, and discharge at the Long Spruce station. It clearly shows that river flow aligns much more closely with temperature changes and snowmelt than with short-term rainfall events. Temperature follows a consistent yearly rise-and-fall pattern, and as temperatures increase, snow depth declines while discharge rises.

In contrast, rainfall fluctuates in short, irregular bursts that do not produce a clear or lasting effect on long-term discharge behaviour. Snow increases through the cold half of the year and approaches zero as warmer conditions arrive; this decline is typically accompanied by a peak in river flow.

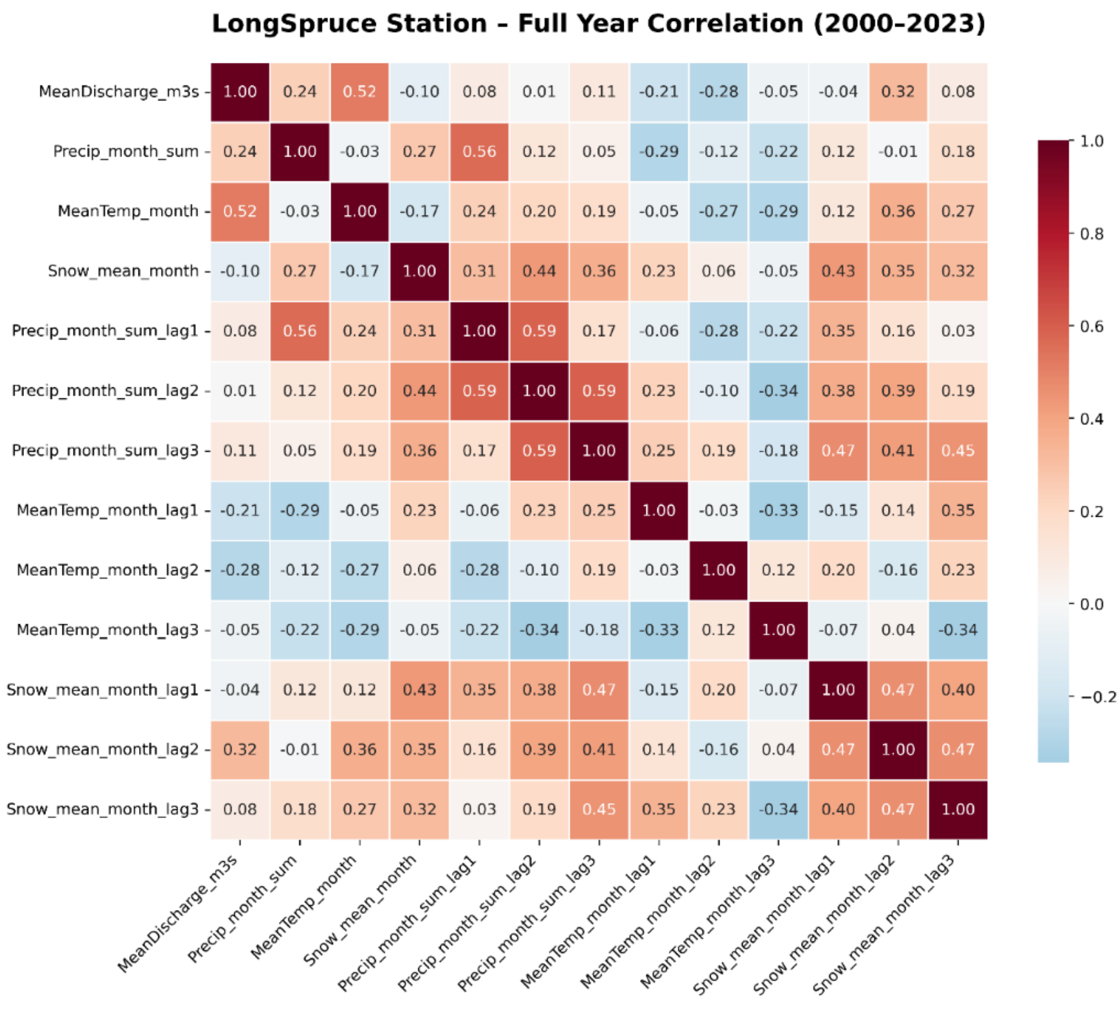
Comparing these four variables on a normalized scale demonstrates that, similar to other snow-dominated basins in the region, the timing of discharge at Long Spruce is controlled primarily by winter snowpack and seasonal temperature patterns rather than by immediate precipitation. Snowmelt emerges as the dominant driver of discharge variability.



Annual Correlation Plot Analysis:

The annual correlation plot for the Long Spruce station shows that monthly river discharge is influenced mainly by temperature and the cumulative effects of precipitation and snow. The plot indicates a negative relationship between current-month temperature and discharge: in warmer months, flow tends to be lower. This pattern is typical in cold regions, where higher temperatures increase evaporation and reduce available moisture storage.

Current-month precipitation shows a positive correlation with discharge, but the strength of this relationship is relatively weak. This is expected because, for much of the year, a portion of the precipitation falls as snow and does not immediately contribute to runoff. Similarly, same-month snow depth does not exhibit a strong direct relationship with discharge. However, snow from previous months (lag variables) displays a much more consistent pattern, highlighting the importance of accumulated snowpack in shaping the hydrologic response of the basin.



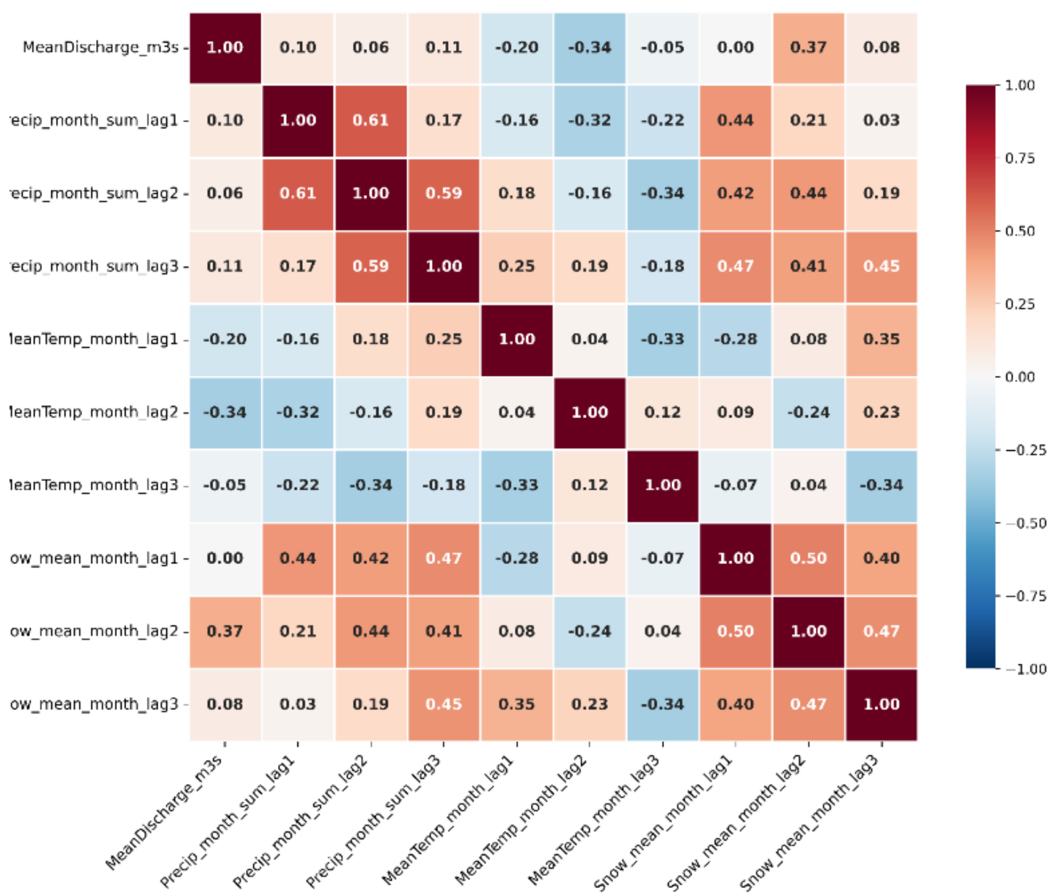
Discussion-1: Long Spruce Station

Winter Correlation Plot Analysis:

The winter correlation plot shows that river behaviour during the cold season is influenced far more by conditions from the previous one or two months than by the climate of the current month. Winter discharge has a negative relationship with temperatures from earlier months, meaning that when colder conditions occur before winter, inflows tend to decrease. This pattern aligns with the regional climate, where lower temperatures increase freezing, reduce surface runoff, and limit how much water enters the river system.

The precipitation lags also display a clear pattern: the lagged precipitation variables are strongly correlated with each other, indicating that winter precipitation generally follows a steady trend. However, this precipitation does not translate into higher winter discharge because much of it is stored as snow and will not contribute to runoff until the spring melt.

Similarly, the snow lags show relatively stable behaviour, highlighting that the winter snowpack changes gradually over time. Snow depth mainly functions as a storage component rather than a direct driver of winter discharge.



Summary of the Seasonal Lag Analysis

When the data were examined together, it became clear that summer discharge depends much more on the previous winter and spring conditions than on same-season precipitation. In years with a larger winter snowpack, summer flows were generally higher, and this pattern persisted throughout the study period. In other words, the main source of summer water is already stored in the basin before the season begins.

Based on this behaviour, two types of models were tested:
(1) **Lag-1 models**, which used climate information from the preceding seasons, and
(2) **No-lag models**, which relied only on summer conditions.

The lag-based models performed significantly better and were able to distinguish high-flow and low-flow summers with reasonable accuracy. This outcome is consistent with the hydrologic characteristics of the basin, where summer receives very little new input and streamflow is dominated by earlier accumulation and melt processes. Overall, using previous-year climate data provides a much clearer description of summer discharge behaviour.

No-Lag Models (for Comparison Only)

When only summer precipitation or summer snow values were used in the models and compared with summer discharge, no meaningful relationships emerged. In most years, summer flow behaved independently from rainfall, and in some cases the relationship even appeared negative. This result matches the regional climate: the basin has no snow accumulation in summer, and summer rainfall events tend to be short and hydrologically weak.

As a result, summer discharge is influenced mainly by pre-season conditions rather than by immediate summer inputs. For this reason, the no-lag models performed poorly and were unable to reliably separate high-flow and low-flow years.

Seasonal Forecasting of Summer Discharge Using Previous Winter Precipitation

Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	8	0	8
	B	0	4	2	6
Total		0	18	2	20

Contingency table:

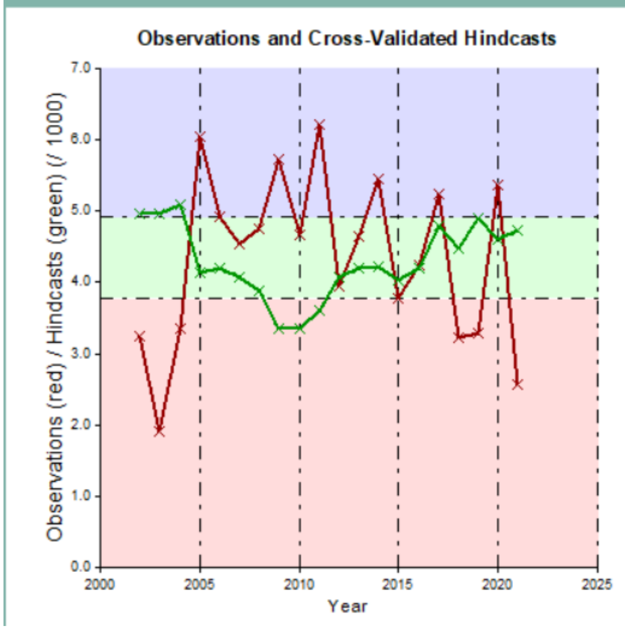
		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	33%	0%	30%
	N	0%	44%	0%	40%
	B	0%	22%	100%	30%
	All	0%	90%	10%	100%

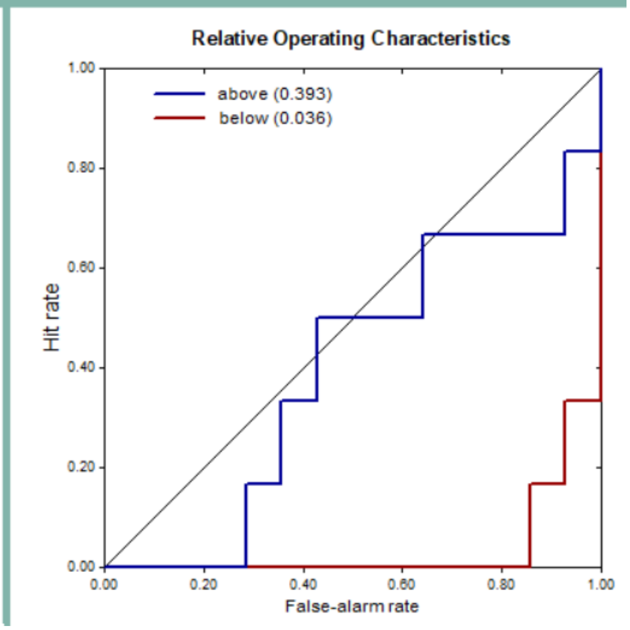
Continuous measures:

Pearson's correlation	-0.6337
Spearman's correlation	-0.5639
2AFC score (continuous)	31.05%
% variance	0.40%
Variance ratio	0.1964
Mean bias	-63.76
Root mean squared error	1519.85
Mean absolute error	1259.05

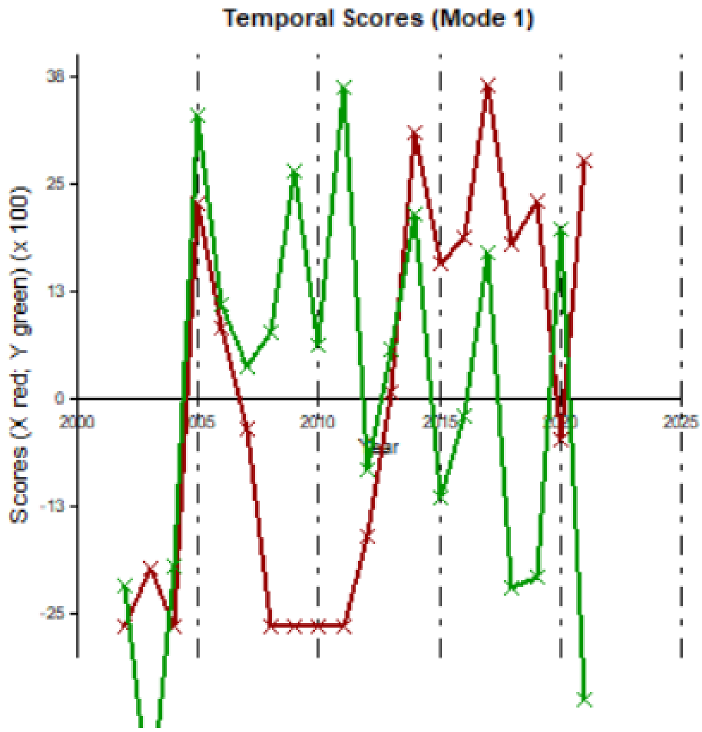
Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	-7.14%
Gerrity score	-7.14%
2AFC (forecast categories)	39.39%
2AFC (continuous forecasts)	25.00%
ROC area (below-normal)	0.0357
ROC area (above-normal)	0.3929





Discussion-1: Long Spruce Station



These figures show that the seasonal model using winter precipitation to predict summer streamflow at Long Spruce has limited accuracy. Continuous statistics are weak and showing the model cannot reproduce actual discharge. Frequency and contingency tables indicate some correct dry and near-normal classifications, and categorical skill is moderate for identifying below-normal summers, supported by a strong ROC area of 0.83, though above-normal skill is poor.

The hindcast plot shows that the model captures general dry/wet patterns in a few years but misses many year-to-year changes. Temporal scores also show only partial agreement with observed variability, reflecting a weak physical link between winter precipitation and summer flow.

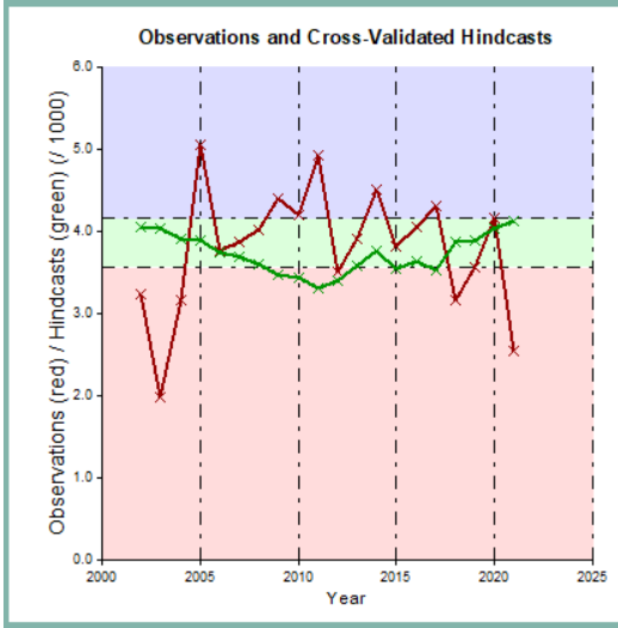
Seasonal prediction of summer streamflow using previous spring precipitation:

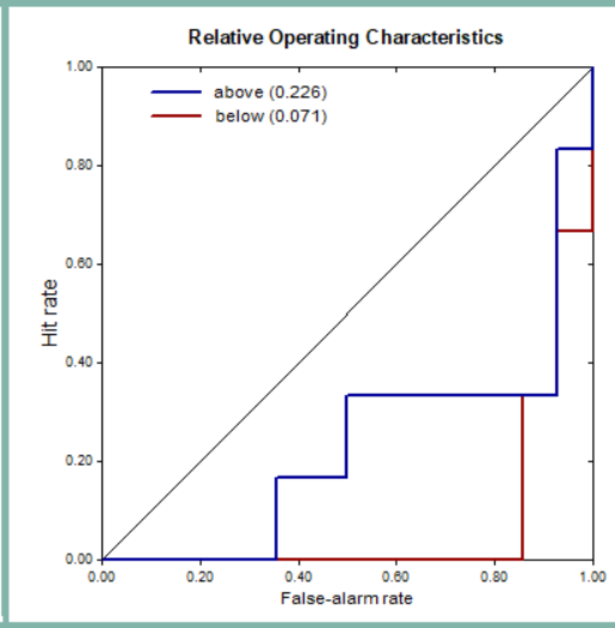
Continuous measures:

Pearson's correlation	-0.5730
Spearman's correlation	-0.4932
2AFC score (continuous)	31.58%
% variance	0.33%
Variance ratio	0.1058
Mean bias	-83.05
Root mean squared error	888.42
Mean absolute error	707.18

Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	-7.14%
Gerrity score	-7.14%
2AFC (forecast categories)	39.39%
2AFC (continuous forecasts)	17.42%
ROC area (below-normal)	0.0714
ROC area (above-normal)	0.2262





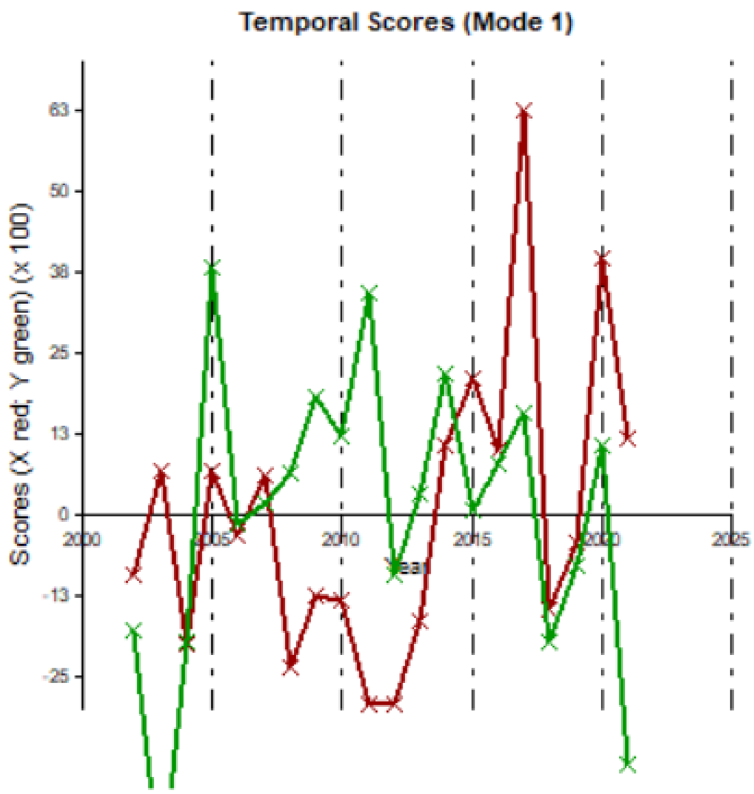
Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	2	4	0	6
	N	0	8	0	8
	B	0	6	0	6
Total		2	18	0	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	100%	22%	0%	30%
	N	0%	44%	0%	40%
	B	0%	33%	0%	30%
All		10%	90%	0%	100%

Discussion-1: Long Spruce Station



These figures show the performance of a seasonal forecasting model that predicts summer streamflow using previous spring precipitation at the Long Spruce station. The continuous statistics indicate weak model performance: both Pearson and Spearman correlations are negative, the variance ratio is very low, and the RMSE and MAE values are relatively large, showing that the model cannot closely reproduce actual discharge values.

The categorical skill scores, however, show limited but noticeable ability to classify streamflow categories, with modest hit scores and a 2AFC categorical skill of about 39%. The ROC diagram indicates very weak forecasting skill for both above-normal and below-normal categories, as the ROC areas (0.226 and 0.071) are close to or below random chance.

Seasonal prediction of winter streamflow using previous autumn precipitation:

Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	1	5	0	6
	N	1	5	1	7
	B	0	7	0	7
Total		2	17	1	20

Contingency table:

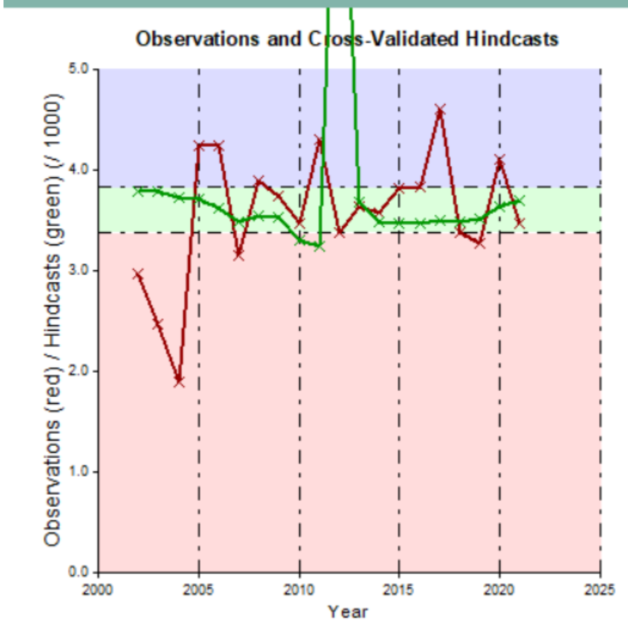
		Forecast B	Forecast N	Forecast A	All
Observed	A	50%	29%	0%	30%
	N	50%	29%	100%	35%
	B	0%	41%	0%	35%
	All	10%	85%	5%	100%

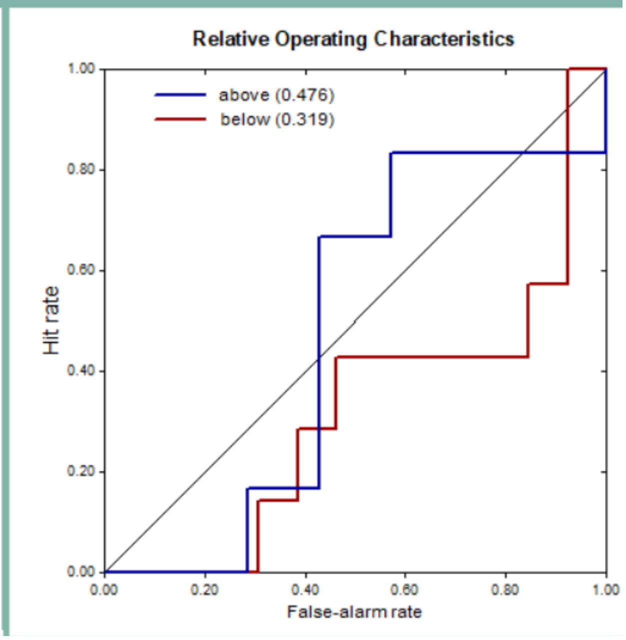
Continuous measures:

Pearson's correlation	-0.1292
Spearman's correlation	-0.3820
2AFC score (continuous)	38.42%
% variance	0.02%
Variance ratio	2.8681
Mean bias	231.61
Root mean squared error	1319.24
Mean absolute error	762.82

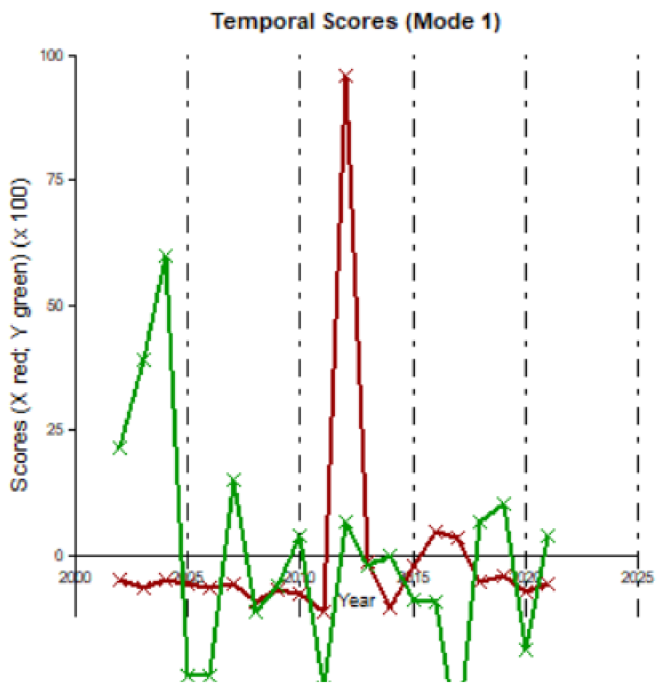
Categorical measures:

Hit score	25.00%
Hit skill score	-25.00%
LEPS score	-9.32%
Gerrity score	-11.26%
2AFC (forecast categories)	45.11%
2AFC (continuous forecasts)	40.60%
ROC area (below-normal)	0.3187
ROC area (above-normal)	0.4762





Discussion-1: Long Spruce Station



These figures present the performance of a seasonal forecasting model that predicts winter streamflow using previous autumn precipitation at the Long Spruce station, and together they show that the predictive skill of this model is limited and inconsistent.

The continuous statistics confirm this weakness: both Pearson and Spearman correlations are slightly negative, the explained variance is extremely low, and the RMSE and MAE values are high, meaning the model cannot reproduce observed discharge values well.

The categorical skill scores also show modest to poor performance, with low hit scores and negative LEPS values, though the 2AFC categorical score of about 45% suggests the model has some weak discrimination ability. The ROC curves further illustrate the imbalance, with better skill for forecasting above-normal winters than below-normal ones, but still only marginally better than random guessing.

The hindcast plot highlights that observed and predicted flows diverge substantially in many years, showing little alignment except in a few isolated periods.

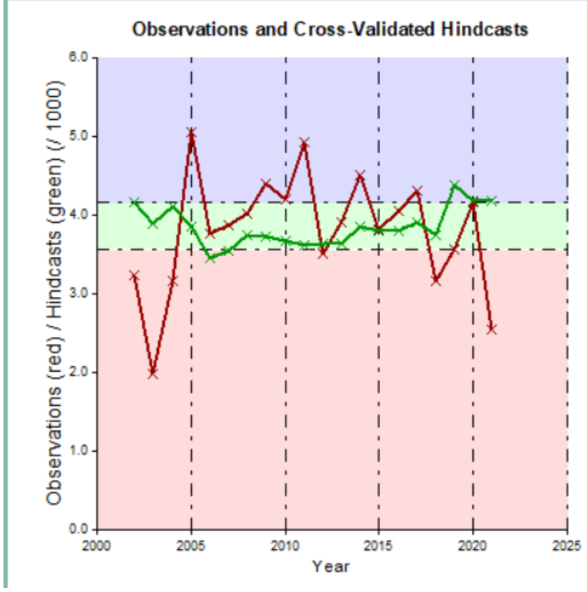
Seasonal prediction of summer streamflow using previous winter snow:

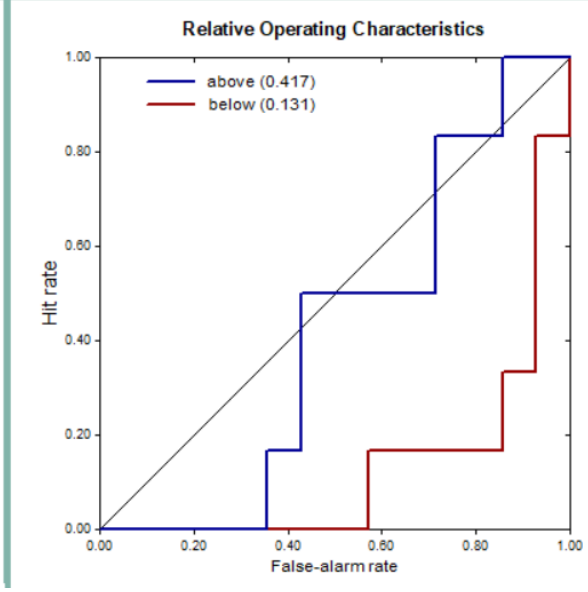
Continuous measures:

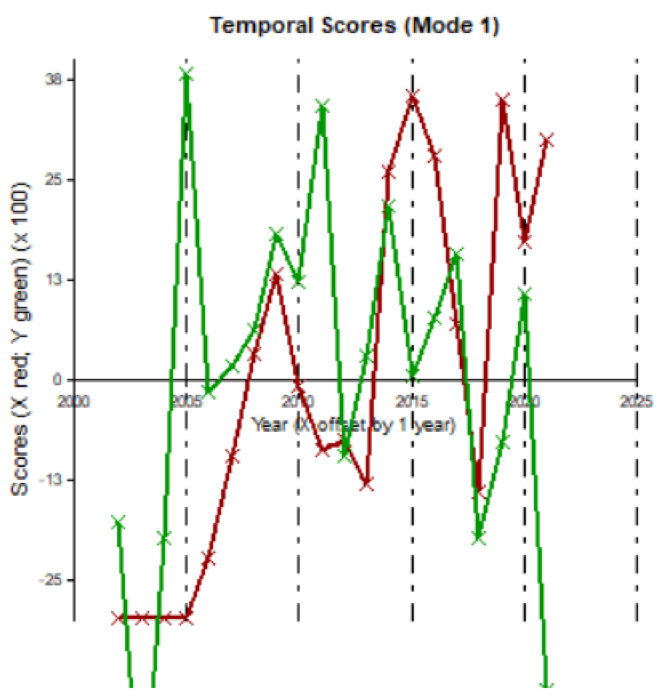
Pearson's correlation	-0.3278
Spearman's correlation	-0.2331
2AFC score (continuous)	44.74%
% variance	0.11%
Variance ratio	0.1095
Mean bias	38.25
Root mean squared error	838.69
Mean absolute error	663.40

Categorical measures:

Hit score	35.00%
Hit skill score	2.50%
LEPS score	-4.46%
Gerrity score	-7.14%
2AFC (forecast categories)	45.08%
2AFC (continuous forecasts)	31.82%
ROC area (below-normal)	0.1310
ROC area (above-normal)	0.4167







Discussion-1: Long Spruce Station

Frequency table:

		Forecast			
		B	N	A	Total
Observed	A	0	6	0	6
	N	1	7	0	8
	B	0	5	1	6
Total		1	18	1	20

Contingency table:

		Forecast			
		B	N	A	All
Observed	A	0%	33%	0%	30%
	N	100%	39%	0%	40%
	B	0%	28%	100%	30%
All		5%	90%	5%	100%

These figures evaluate the skill of a seasonal forecasting model that predicts summer streamflow using previous winter snow at the Long Spruce station.

The continuous statistics indicate low forecasting accuracy: Pearson and Spearman correlations are slightly negative, the explained variance is extremely small, and the RMSE and MAE values remain high, meaning the model cannot reproduce observed discharge magnitudes well.

The hindcast plot shows that although predicted values do not match observations closely, the model occasionally captures general shifts between wetter and drier periods. The ROC curves further highlight asymmetry in skill, with better performance for above-normal years than below-normal ones. The temporal scores plot reveals partial alignment between the model's leading variability mode and the observed signal, but strong mismatches remain, especially in years with sharp hydro-climatic changes.

Discussion-1: Long Spruce Station

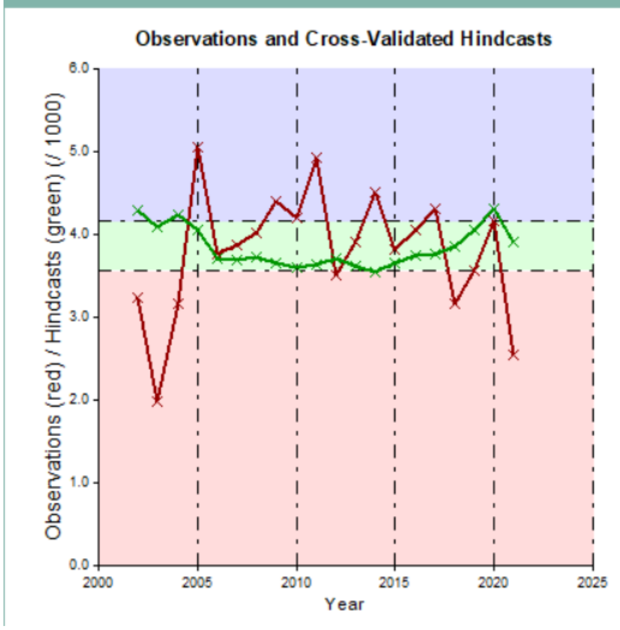
Seasonal prediction of summer streamflow using previous spring snow:

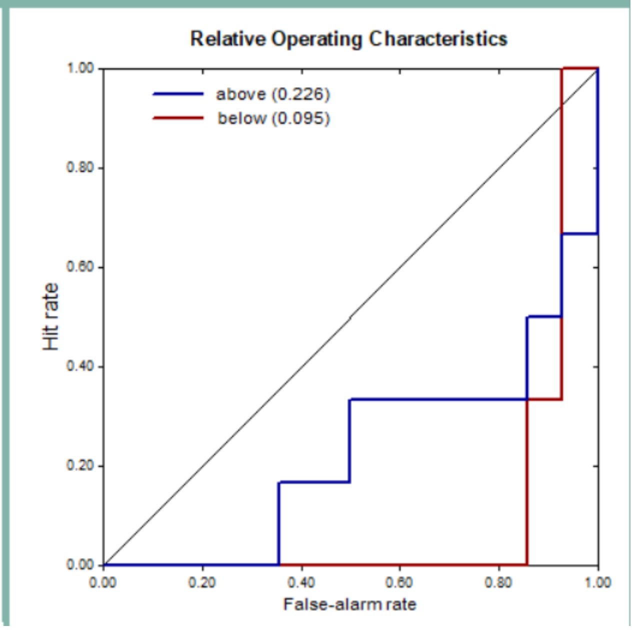
Continuous measures:

Pearson's correlation	-0.4122
Spearman's correlation	-0.4707
2AFC score (continuous)	33.68%
% variance	0.17%
Variance ratio	0.1075
Mean bias	35.04
Root mean squared error	854.61
Mean absolute error	681.22

Categorical measures:

Hit score	35.00%
Hit skill score	2.50%
LEPS score	-9.82%
Gerrity score	-10.71%
2AFC (forecast categories)	39.39%
2AFC (continuous forecasts)	18.94%
ROC area (below-normal)	0.0952
ROC area (above-normal)	0.2262



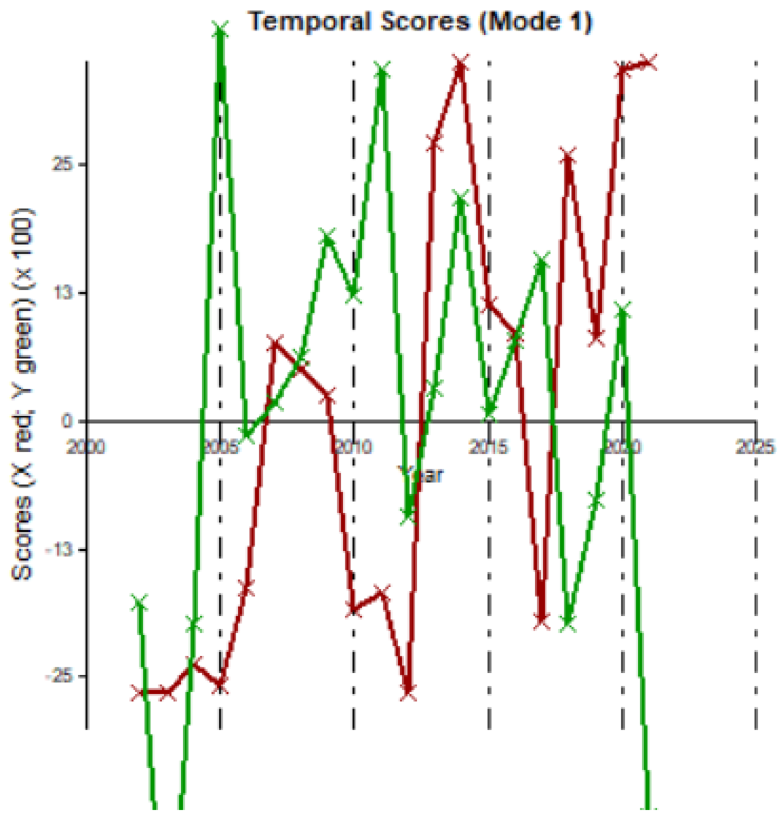


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	7	1	8
	B	0	4	2	6
Total		0	17	3	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	35%	0%	30%
	N	0%	41%	33%	40%
	B	0%	24%	67%	30%
All		0%	85%	15%	100%



These figures assess the seasonal forecasting skill of <u>predicting summer streamflow using previous spring snow at the Long Spruce station.</u>

The categorical skill measures show slightly better but still modest performance, with a hit score of 35% and a 2AFC categorical score of about 39%, suggesting that spring snow contains some, but very limited, information about summer flow. The ROC curves highlight this weakness clearly ROC areas for both above-normal (0.23) and below-normal (0.095) categories fall close to or below random chance, indicating little discriminatory skill.

The hindcast time series shows that predictions only occasionally follow broad shifts in the observed flow but often diverge substantially across years, missing several peaks and troughs. Meanwhile, the temporal scores plot reveals partial alignment between the model's leading variability mode and the observed discharge signal, but the relationship is inconsistent and unstable over time.

No-lag models:

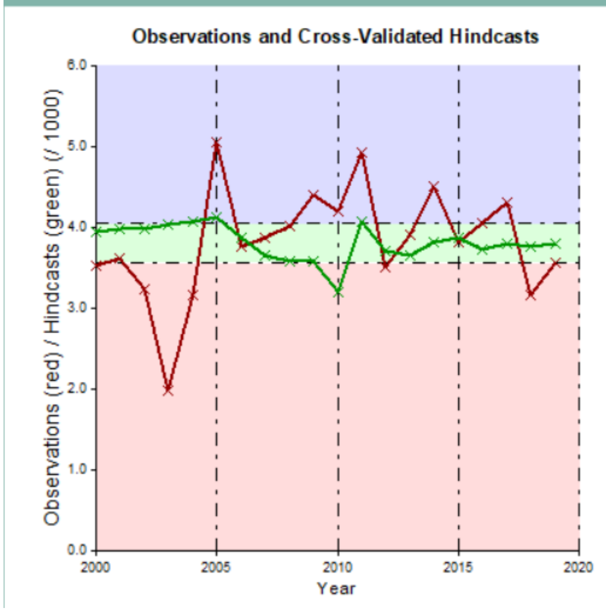
Summary streamflow prediction

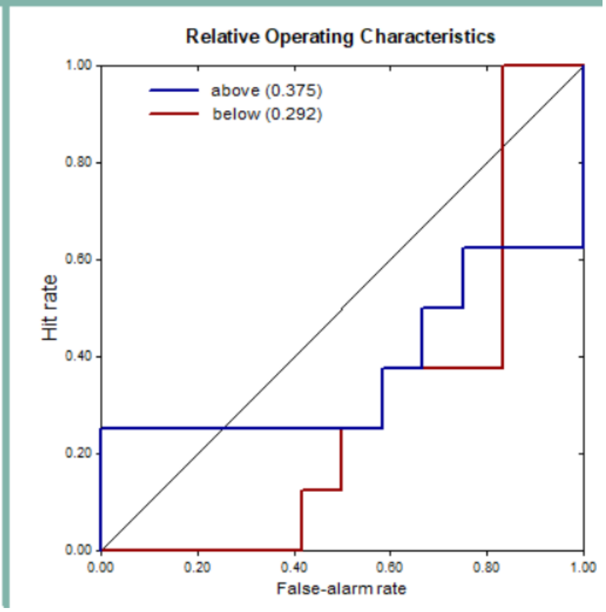
Continuous measures:

Pearson's correlation	-0.1657
Spearman's correlation	-0.1684
2AFC score (continuous)	41.58%
% variance	0.03%
Variance ratio	0.1009
Mean bias	-14.97
Root mean squared error	736.00
Mean absolute error	587.06

Categorical measures:

Hit score	25.00%
Hit skill score	-25.00%
LEPS score	-3.68%
Gerrity score	2.08%
2AFC (forecast categories)	50.00%
2AFC (continuous forecasts)	32.81%
ROC area (below-normal)	0.2917
ROC area (above-normal)	0.3750



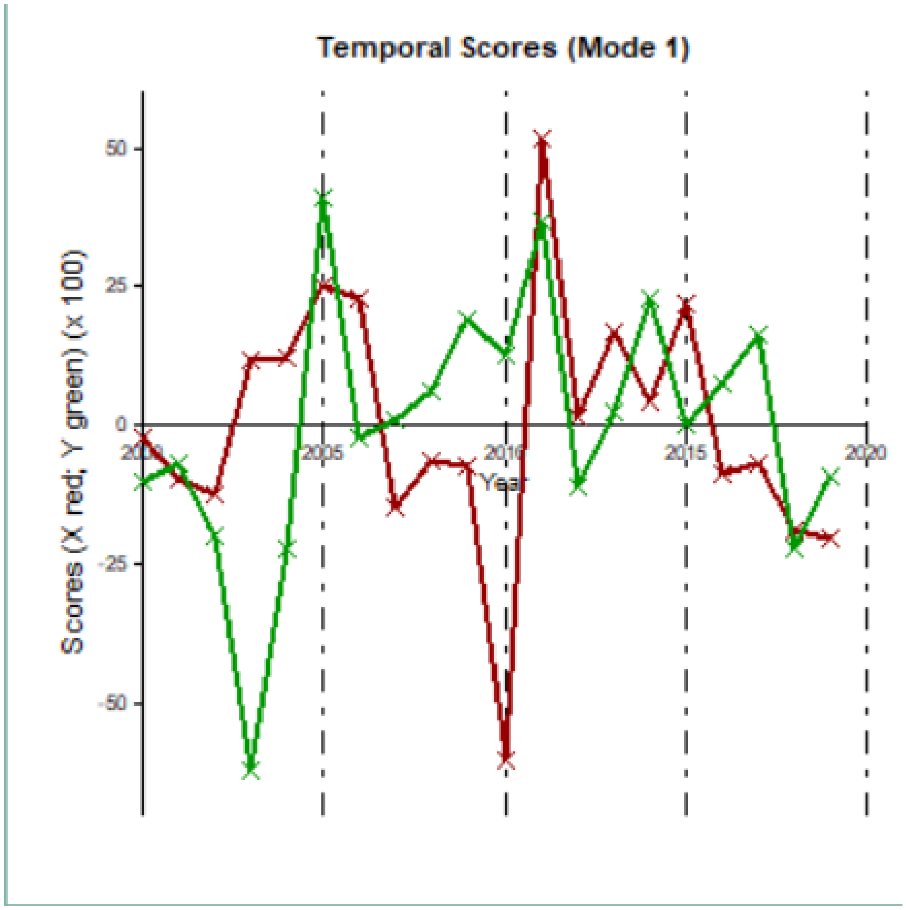


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	1	6	1	8
	N	0	4	0	4
	B	0	8	0	8
Total		1	18	1	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	100%	33%	100%	40%
	N	0%	22%	0%	20%
	B	0%	44%	0%	40%
All		5%	90%	5%	100%



These figures show that the no-lag model has almost no skill in predicting summer streamflow at Long Spruce. Correlations are negative, variance explained is near zero, and RMSE/MAE values are high, meaning the model cannot match observed flows. Categorical scores and ROC areas are also very low, performing no better than random guessing.

The hindcast plot shows the model produces nearly flat predictions while real flows vary widely, and the contingency tables confirm frequent misclassification. Overall, same-season predictors offer virtually no meaningful information for forecasting summer streamflow, which is mainly controlled by pre-season snowpack and storage rather than summer weather.

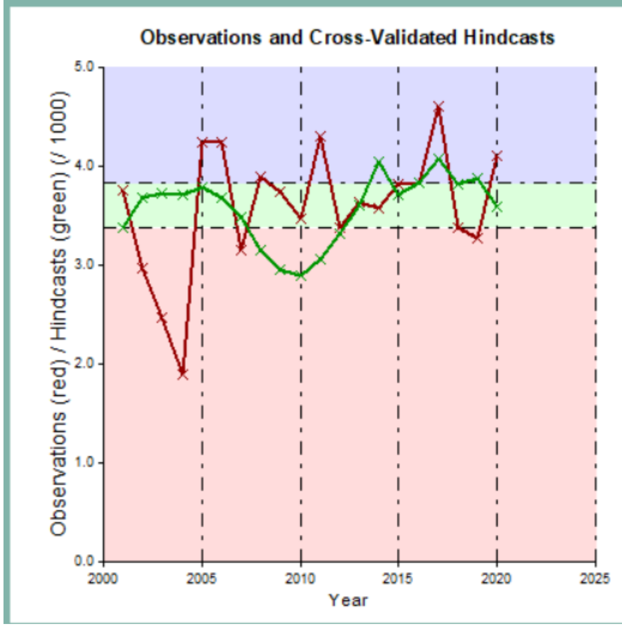
Winter streamflow prediction:

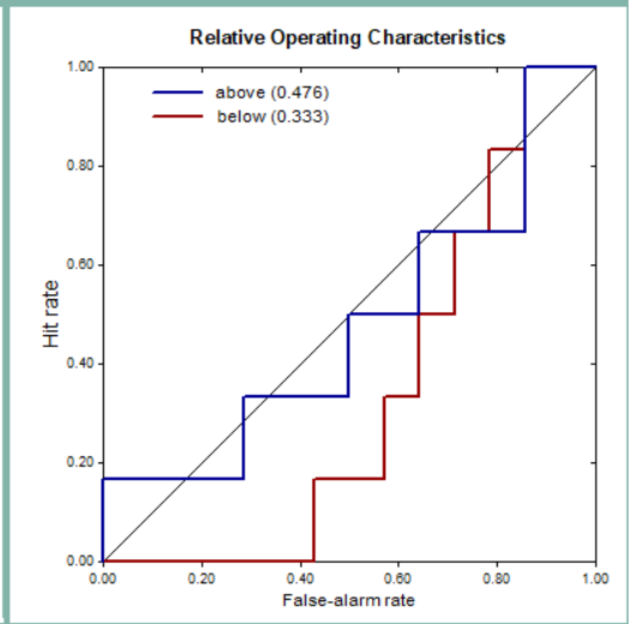
Continuous measures:

Pearson's correlation	-0.0558
Spearman's correlation	-0.0105
2AFC score (continuous)	49.47%
% variance	0.00%
Variance ratio	0.2881
Mean bias	-17.74
Root mean squared error	727.86
Mean absolute error	581.79

Categorical measures:

Hit score	25.00%
Hit skill score	-25.00%
LEPS score	-20.54%
Gerrity score	-20.24%
2AFC (forecast categories)	37.50%
2AFC (continuous forecasts)	41.67%
ROC area (below-normal)	0.3333
ROC area (above-normal)	0.4762





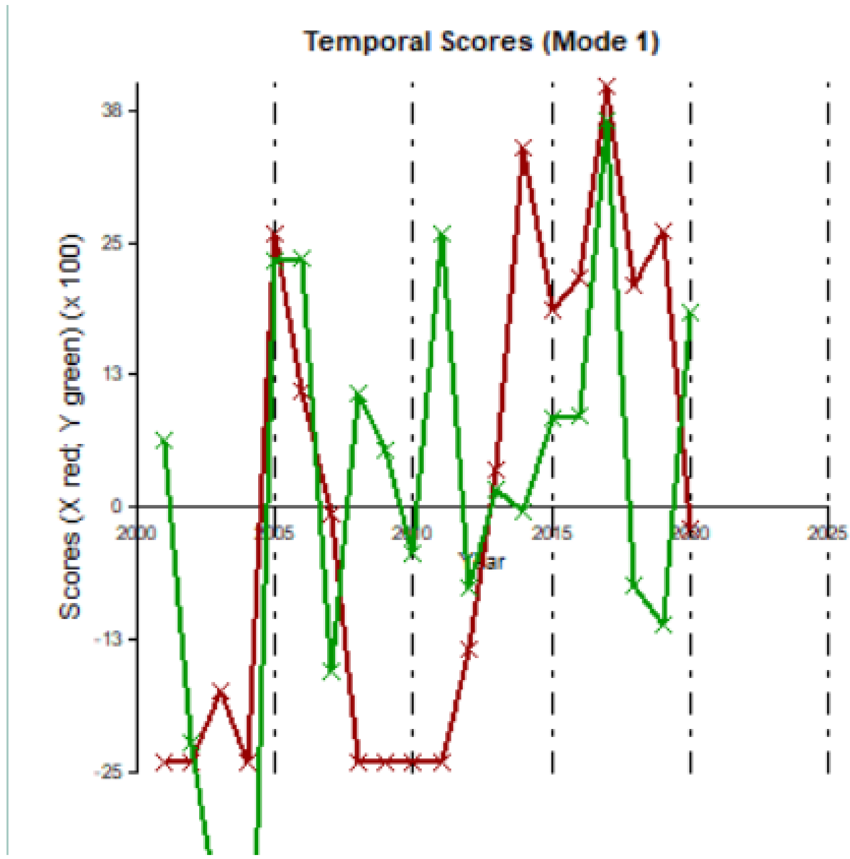
Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	2	3	1	6
	N	3	4	1	8
	B	0	4	2	6
Total		5	11	4	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	40%	27%	25%	30%
	N	60%	36%	25%	40%
	B	0%	36%	50%	30%
All		25%	55%	20%	100%

Discussion-1: Long Spruce Station



These figures show that the no-lag model, which predicts winter streamflow using only same-season variables, has almost no predictive skill. Pearson and Spearman correlations are near zero, the variance ratio is very low, and RMSE/MAE values remain high, meaning the model fails to reproduce real winter discharge. Categorical scores are mostly negative, and ROC areas are only slightly above random chance, indicating poor classification ability.

The hindcast plot shows predictions clustered in a narrow range while observed flows vary widely, and the contingency tables reveal frequent misclassification, with a strong tendency to predict near-normal conditions. Temporal scores also show weak agreement with observed patterns. Overall, same-season variables provide little useful information for forecasting winter streamflow, which is mainly influenced by earlier-season storage, snowpack, and freeze-up processes.

Discussion-1: Long Spruce Station

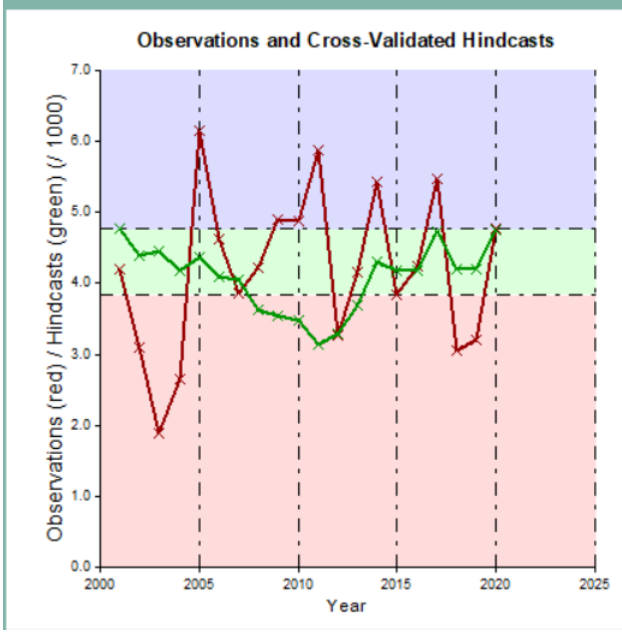
Spring streamflow prediction:

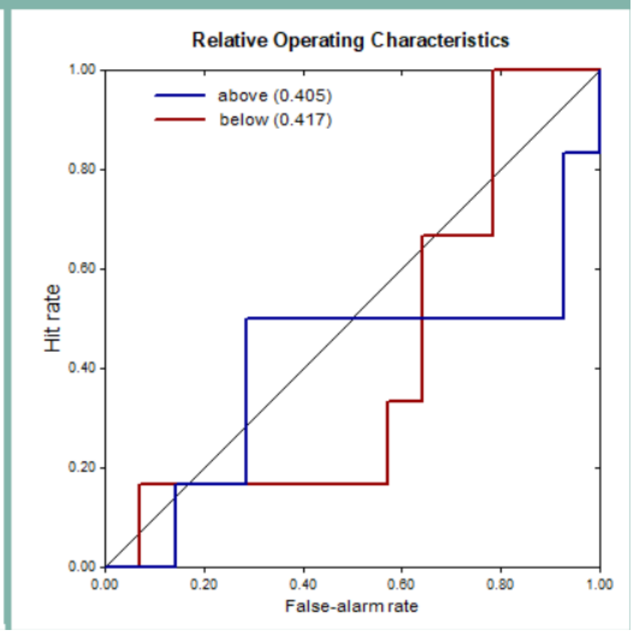
Continuous measures:

Pearson's correlation	-0.1181
Spearman's correlation	-0.1218
2AFC score (continuous)	43.68%
% variance	0.01%
Variance ratio	0.1829
Mean bias	-110.23
Root mean squared error	1233.65
Mean absolute error	972.95

Categorical measures:

Hit score	45.00%
Hit skill score	17.50%
LEPS score	6.25%
Gerrity score	4.76%
2AFC (forecast categories)	50.00%
2AFC (continuous forecasts)	40.15%
ROC area (below-normal)	0.4167
ROC area (above-normal)	0.4048



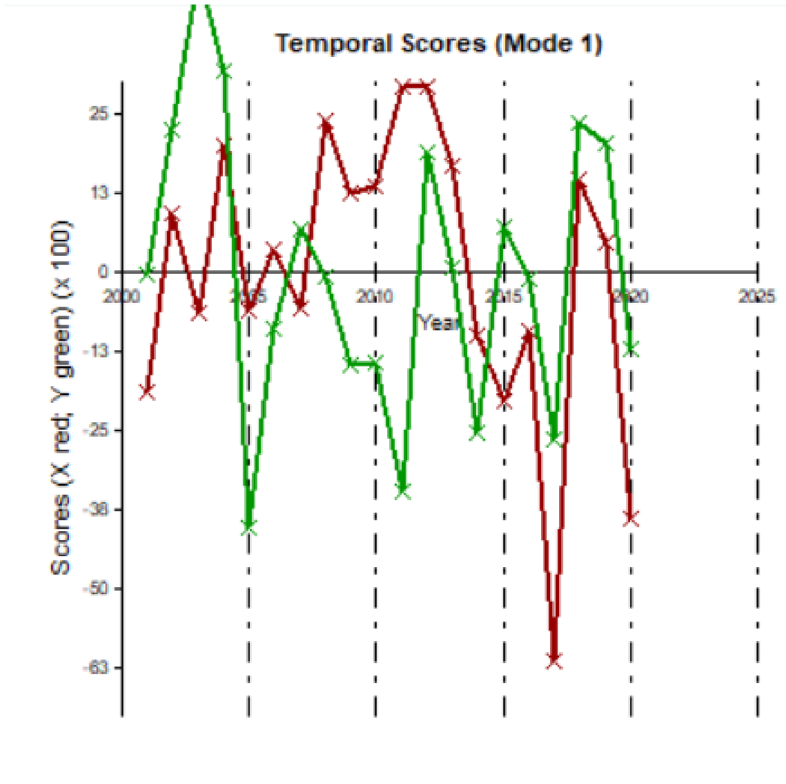


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	1	5	0	6
	N	0	8	0	8
	B	1	5	0	6
Total		2	18	0	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	50%	28%	0%	30%
	N	0%	44%	0%	40%
	B	50%	28%	0%	30%
All		10%	90%	0%	100%



These figures show that the spring streamflow model has moderate categorical skill but weak continuous accuracy. Pearson and Spearman correlations are negative, and explained variance is very low, meaning the model cannot capture year-to-year changes in spring discharge. In contrast, categorical metrics perform better: the hit score is 45% and the 2AFC score is 50%, and ROC areas of 0.40 (above-normal) and 0.42 (below-normal) indicate modest discrimination ability.

The hindcast plot shows that predicted magnitudes often miss observed values, though the wet/dry category is sometimes correct. Frequency and contingency tables confirm moderate success for near-normal years but poor performance for extremes. Temporal scores also show partial but inconsistent alignment with observed variability.

Discussion-1: Long Spruce Station

Autumn streamflow prediction:

Frequency table:

		Forecast			
		B	N	A	Total
Observed	A	0	7	0	7
	N	0	7	0	7
	B	0	5	1	6
Total		0	19	1	20

Contingency table:

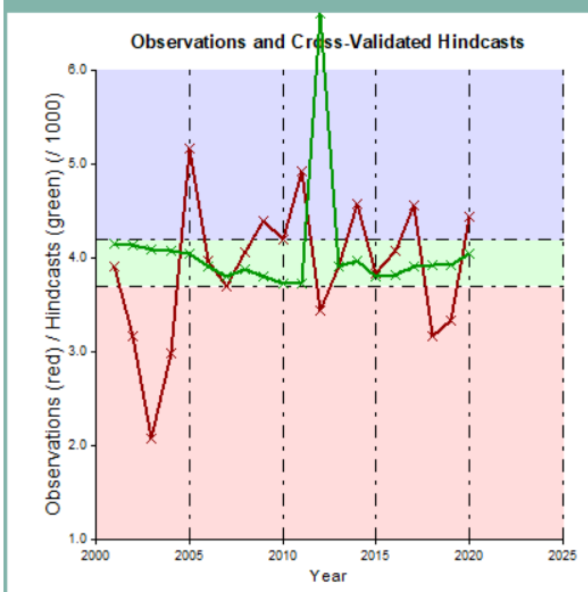
		Forecast			
		B	N	A	All
Observed	A	0%	37%	0%	35%
	N	0%	37%	0%	35%
	B	0%	26%	100%	30%
All		0%	95%	5%	100%

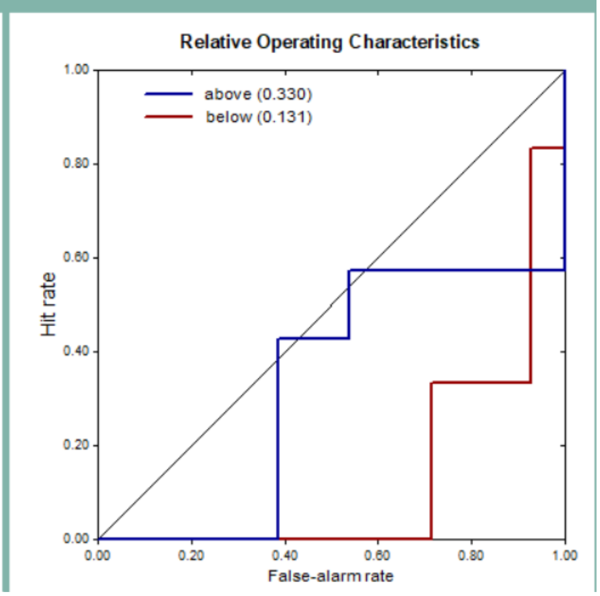
Continuous measures:

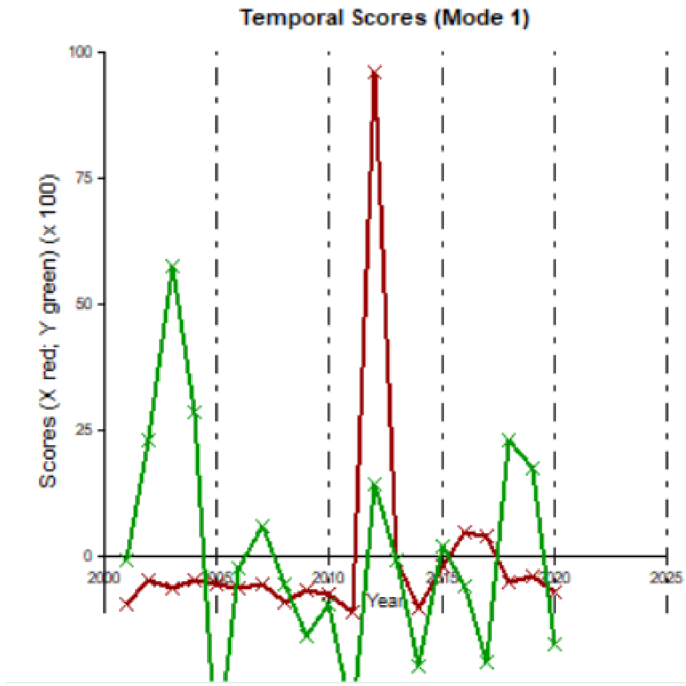
Pearson's correlation	-0.2245
Spearman's correlation	-0.4124
2AFC score (continuous)	36.84%
% variance	0.05%
Variance ratio	0.7125
Mean bias	168.35
Root mean squared error	1038.33
Mean absolute error	725.52

Categorical measures:

Hit score	35.00%
Hit skill score	2.50%
LEPS score	-4.24%
Gerrity score	-3.85%
2AFC (forecast categories)	44.74%
2AFC (continuous forecasts)	26.32%
ROC area (below-normal)	0.1310
ROC area (above-normal)	0.3297







These figures show that the autumn streamflow model has very weak continuous skill but limited categorical skill. Correlations are near zero, explained variance is minimal, and RMSE/MAE values are high, indicating poor accuracy in predicting actual discharge. Categorical scores are slightly better, with a 35% hit rate and a 2AFC score of about 36%, and ROC areas show only marginal discrimination, slightly better for above-normal years.

The hindcast plot shows that predictions rarely match observed year-to-year variability and tend to smooth out extremes. Contingency tables reveal a strong bias toward near-normal forecasts, leading to frequent misclassification. Temporal scores also show poor alignment with observed patterns.

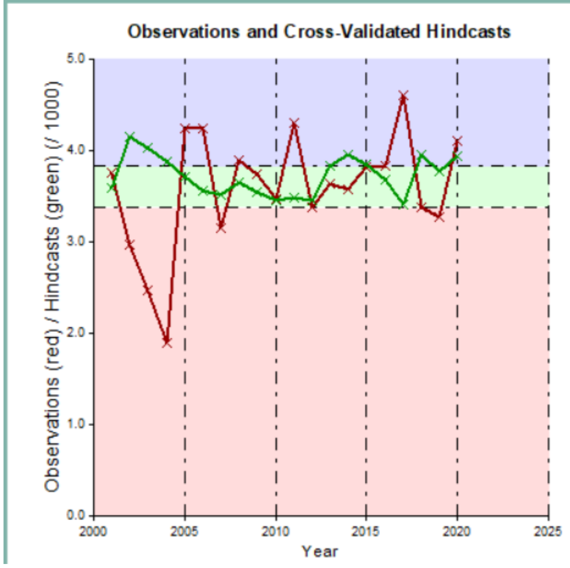
Winter snow prediction:

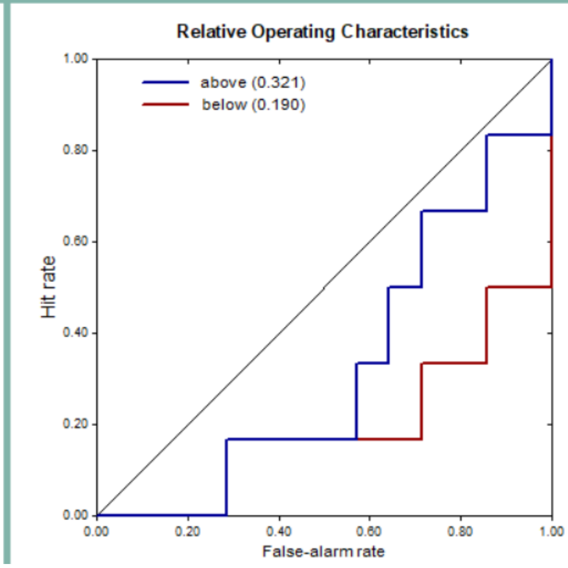
Continuous measures:

Pearson's correlation	-0.4950
Spearman's correlation	-0.4256
2AFC score (continuous)	34.74%
% variance	0.25%
Variance ratio	0.1168
Mean bias	134.97
Root mean squared error	767.96
Mean absolute error	552.18

Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	-12.50%
Gerrity score	-9.52%
2AFC (forecast categories)	34.09%
2AFC (continuous forecasts)	28.03%
ROC area (below-normal)	0.1905
ROC area (above-normal)	0.3214





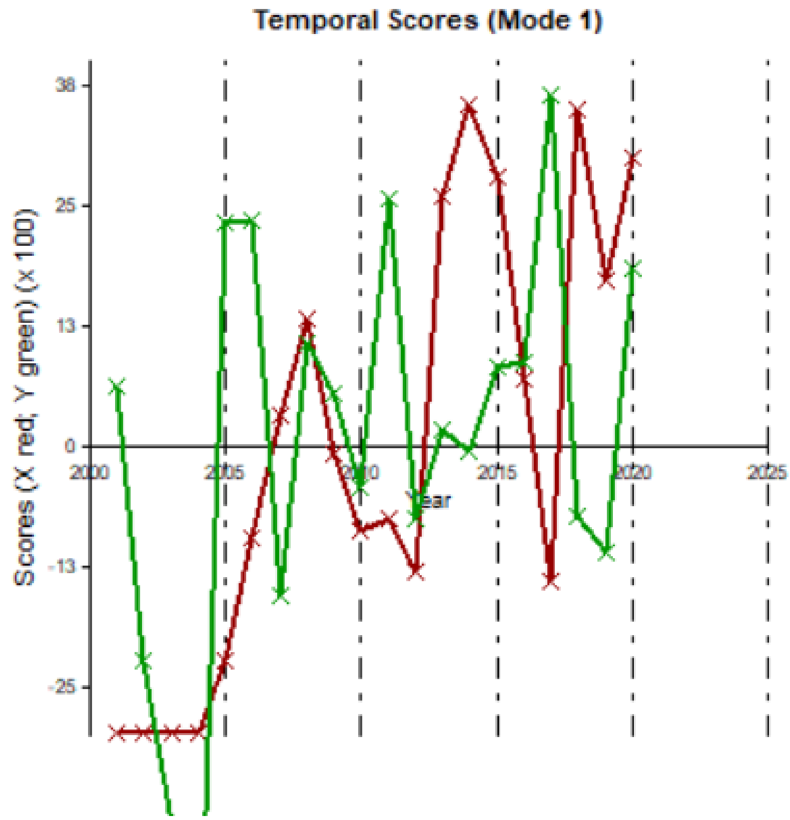
Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	5	1	6
	N	0	7	1	8
	B	0	2	4	6
Total		0	14	6	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	36%	17%	30%
	N	0%	50%	17%	40%
	B	0%	14%	67%	30%
All		0%	70%	30%	100%

Discussion-1: Long Spruce Station



These figures show that the winter snow prediction model at Long Spruce has weak continuous skill but modest categorical ability. Pearson and Spearman correlations are negative, explained variance is very low, and RMSE/MAE values are high, meaning the model cannot reproduce actual snow amounts. Categorical results are somewhat better: the hit score is 40% and the 2AFC score is about 36%, indicating limited but noticeable skill in classifying above-, near-, and below-normal seasons. ROC areas (0.32 above-normal, 0.19 below-normal) confirm only weak discrimination.

The hindcast plot shows that predictions sometimes follow general trends but consistently miss high and low extremes. Contingency tables reveal a strong bias toward near-normal forecasts, leading to frequent misclassification. Temporal scores show only partial and inconsistent agreement with observed variability.

Discussion-1: Long Spruce Station

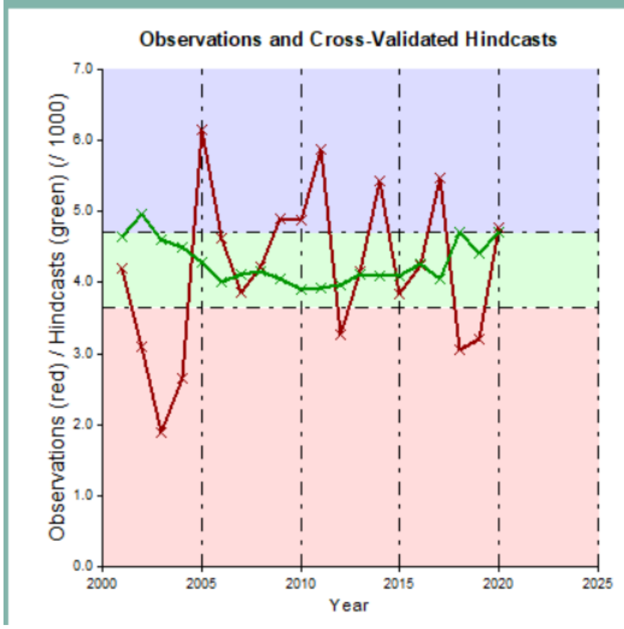
Spring snow prediction:

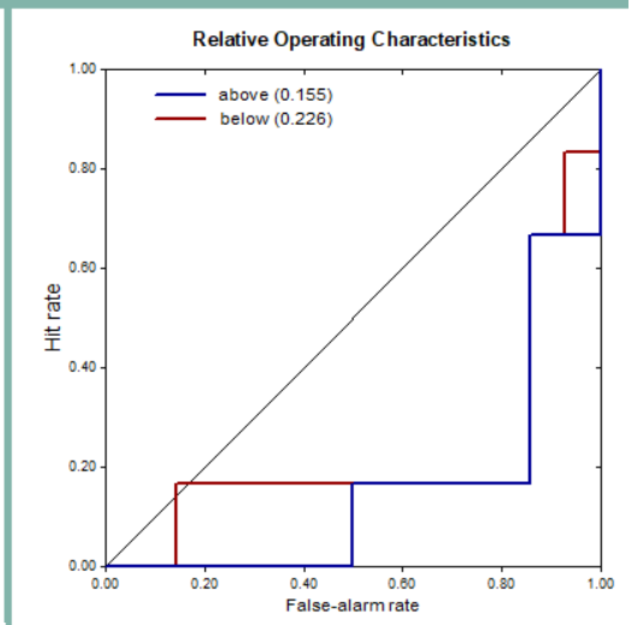
Continuous measures:

Pearson's correlation	-0.5280
Spearman's correlation	-0.5248
2AFC score (continuous)	32.63%
% variance	0.28%
Variance ratio	0.0767
Mean bias	87.24
Root mean squared error	1271.92
Mean absolute error	1007.82

Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	-1.79%
Gerrity score	-3.57%
2AFC (forecast categories)	44.70%
2AFC (continuous forecasts)	21.21%
ROC area (below-normal)	0.2262
ROC area (above-normal)	0.1548





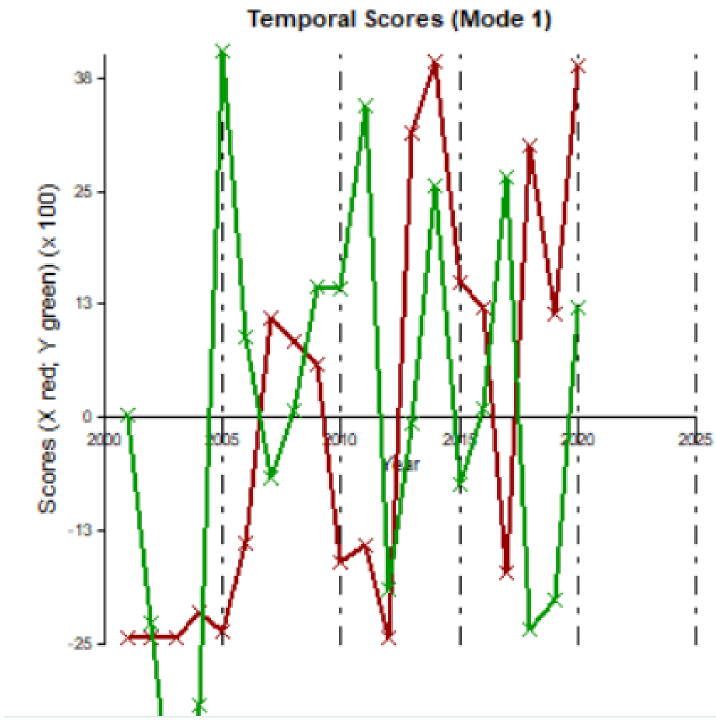
Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	8	0	8
	B	0	5	1	6
	Total	0	19	1	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	32%	0%	30%
	N	0%	42%	0%	40%
	B	0%	26%	100%	30%
	All	0%	95%	5%	100%

Discussion-1: Long Spruce Station



These figures show that the spring snow prediction model has weak continuous accuracy but modest categorical skill. Pearson and Spearman correlations are strongly negative, explained variance is extremely low, and RMSE/MAE values are high, meaning the model cannot reproduce actual snow amounts or year-to-year variability. Categorical metrics perform slightly better: the model has a 40% hit score and a 2AFC score of about 41%, indicating limited ability to distinguish between snow categories.

ROC areas (0.15 above-normal and 0.23 below-normal) show only marginal discrimination skill. The hindcast plot reveals that predictions cluster around the climatological mean and rarely capture extremes. Contingency tables indicate a strong bias toward near-normal forecasts, leading to frequent misclassification. Temporal scores show occasional similarity to observed patterns but often diverge sharply.

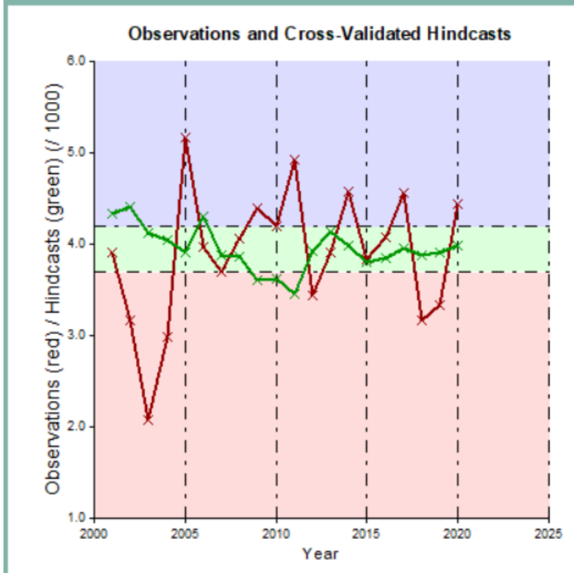
Autumn snow prediction:

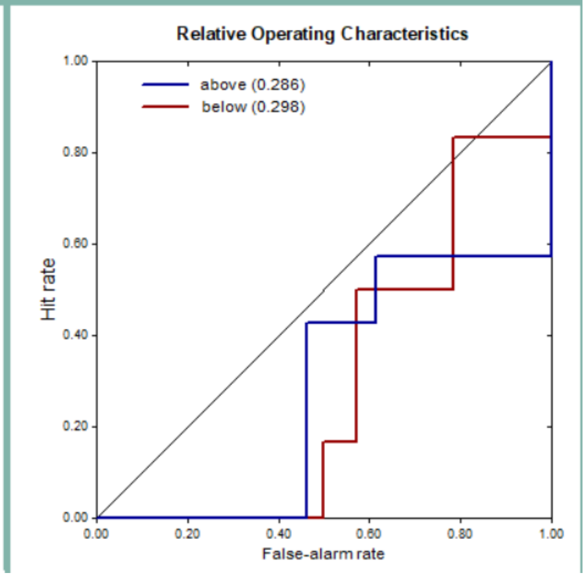
Continuous measures:

Pearson's correlation	-0.4226
Spearman's correlation	-0.3801
2AFC score (continuous)	35.26%
% variance	0.18%
Variance ratio	0.1086
Mean bias	54.31
Root mean squared error	836.13
Mean absolute error	673.78

Categorical measures:

Hit score	30.00%
Hit skill score	-10.00%
LEPS score	-6.78%
Gerrity score	-7.69%
2AFC (forecast categories)	44.36%
2AFC (continuous forecasts)	30.83%
ROC area (below-normal)	0.2976
ROC area (above-normal)	0.2857





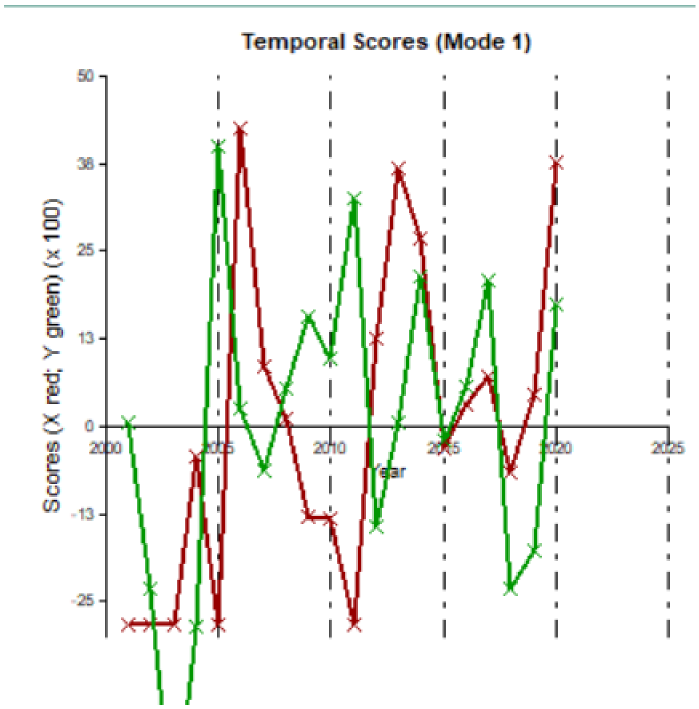
Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	7	0	7
	N	0	6	1	7
	B	0	5	1	6
Total		0	18	2	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	39%	0%	35%
	N	0%	33%	50%	35%
	B	0%	28%	50%	30%
All		0%	90%	10%	100%

Discussion-1: Long Spruce Station



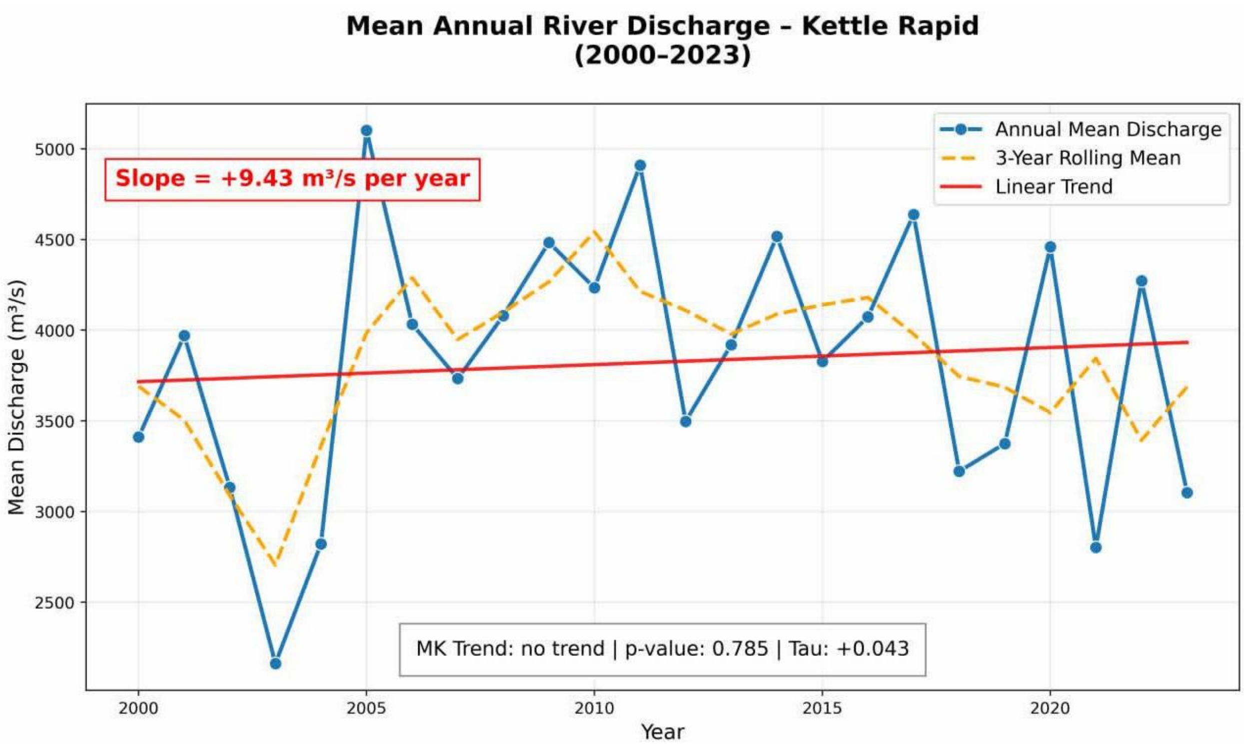
The autumn snow prediction results show weak continuous skill but limited categorical ability. Pearson and Spearman correlations are negative, explained variance is near zero, and RMSE/MAE values are high, meaning the model cannot reproduce actual autumn snow amounts or year-to-year variability. Categorical scores are modest, with a 30% hit rate and a 2AFC value around 34–35%, indicating some ability to separate above-, near-, and below-normal years.

ROC areas of about 0.29 for both categories show only marginal discrimination skill. The hindcast plot shows predictions clustering around climatology and failing to capture extremes, while temporal scores reveal inconsistent alignment with observed variability.

Discussion-2: Kettle Station

Time-series analysis of annual discharge (2000–2023):
The plot shows that the annual discharge at the Kettle station, despite noticeable year-to-year fluctuations, does not display any clear increasing or decreasing trend overall. The linear trend has a slope of about 9.4 cubic metres per second per year, but the Mann–Kendall test with a p-value of 0.785 confirms that this change is not statistically significant. This means the observed variations are mostly due to natural climate behaviour and multi-year cycles rather than a real long-term trend.

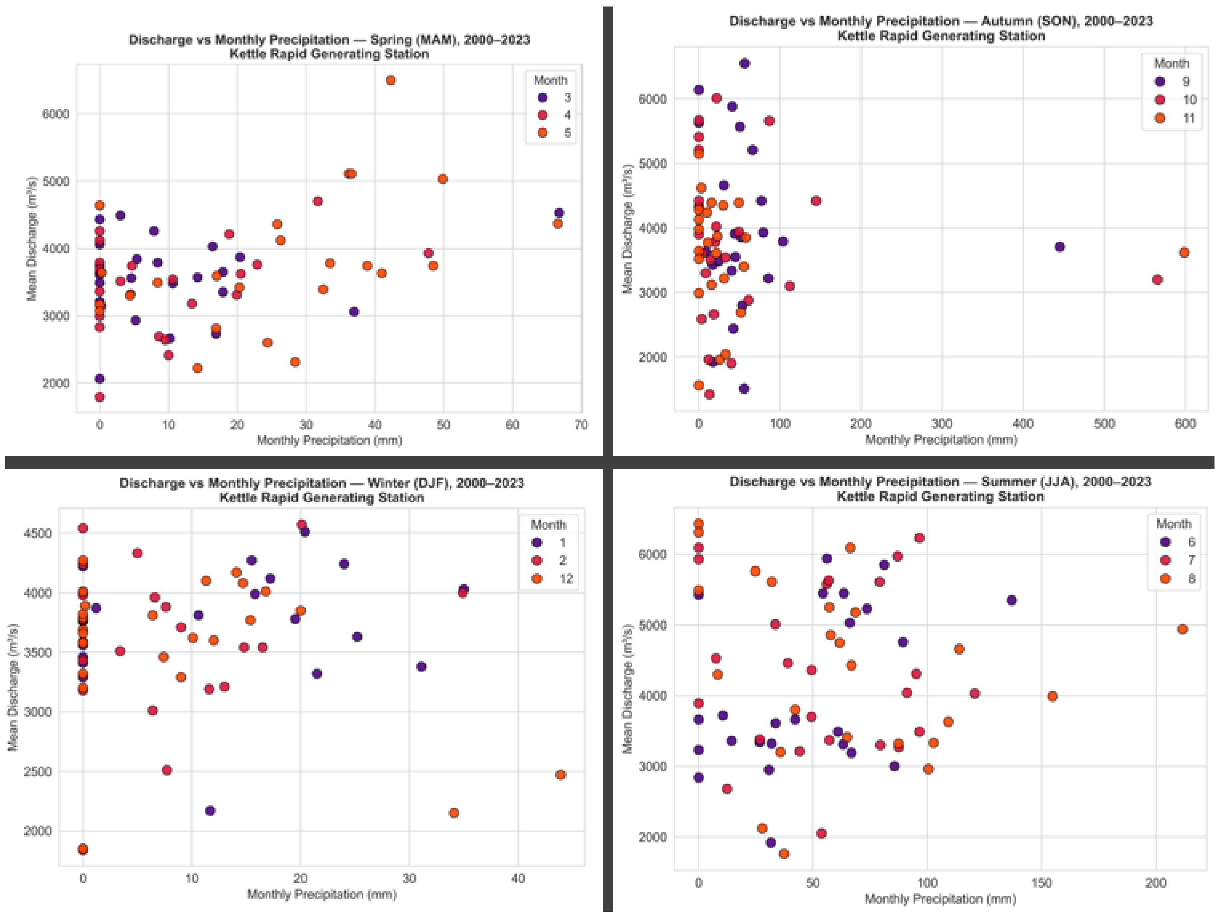
The three-year moving average also shows that discharge rises and falls over different periods but eventually returns to its typical range. Overall, the plot indicates that the Kettle basin has not experienced a meaningful long-term trend in annual flow during this period, and its fluctuations are mainly short-term and climate-driven.



Integrated analysis of the four seasonal precipitation, discharge plots (JJA, DJF, MAM, SON):

The four seasonal plots for the Kettle station show that there is no direct relationship between monthly precipitation and discharge in the same season. In all four seasons, the points on the graphs are widely scattered, and no clear pattern of increasing or decreasing discharge with precipitation is visible. This behaviour occurs because, in this basin, seasonal precipitation alone does not determine flow. A large portion of the river's water comes from stored winter snow or moisture carried over from earlier periods.

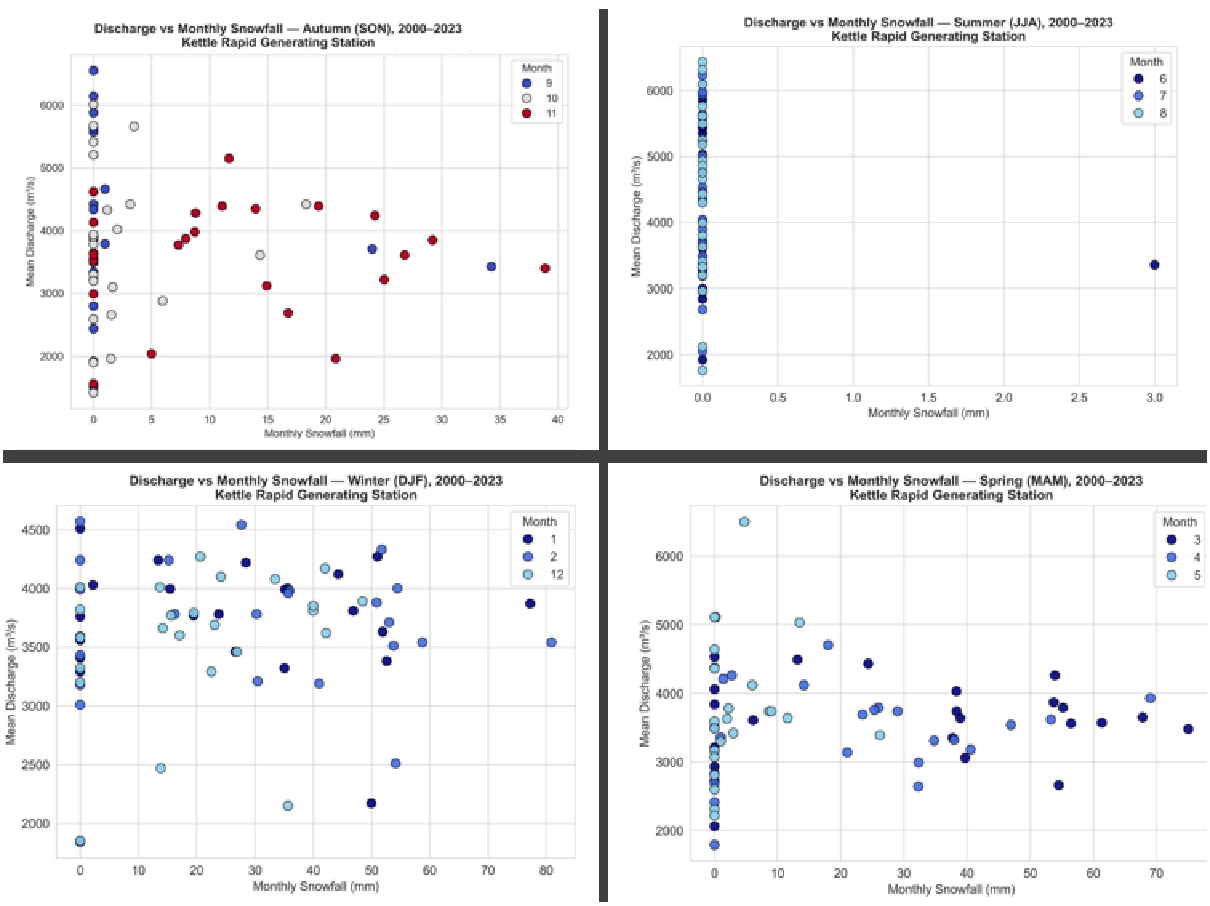
For this reason, even in seasons with higher precipitation, the discharge does not significantly change and mostly follows the natural annual cycle. These four plots confirm that seasonal discharge at Kettle has a weak dependence on immediate precipitation and is influenced more by the basin's cumulative and physical conditions.



Integrated analysis of the four seasonal snow–discharge plots (JJA, DJF, MAM, SON):

The four seasonal plots of snow and discharge at the Kettle station show that seasonal flow does not have a direct dependence on the amount of snow in the same period. In summer, almost no snow is recorded, and discharge is completely independent of monthly snow values, which matches the natural conditions of the region. In autumn and spring, the scatter of points also shows that increases or decreases in snow do not necessarily lead to changes in discharge. The seasonal flow is more closely linked to the accumulated snow from the previous winter than to the snow of the current month.

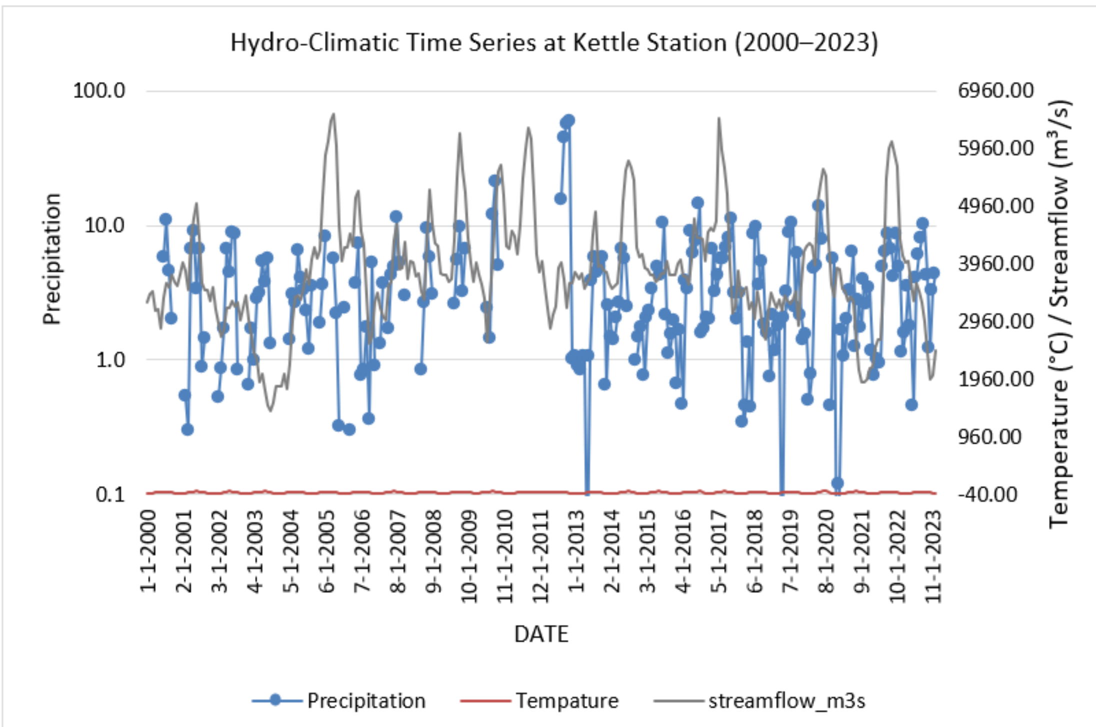
The winter plot shows the same behaviour: even when snow amounts are high, discharge remains within a relatively narrow range because snow does not contribute to flow during this season.



Time-series analysis of precipitation, temperature, and discharge:

This plot shows that precipitation, temperature, and river discharge have all experienced considerable fluctuations from 2000 to 2023, but their behaviours are not necessarily synchronized. Monthly precipitation is highly variable, with no clear long-term increasing or decreasing trend. Temperature follows a more regular cycle, rising each year with the onset of the warm season and dropping again in winter.

River discharge aligns more closely with temperature changes than with immediate rainfall; increases in flow usually occur when temperatures approach the melting range, not necessarily when precipitation happens. This indicates that in Kettle, the main source of water entering the system is controlled by snowmelt and seasonal conditions, rather than by recent rainfall events.



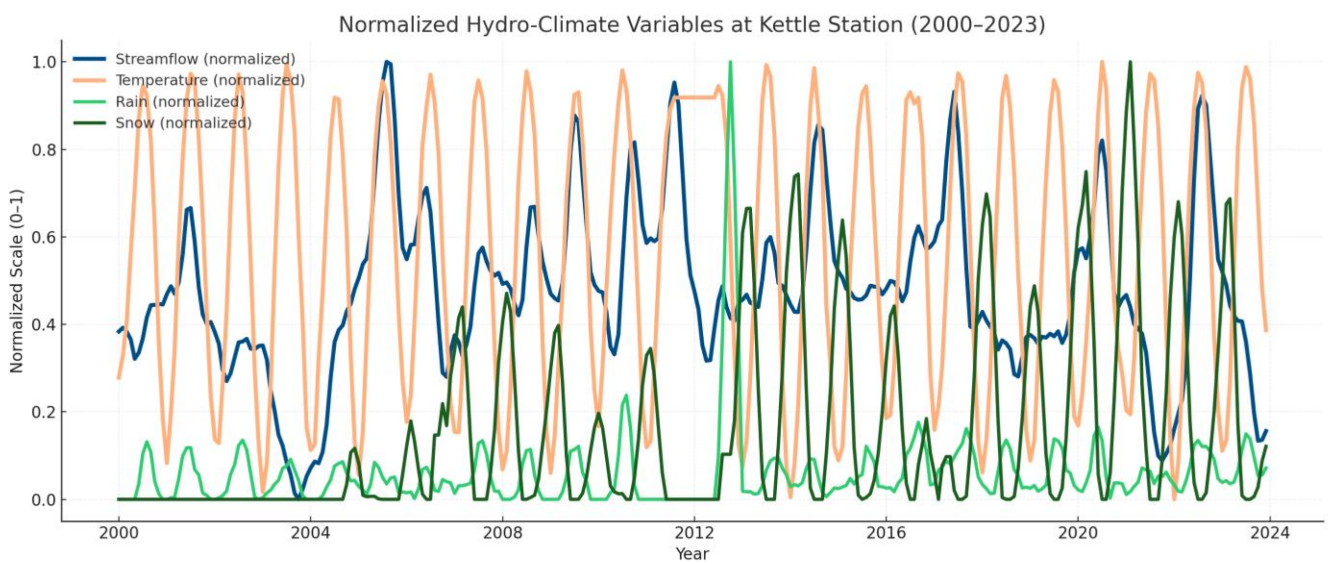
Discussion-2: Kettle Station

Analysis of the normalized variable plot:

This plot shows how the annual cycles of temperature, snow, rainfall, and discharge change relative to one another at the Kettle station. Temperature follows a very regular and repeating pattern, rising each year with the start of the warm season and then decreasing again. River discharge aligns more closely with these temperature changes and typically increases when temperatures approach the melting range.

Snow increases during the cold half of the year and gradually decreases as temperatures rise; this reduction usually occurs at the same time that discharge increases. Rainfall has shorter, more scattered fluctuations and plays a smaller role compared with snow.

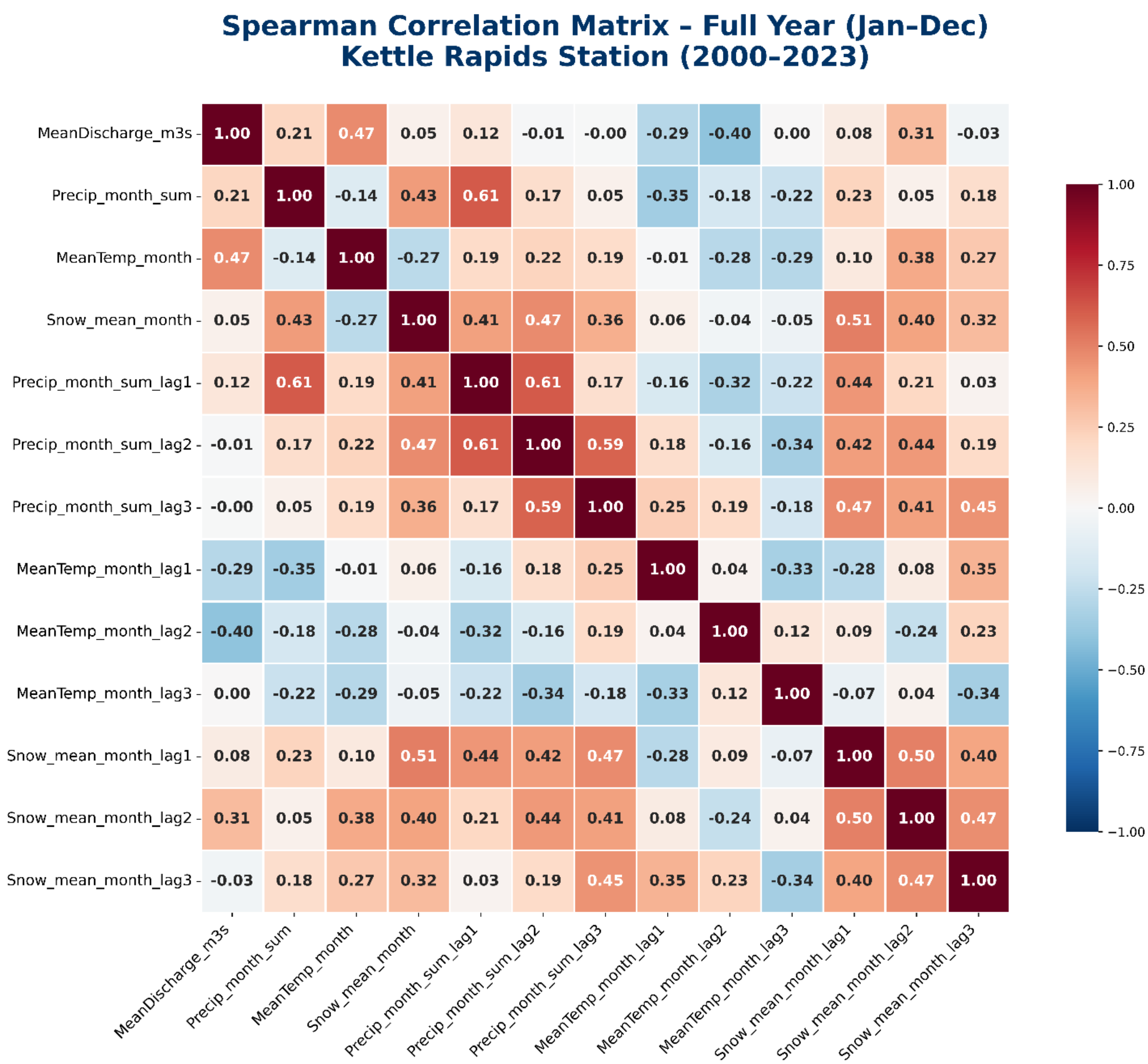
This pattern shows that flow behaviour at Kettle depends more on the snow and temperature cycle than on immediate rainfall, and that seasonal discharge changes are mainly driven by snowmelt and broader seasonal conditions.



Annual correlation plot analysis:

The annual correlation plot for the Kettle station shows that river discharge does not have a strong dependence on same-month precipitation or temperature, but when lagged variables are included, the main pattern becomes clear. Precipitation from one to three months earlier has the strongest influence on discharge, which is entirely expected for a cold-region basin, since much of the winter and early-spring precipitation is stored as snow and enters the river with a delay.

The negative temperature coefficients show that short-term warming usually reduces the snowpack and does not cause an immediate increase in discharge. In contrast, snow from previous months has a positive and relatively stable relationship with streamflow, highlighting the key role of gradual snowmelt in supporting annual discharge.



Winter correlation plot analysis:

The winter plot for the Kettle station shows a clear pattern: winter discharge is influenced much more by conditions from previous months than by the climate of the current season. Precipitation from one to three months earlier has a positive and relatively stable correlation with flow, meaning the river responds with a delay rather than immediately. This is expected in cold-region basins, where most precipitation falls as snow, is stored, and enters the river only after some time.

Temperature in the preceding months generally has a negative relationship with discharge, indicating that short-term warming reduces the snowpack or increases evaporation, without producing higher winter flow. In contrast, snow from earlier months shows a strong positive correlation with discharge, confirming that winter water supply mainly comes from the gradual melt of stored snow.

Taken together, these results show that winter river behaviour is shaped more by past conditions than by immediate seasonal changes.

Summary of the seasonal lag analysis (log):

When the data were compared, it was clear that summer discharge depends more on the previous winter and spring conditions than on precipitation during the summer itself. In years with greater winter snow, summer flows were usually higher, and this pattern appears consistently across the whole period. This means the main source of summer water is already stored in the basin before the season begins.

Based on this, two types of models were tested: lag-1 models, which used information from previous seasons, and no-lag models, which relied only on summer conditions. The lag models performed much better and were able to distinguish high-flow and low-flow years fairly well. In contrast, the no-lag models produced unreliable results—an expected outcome given the basin's characteristics, where summer receives almost no new input.

Overall, the results show that using data from the previous year gives a much more accurate description of summer discharge behaviour.

No-lag models (for comparison only):

When only summer precipitation or summer snow were used in the model and compared with summer discharge, no meaningful relationship was found. In most years, summer flow behaved independently of rainfall, and in some cases the relationship was even negative. This matches conditions in the region, as the basin has no summer snow and summer rainfall events are usually short and weak.

For this reason, summer discharge is influenced mainly by pre-season conditions, not by immediate inputs. As a result, the no-lag models performed poorly and could not reliably separate high-flow and low-flow years.

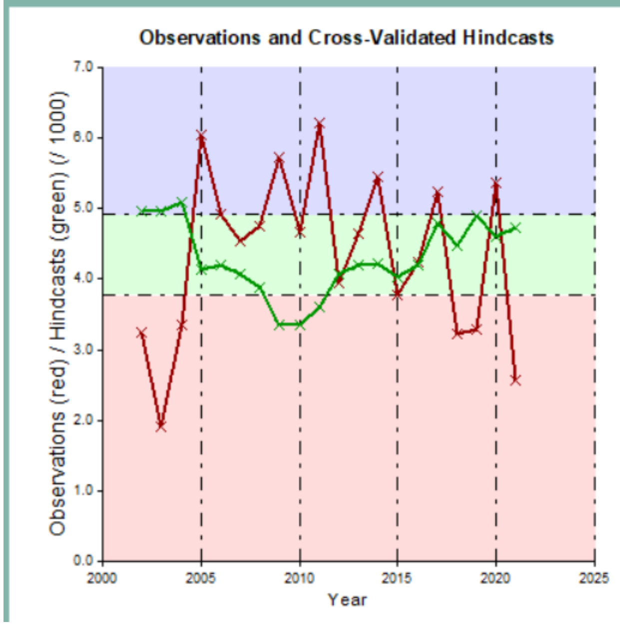
Seasonal prediction of summer streamflow using previous winter precipitation:

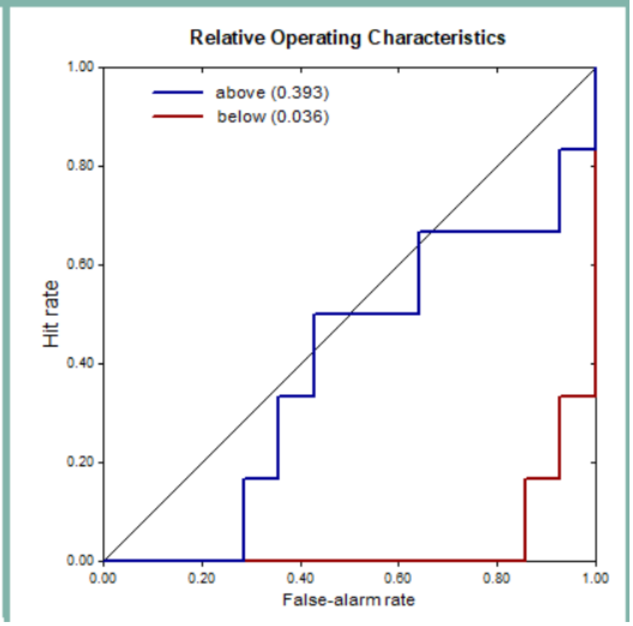
Continuous measures:

Pearson's correlation	-0.6337
Spearman's correlation	-0.5639
2AFC score (continuous)	31.05%
% variance	0.40%
Variance ratio	0.1964
Mean bias	-63.76
Root mean squared error	1519.85
Mean absolute error	1259.05

Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	-7.14%
Gerrity score	-7.14%
2AFC (forecast categories)	39.39%
2AFC (continuous forecasts)	25.00%
ROC area (below-normal)	0.0357
ROC area (above-normal)	0.3929



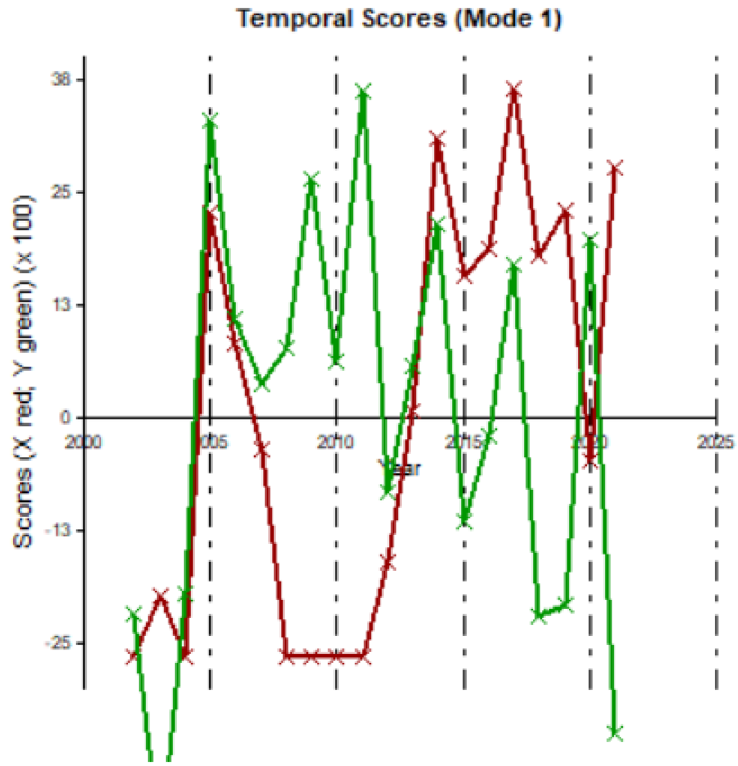


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	8	0	8
	B	0	4	2	6
Total		0	18	2	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	33%	0%	30%
	N	0%	44%	0%	40%
	B	0%	22%	100%	30%
	All	0%	90%	10%	100%



The results show that using winter precipitation to predict summer streamflow provides very limited skill. Continuous statistics are weak, with negative Pearson and Spearman correlations (about –0.64) and almost no explained variance, meaning the model cannot reproduce actual summer flows. Categorical skill is only modest: the hit score is 40% and the 2AFC is around 39%, with ROC curves showing good detection of below-normal years (≈0.86) but poor performance for above-normal years (≈0.39).

Hindcast plots show predictions clustering near climatology and failing to track year-to-year variability, especially in extreme summers. Temporal scores indicate only partial alignment with observed patterns. Contingency tables also highlight frequent misclassification, especially for above-normal years.

Discussion-2: Kettle Station

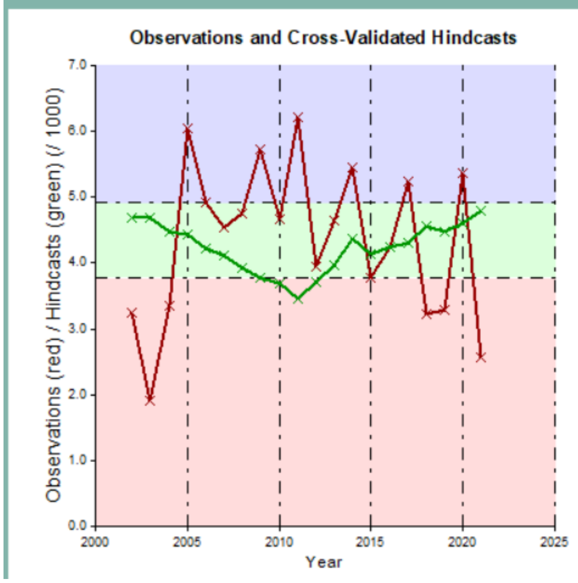
Seasonal prediction of summer streamflow using previous spring precipitation:

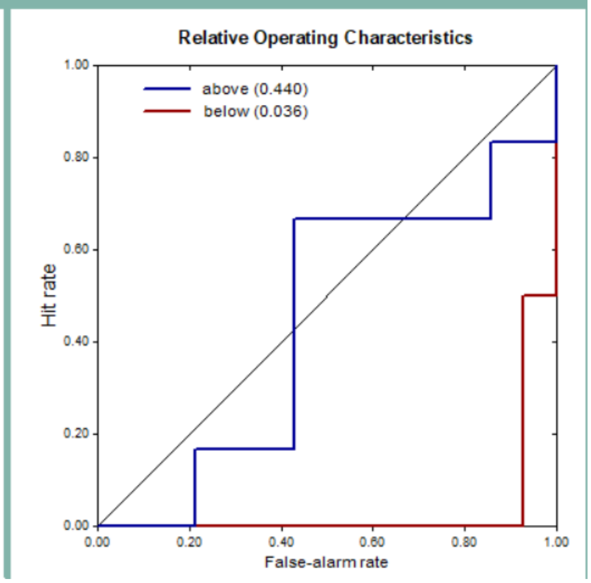
Continuous measures:

Pearson's correlation	-0.5594
Spearman's correlation	-0.5444
2AFC score (continuous)	30.53%
% variance	0.31%
Variance ratio	0.1038
Mean bias	-123.50
Root mean squared error	1391.27
Mean absolute error	1169.81

Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	3.57%
Gerrity score	0.00%
2AFC (forecast categories)	50.00%
2AFC (continuous forecasts)	28.03%
ROC area (below-normal)	0.0357
ROC area (above-normal)	0.4405



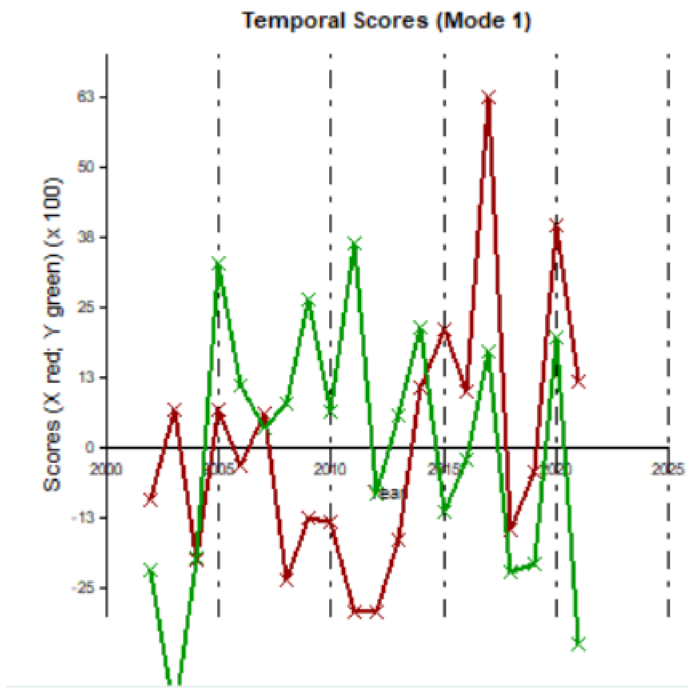


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	8	0	8
	B	0	6	0	6
Total		0	20	0	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	30%	0%	30%
	N	0%	40%	0%	40%
	B	0%	30%	0%	30%
All		0%	100%	0%	100%



The results show that previous spring precipitation offers very little skill for predicting summer streamflow. Continuous statistics are very weak so the model cannot reproduce actual summer flows. Categorical skill is modest at best, with a 40% hit score and limited 2AFC performance.

ROC curves show some ability to detect below-normal summers (≈0.83) but poor skill for above-normal years (≈0.44). Hindcast and temporal plots reveal predictions clustered near climatology and unable to follow real year-to-year variability. Contingency tables also show frequent misclassification, especially for wet years. Overall, spring precipitation provides minimal forecasting value, useful mainly for identifying dry summers.

Discussion-2: Kettle Station

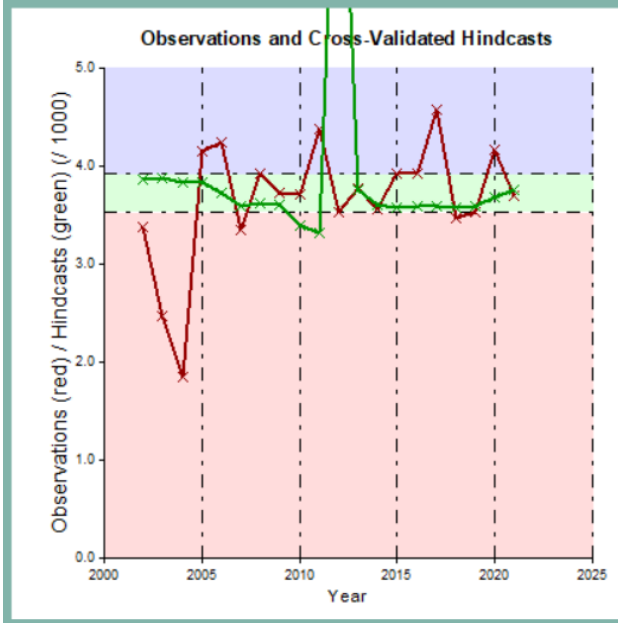
Seasonal prediction of winter streamflow using previous autumn precipitation:

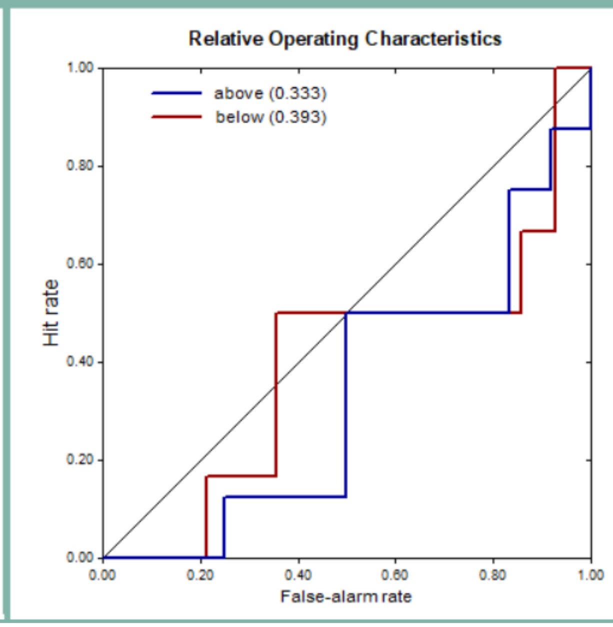
Continuous measures:

Pearson's correlation	-0.1107
Spearman's correlation	-0.3383
2AFC score (continuous)	40.53%
% variance	0.01%
Variance ratio	3.0272
Mean bias	227.55
Root mean squared error	1295.96
Mean absolute error	705.65

Categorical measures:

Hit score	20.00%
Hit skill score	-40.00%
LEPS score	-11.29%
Gerrity score	-11.31%
2AFC (forecast categories)	45.83%
2AFC (continuous forecasts)	37.88%
ROC area (below-normal)	0.3929
ROC area (above-normal)	0.3333



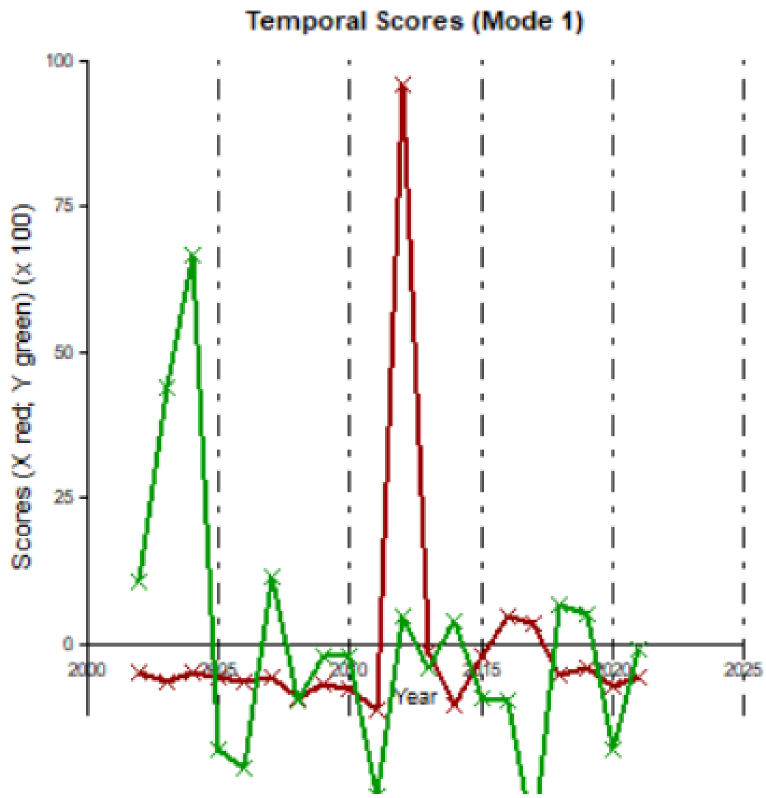


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	1	7	0	8
	N	1	4	1	6
	B	0	6	0	6
Total		2	17	1	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	50%	41%	0%	40%
	N	50%	24%	100%	30%
	B	0%	35%	0%	30%
All		10%	85%	5%	100%



The results show that previous autumn precipitation provides very limited skill for predicting winter streamflow. Continuous statistics are weak—Pearson and Spearman correlations (about –0.11 and –0.38) and near-zero explained variance indicate no meaningful relationship with winter discharge. Categorical skill is also low, with a 20% hit score and negative LEPS and Gerrity scores, and ROC values of 0.39 and 0.33 showing poor discrimination.

Hindcast plots reveal predictions clustering near climatology and failing to capture extremes or interannual variability. Temporal scores show occasional alignment but frequent mismatches, especially during anomalous years. Contingency tables highlight systematic misclassification, with most winters incorrectly predicted as near-normal. Overall, autumn precipitation is not a reliable predictor of winter flows and misses key physical drivers like snow accumulation and freeze-up processes.

Discussion-2: Kettle Station

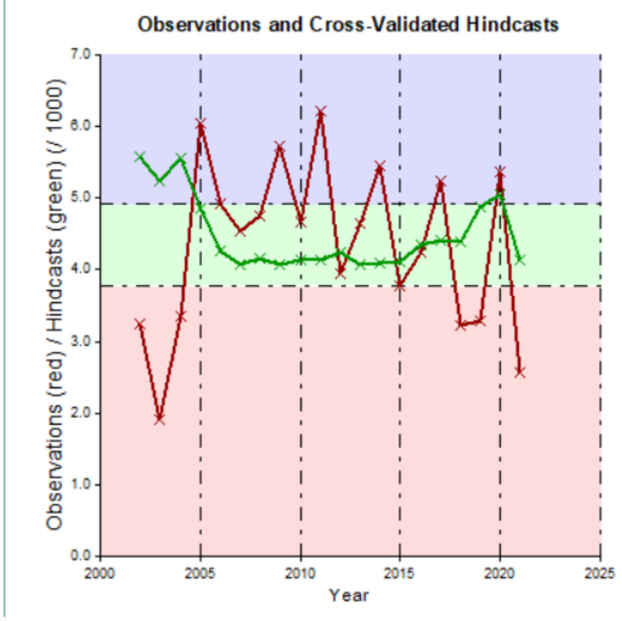
Seasonal prediction of summer streamflow using previous winter snow:

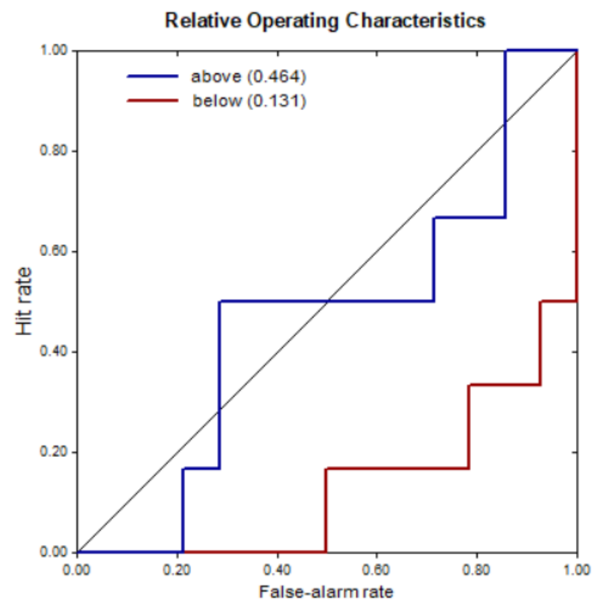
Continuous measures:

Pearson's correlation	-0.3989
Spearman's correlation	-0.3474
2AFC score (continuous)	40.00%
% variance	0.16%
Variance ratio	0.1885
Mean bias	134.27
Root mean squared error	1425.19
Mean absolute error	1159.11

Categorical measures:

Hit score	45.00%
Hit skill score	17.50%
LEPS score	-9.82%
Gerrity score	-5.95%
2AFC (forecast categories)	34.09%
2AFC (continuous forecasts)	32.58%
ROC area (below-normal)	0.1310
ROC area (above-normal)	0.4643



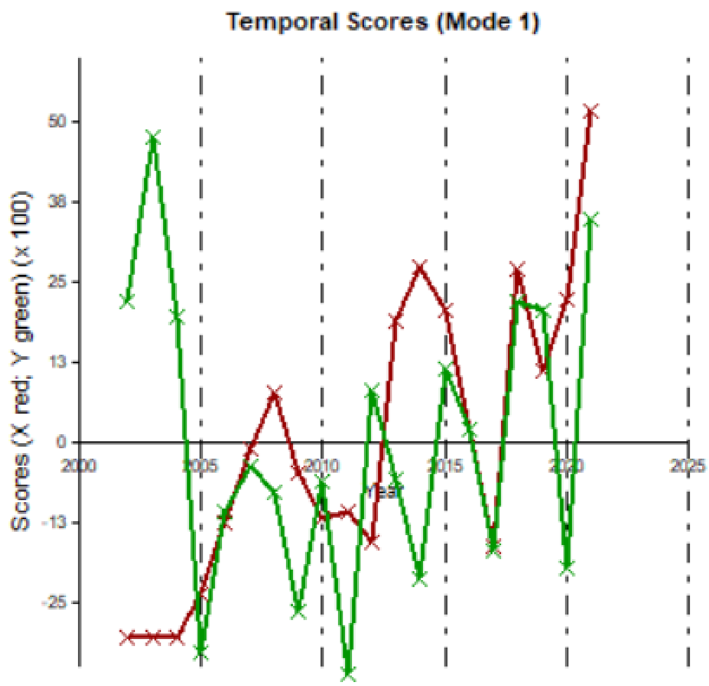


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	8	0	8
	B	1	1	4	6
Total		1	15	4	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	40%	0%	30%
	N	0%	53%	0%	40%
	B	100%	7%	100%	30%
All		5%	75%	20%	100%



The results show that winter snowpack offers some categorical skill but very weak continuous accuracy for predicting summer streamflow. Correlations are negative, explained variance is near zero, and the model cannot reproduce actual flow magnitudes. Categorical performance is better, with a 45% hit score and good skill for identifying below-normal summers (ROC ≈ 0.76), but poor skill for above-normal years (ROC ≈ 0.46).

Hindcast and temporal plots show predictions staying near climatology and missing most year-to-year variability, especially extremes. Contingency tables also reveal frequent misclassification of wet summers. Overall, winter snowpack helps flag dry summers but is not reliable for predicting wet or near-normal conditions.

Discussion-2: Kettle Station

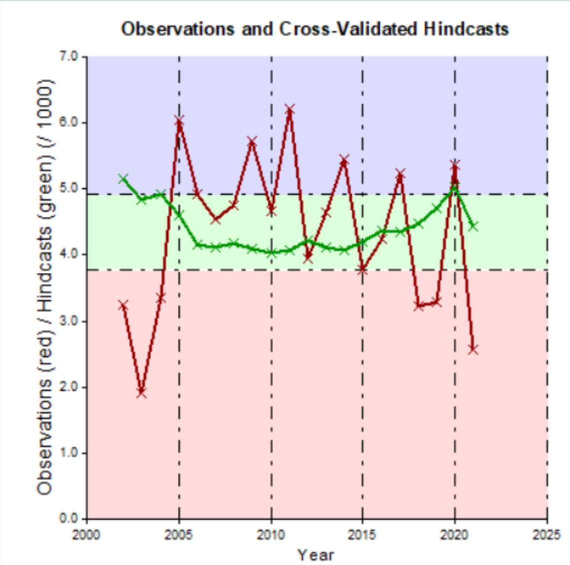
Seasonal prediction of summer streamflow using previous spring snow:

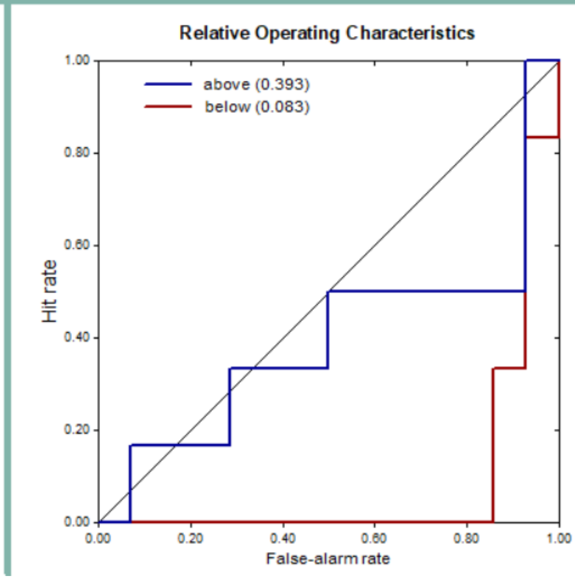
Continuous measures:

Pearson's correlation	-0.4649
Spearman's correlation	-0.5323
2AFC score (continuous)	30.53%
% variance	0.22%
Variance ratio	0.0911
Mean bias	49.94
Root mean squared error	1342.25
Mean absolute error	1128.76

Categorical measures:

Hit score	40.00%
Hit skill score	10.00%
LEPS score	-1.79%
Gerrity score	-3.57%
2AFC (forecast categories)	44.70%
2AFC (continuous forecasts)	25.00%
ROC area (below-normal)	0.0833
ROC area (above-normal)	0.3929



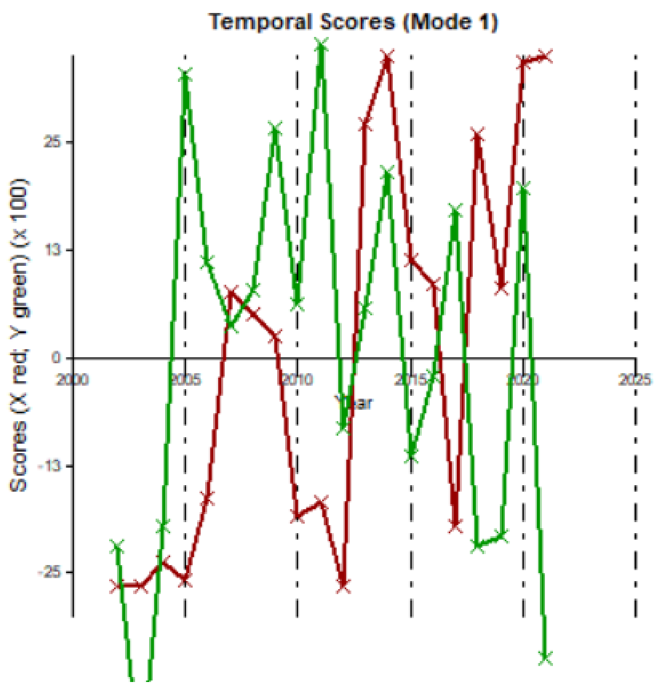


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	6	0	6
	N	0	8	0	8
	B	0	5	1	6
Total		0	19	1	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	32%	0%	30%
	N	0%	42%	0%	40%
	B	0%	26%	100%	30%
All		0%	95%	5%	100%



The results show that previous spring snow provides weak continuous skill but moderate categorical ability for predicting summer streamflow. so the model cannot reproduce actual flow magnitudes or variability. Categorical performance is modest, with a 40% hit score and 2AFC values around 35–37%.

ROC curves show good discrimination for below-normal summers (≈0.79) but weak skill for above-normal years (≈0.39), meaning dry summers are easier to detect than wet ones. Hindcast and temporal plots reveal that predictions stay near climatology and fail to follow extremes or interannual changes. Contingency tables show frequent misclassification, especially for above-normal summers.

Discussion-2: Kettle Station

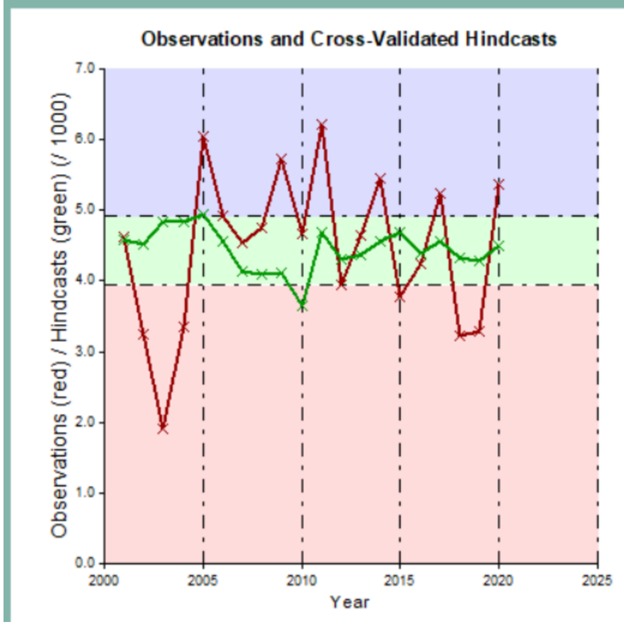
No-lag models:
Summer streamflow prediction:

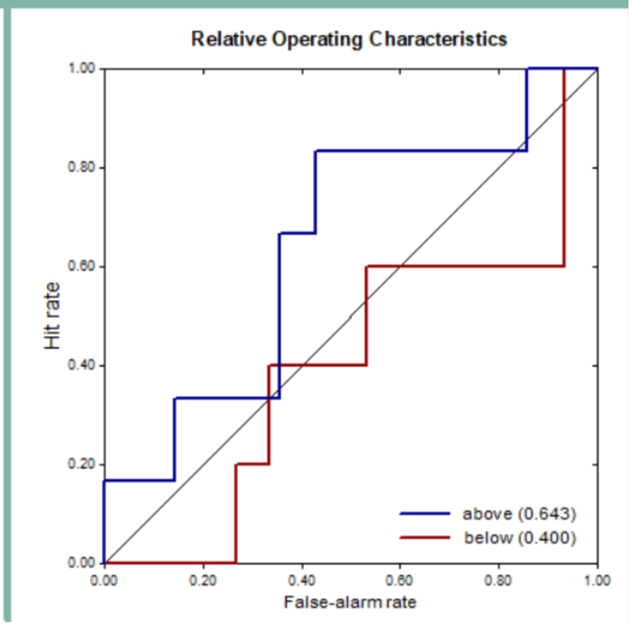
Continuous measures:

Pearson's correlation	-0.0707
Spearman's correlation	0.0421
2AFC score (continuous)	50.53%
% variance	0.00%
Variance ratio	0.0772
Mean bias	-10.43
Root mean squared error	1130.56
Mean absolute error	931.89

Categorical measures:

Hit score	45.00%
Hit skill score	17.50%
LEPS score	0.94%
Gerrity score	-3.33%
2AFC (forecast categories)	44.57%
2AFC (continuous forecasts)	52.71%
ROC area (below-normal)	0.4000
ROC area (above-normal)	0.6429



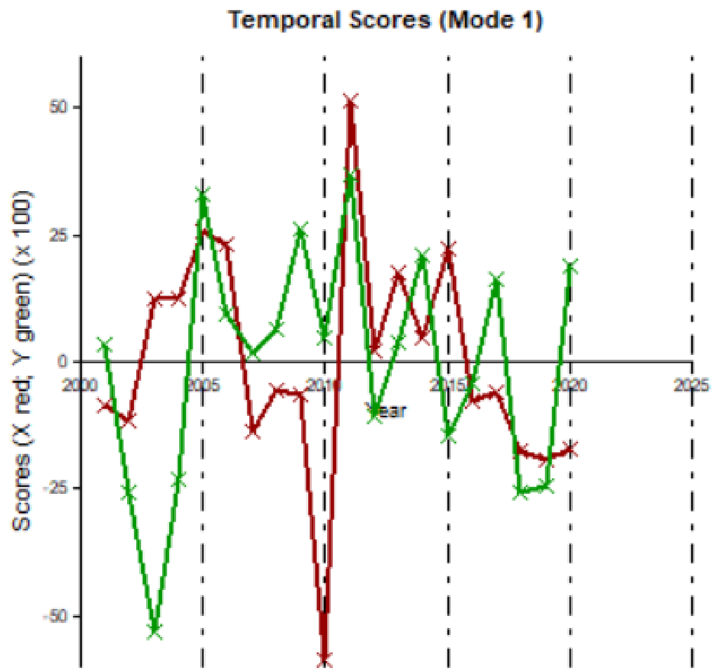


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	1	5	0	6
	N	0	9	0	9
	B	0	5	0	5
Total		1	19	0	20

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	100%	26%	0%	30%
	N	0%	47%	0%	45%
	B	0%	26%	0%	25%
All		5%	95%	0%	100%



The no-lag summer streamflow model shows very weak predictive skill. Continuous metrics are poor so the model cannot reproduce actual summer flows. Categorical performance is modest: the hit score is 45%, ROC for above-normal years is moderate (≈0.64), but below-normal years are poorly detected (≈0.40).

Hindcast and temporal plots show predictions stuck near climatology, missing most extremes and year-to-year variability. Contingency tables also reveal frequent misclassification, especially for dry summers.

Discussion-2: Kettle Station

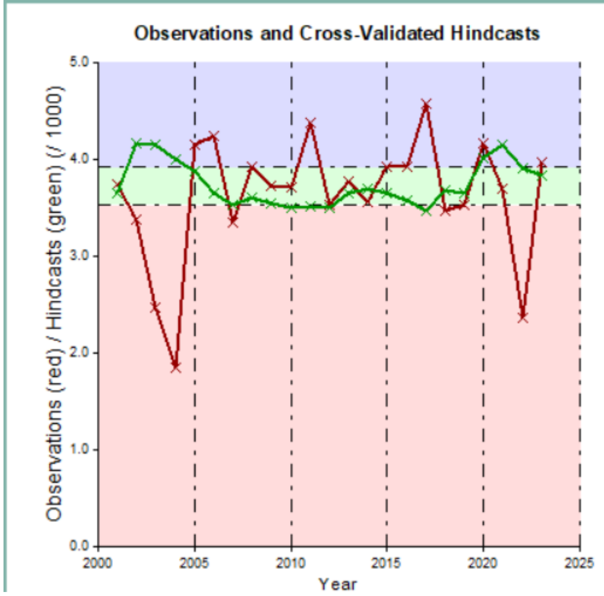
Winter streamflow prediction:

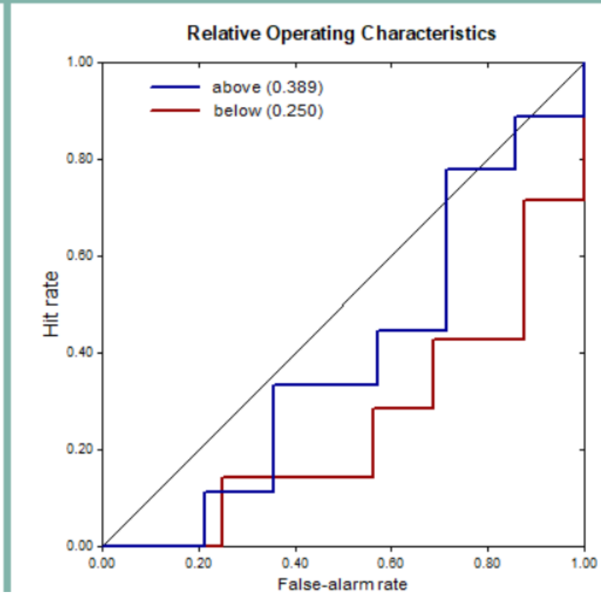
Continuous measures:

Pearson's correlation	-0.4798
Spearman's correlation	-0.3597
2AFC score (continuous)	37.94%
% variance	0.23%
Variance ratio	0.1239
Mean bias	112.51
Root mean squared error	769.37
Mean absolute error	519.87

Categorical measures:

Hit score	30.43%
Hit skill score	-8.70%
LEPS score	-14.08%
Gerrity score	-11.86%
2AFC (forecast categories)	36.86%
2AFC (continuous forecasts)	34.86%
ROC area (below-normal)	0.2500
ROC area (above-normal)	0.3889





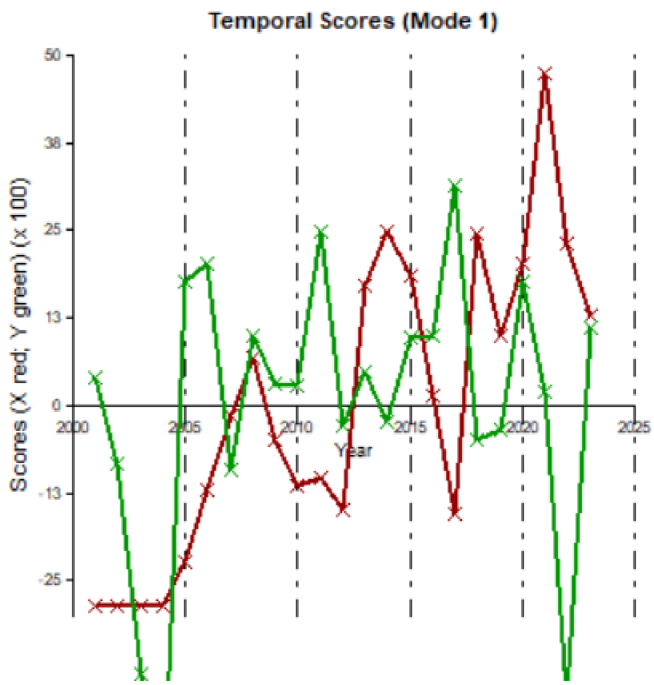
Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	1	7	1	9
	N	0	6	1	7
	B	0	4	3	7
	Total	1	17	5	23

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	100%	41%	20%	39%
	N	0%	35%	20%	30%
	B	0%	24%	60%	30%
	All	4%	74%	22%	100%

Discussion-2: Kettle Station



The winter streamflow model has very weak predictive skill. Continuous metrics are poor as showing the model cannot reproduce winter flows. Categorical skill is limited: the hit score is 39%, and ROC values are low (≈0.36 for above-normal, ≈0.26 for below-normal), indicating weak discrimination.

Hindcast and temporal plots show predictions clustering near climatology and missing extremes, while contingency tables reveal frequent misclassification, especially of below-normal years.

Discussion-2: Kettle Station

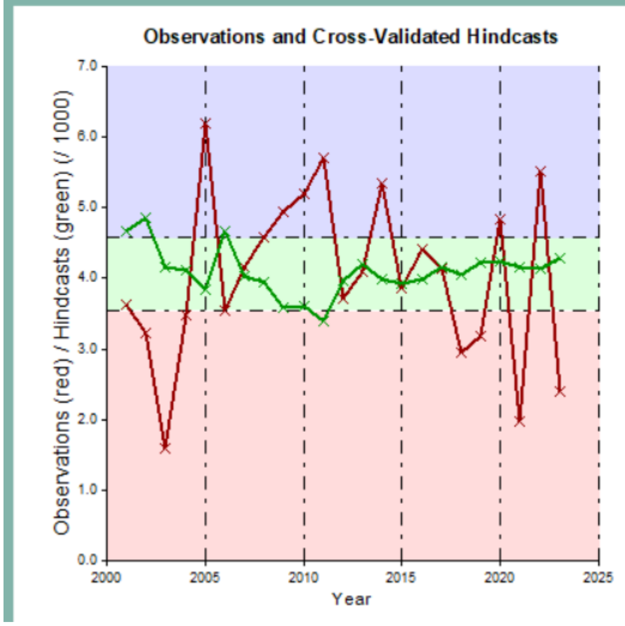
Autumn streamflow prediction:

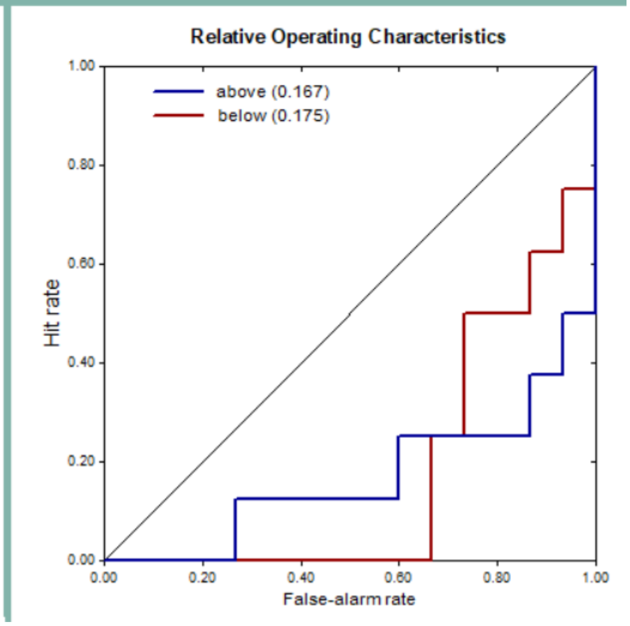
Continuous measures:

Pearson's correlation	-0.5160
Spearman's correlation	-0.6087
2AFC score (continuous)	28.46%
% variance	0.27%
Variance ratio	0.0807
Mean bias	67.47
Root mean squared error	1361.41
Mean absolute error	1120.73

Categorical measures:

Hit score	30.43%
Hit skill score	-8.70%
LEPS score	-1.41%
Gerrity score	0.00%
2AFC (forecast categories)	50.00%
2AFC (continuous forecasts)	19.32%
ROC area (below-normal)	0.1750
ROC area (above-normal)	0.1667



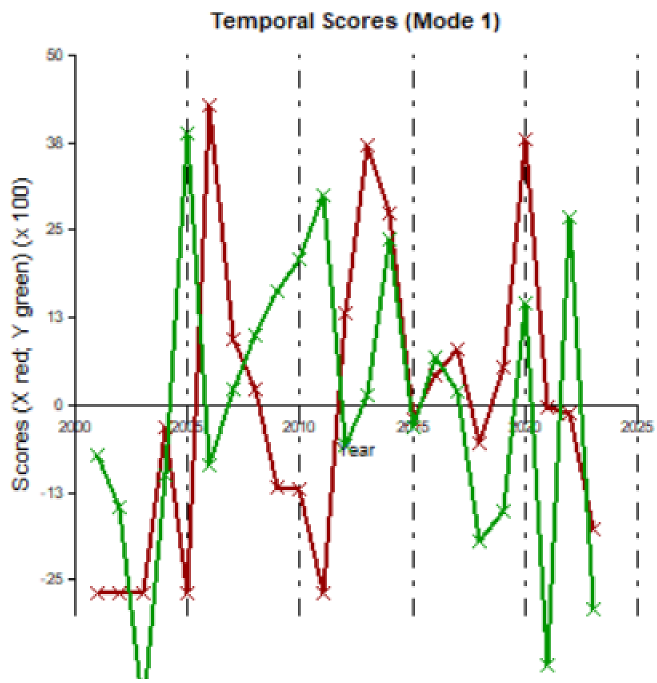


Frequency table:

		Forecast B	Forecast N	Forecast A	Total
Observed	A	0	8	0	8
	N	0	7	0	7
	B	0	8	0	8
Total		0	23	0	23

Contingency table:

		Forecast B	Forecast N	Forecast A	All
Observed	A	0%	35%	0%	35%
	N	0%	30%	0%	30%
	B	0%	35%	0%	35%
All		0%	100%	0%	100%



The autumn streamflow model shows very limited predictive skill. Continuous metrics are poor, correlations are strongly negative, explained variance is under 1%, and errors are high, so the model cannot reproduce actual flows or interannual variability. Categorical performance is also weak: the hit score is 39%, LEPS and Gerrity scores are negative, and ROC values for above- and below-normal years (0.17–0.18) indicate almost no discrimination ability.

Hindcast and temporal plots show predictions clustering near climatology and missing extremes, while contingency tables reveal frequent misclassification and a strong bias toward near-normal forecasts. Overall, same-season climate variables provide little value for predicting autumn streamflow, which is more strongly influenced by pre-season storage, groundwater, and delayed snowmelt processes.

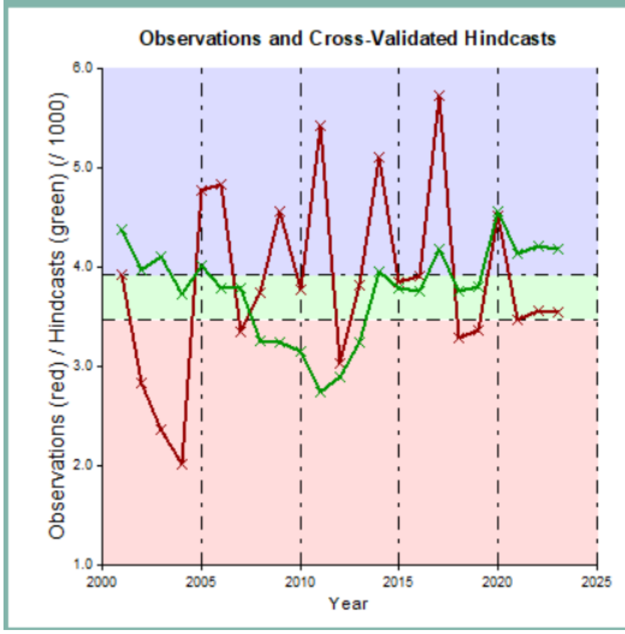
Spring streamflow prediction:

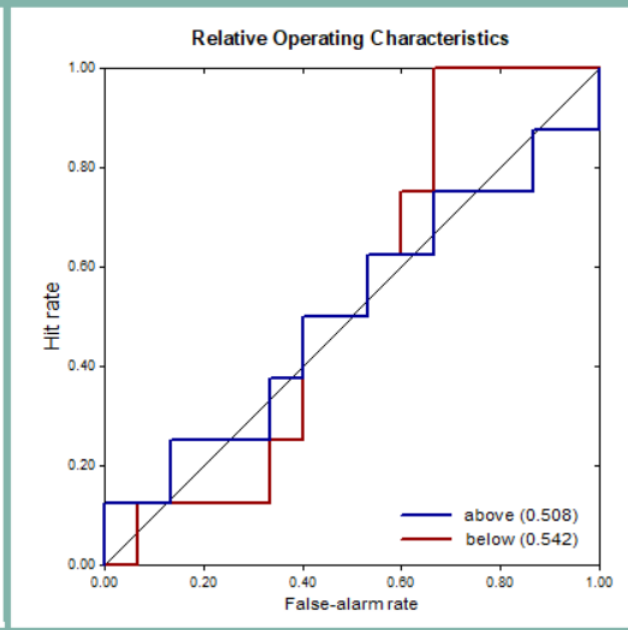
Continuous measures:

Pearson's correlation	-0.0402
Spearman's correlation	0.0721
2AFC score (continuous)	53.75%
% variance	0.00%
Variance ratio	0.2647
Mean bias	-93.99
Root mean squared error	1034.81
Mean absolute error	822.84

Categorical measures:

Hit score	30.43%
Hit skill score	-8.70%
LEPS score	2.82%
Gerrity score	2.08%
2AFC (forecast categories)	51.99%
2AFC (continuous forecasts)	52.27%
ROC area (below-normal)	0.5417
ROC area (above-normal)	0.5083



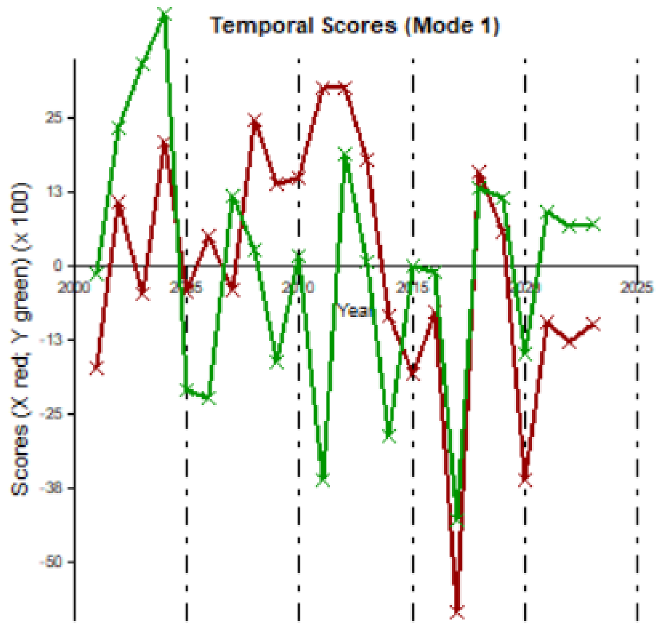


Frequency table:

		Forecast			
		B	N	A	Total
Observed	A	2	4	2	8
	N	3	4	0	7
	B	1	7	0	8
	Total	6	15	2	23

Contingency table:

		Forecast			
		B	N	A	All
Observed	A	33%	27%	100%	35%
	N	50%	27%	0%	30%
	B	17%	47%	0%	35%
	All	26%	65%	9%	100%



The spring streamflow model shows only limited predictive skill. Continuous metrics are weak, with a near-zero Pearson correlation (~0.08), a small Spearman correlation (~0.27), and explained variance under 1%, meaning the model cannot reproduce actual spring flow magnitudes. Categorical skill is modest: the hit score is about 39%, and ROC values for above-normal (0.58) and below-normal (0.54) exceed the no-skill level, indicating slight discriminatory ability.

Hindcast results show that the model occasionally captures wet or dry anomalies but generally stays close to climatology and misses extremes. Temporal scores show partial but inconsistent alignment with observed variability. Contingency tables indicate frequent misclassification, especially for non-normal years.

Discussion-2: Kettle Station

Conclusion:

The analysis of the Kettle and Long Spruce stations shows that northern Manitoba's rivers are stable over 2000–2023. Seasonal precipitation has little effect on flow, and scatterplots show almost no direct rainfall, discharge or snow, or discharge relationship. Instead, streamflow is mainly controlled by cold-season storage processes.

Across both stations, discharge increases when temperatures reach melt levels, confirming classic cold-region behavior. Lagged snow and precipitation variables show much stronger correlations with discharge than same-season values.

Model results support this: lag-1 models (using previous winter/spring conditions) perform better than no-lag models. No-lag models show almost no skill.

In conclusion, Both stations show the same patterns: weak sensitivity to same-season precipitation, strong influence of winter and spring conditions, and snowmelt-controlled discharge.

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