# Preseason Climate Controls on Summer Fire Weather in Manitoba

**Course:**

**Hydroclimatology for Water Resources Management**

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## Abstract

Wildfire risk planning in Manitoba requires information not only on short-term weather, but also on how preseason climate conditions shape summer fire danger. In this project, I investigated whether daily summer fire danger, expressed as the Canadian Fire Weather Index (FWI), can be predicted from spring (MAM) climate summaries and a large-scale ENSO index (Niño 3.4). Daily station data from 1953-2025 were used to construct preseason features (temperature, relative humidity, wind, and precipitation statistics for March-May) and to define a binary target indicating high fire danger (FWI $\geq$ 20) for each June-August (JJA) day. Models were trained on years before 2010 and evaluated on 2010-2025. I compared a stratified dummy classifier, logistic regression, random forest, and gradient boosting. Tree-based models achieved high overall accuracy (>0.81) and low Brier scores (~0.15) but rarely detected high-FWI days (recall $\leq$ 0.02). In contrast, logistic regression sacrificed accuracy (~0.57) but substantially improved high-FWI recall (~0.58) with modest precision (~0.23) and F1 ($\approx$ 0.33). Adding a spring ENSO predictor (MAM mean Niño 3.4) slightly improved the logistic model (small gains in accuracy and Brier score, almost unchanged precision/recall), while leaving the qualitative behavior of the tree models unchanged. Overall, preseason local climate contains useful information about summer fire danger, and logistic regression appears more suitable than complex tree ensembles when the priority is to detect high-risk days rather than maximize overall accuracy.

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# 1 Introduction

Wildfires are a recurring natural hazard in Canada and an increasingly important concern under a warming climate. They threaten communities, infrastructure, ecosystems, and air quality, and they also generate high economic and health costs. Operational agencies rely on the Canadian Forest Fire Weather Index (FWI) system to quantify day-to-day fire danger based on temperature, humidity, wind, and precipitation. While FWI is effective for short-term fire weather assessment, it is typically driven by daily weather forecasts, which only provide a few days of lead time for planning.

For fire and land managers, it is often just as important to know how severe an upcoming season is likely to be, not only what will happen in the next 3 to 5 days. If we can say in advance that a given summer is more likely to have many high-FWI days, agencies can adjust staffing levels, preparedness, and fuel-management activities. Recent work with dynamical seasonal forecast systems has shown that there is measurable skill in predicting anomalies of fire-danger indices such as the Canadian Fire Weather Index (FWI) at monthly to seasonal lead times, particularly when the forecasts are driven by coupled ocean–atmosphere models that capture large-scale climate modes such as ENSO and the Indian Ocean Dipole (Bedia et al., 2018; Di Giuseppe et al., 2024). Complementary studies using statistical post-processing and machine-learning approaches indicate that fire-danger indices and derived predictive models perform very differently across regions, and that their skill can be substantially improved when the FWI formulation and/or model parameters are calibrated for specific countries or climate regimes rather than applied globally in an unmodified way (Bedia et al., 2018; Lazebnik et al., 2025). Together, these results suggest real potential for seasonal fire-danger prediction but also highlight the need for regionally tailored analyses and calibration before such products can be used operationally.

Spring climate in Manitoba can precondition fuels and landscapes: warm, dry, and windy March-May conditions may lead to drier fuels and higher background fire danger once summer begins. At the same time, large-scale climate models such as the El Niño-Southern Oscillation (ENSO) can influence atmospheric circulation patterns over North America and potentially modulate regional fire weather. If the spring ENSO state, for example, the Niño 3.4 index, is systematically related to summer FWI in Manitoba, it could provide useful seasonal-scale guidance that is available months before the fire season peaks.

However, it is not obvious in advance how strong these relationships are, or whether preseason local climate and ENSO provide enough information to predict individual high-FWI days or at least the overall frequency of high-risk days in each summer. This project is motivated by that gap. The goal is to quantify how spring climate and ENSO relate to summer FWI in Manitoba, and to test whether relatively simple statistical and machine-learning models, inspired by the approaches used in recent fire-danger and ENSO studies, can turn this preseason information into practical predictions of high fire danger days.

# 2 Data

## 2.1 Fire weather and station data

The main dataset consists of daily fire weather and FWI records from the Canadian Wildland Fire Information System (CWFIS) for the period 1953 to 2025. The original archive contains stations across Canada. For this study, the data were first combined into a single dataset and then filtered to the Manitoba province boundary. In recent years, this selection used explicit location metadata. For older records, where location fields were missing, stations were assigned to Manitoba based on their identification codes. This procedure may lead to some loss or misclassification of stations, particularly in the earliest decades, but is expected to retain most long-term Manitoba FWI records. The spatial distribution of the selected fire-weather stations within the Manitoba boundary is shown in Figure 1.

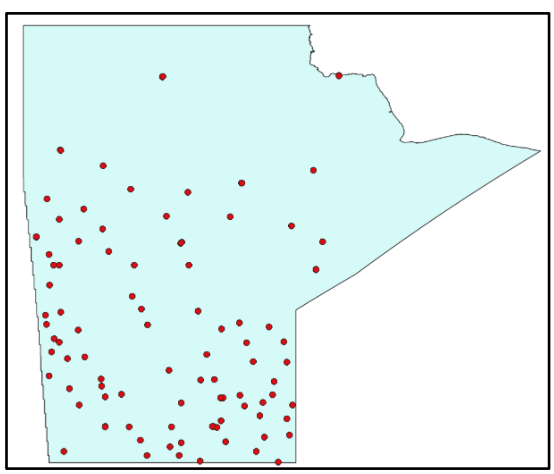

*Figure 1: Location of fire-weather stations used in this study within the province of Manitoba (red dots)*

After cleaning and regional filtering, each daily record includes date (rep_date), station identifier (aes), FWI (fwi), air temperature (temp), relative humidity (rh), wind speed (ws), and daily precipitation (precip). The date field was converted to a datetime object, from which year, month, day, and day of year (doy) were derived. Spring (preseason) is defined as March to May (MAM) and summer as June to August (JJA). MAM data are used to compute preseason station year statistics, and JJA data are used to define the daily high FWI target.

## 2.2 ENSO data

Large-scale climate forcing is represented by a monthly Niño 3.4 index based on the ERSSTv5 sea surface temperature analysis, obtained from NOAA. The ENSO file contains one index value per month. For each year, a spring ENSO index, ENSO_MAM, was computed as the mean Niño 3.4 value in March, April, and May. This annual series was merged by year into the preseason feature table and linked to all JJA daily records in that year.

## 2.3 Data limitations and quality control

The Manitoba subset has uneven temporal coverage. Early decades contain fewer stations and more gaps, while coverage is denser in recent years. Some records contain missing or invalid rep_date or missing FWI. These entries were removed using a robust date parser and by dropping JJA days without a valid FWI. In the ENSO file, flag values such as -99.99 and -9999 were treated as missing before computing ENSO_MAM, and years without valid March, April, or May values were excluded from ENSO-based analyses.

The datasets contain fire weather variables and FWI, but not observed fire occurrences or burned areas. FWI is therefore used as a proxy for potential fire danger rather than actual fire activity. Results should be interpreted with these limitations in mind, especially the sparser and less certain coverage in the earliest part of the record and the use of FWI as an index rather than a direct measure of wildfires.

# 3 Methods

## 3.1 Preprocessing and seasonal subsets

The daily Manitoba subset of the CWFIS archive was first combined into a single dataset. The variable rep_date was converted to a datetime object, and the corresponding year, month, day, and day of year (doy) were derived. Records with invalid or missing dates were removed. The analysis was organized around two seasons. Spring, referred to as the preseason, was defined as March to May (MAM), and summer as June to August (JJA). Daily MAM data were used to construct preseason climate features at the station and year level. Daily JJA data were used to define the prediction target and to build the daily dataset for model fitting. JJA records with missing FWI values were excluded so that the target variable was always well defined.

## 3.2 Construction of preseason MAM features

To characterize preseason conditions, daily MAM data were grouped by station identifier (aes) and year. For each station and year, summary statistics were computed from the daily values of temp, rh, ws, and precip. From the temp, the mean, standard deviation, and maximum over March to May were calculated. From the rh, the mean and minimum over the same period were obtained. From the ws, the mean and maximum were calculated. The variable precip was summarized using the total precipitation over MAM, together with counts of wet and dry days. Wet days were defined as days with precip $> 0.1$, and dry days as days with precip $\leq 0.1$. The threshold of 0.1 mm was chosen as a small but nonzero cutoff intended to exclude trace or noise level precipitation while still counting days with measurable rainfall. This set of station-year features provides a compact description of how warm, dry, windy, and wet the spring was at each station prior to the fire season.

## 3.3 ENSO index

Large-scale climate forcing was represented by the Niño 3.4 index derived from the ERSSTv5 sea surface temperature analysis provided by NOAA. The ENSO dataset contains one Niño 3.4 value per calendar month. For each year, a spring ENSO index, denoted ENSO_MAM, was computed as the mean of the March, April, and May Niño 3.4 values. This procedure yields a single ENSO value for each year. The annual ENSO_MAM series was then merged by year into the station year

MAM feature table, so that each station and year was associated with both local preseason climate statistics and the corresponding large-scale ENSO state.

## 3.4 JJA daily dataset and target definition

The JJA subset of the Manitoba daily data was merged with the station year MAM feature table using aes and year as keys. This produced a daily dataset in which each JJA record contains the date and calendar variables (rep_date, year, month, and doy), the observed daily fire weather index FWI, the preseason MAM features for that station and year, and the spring ENSO index ENSO_MAM for that year. The prediction problem was formulated as a binary classification task at the daily scale. A high fire danger day was defined as one with FWI $\geq 20$. For each JJA day, the binary target variable y was set to 1 if FWI $\geq 20$ and to 0 otherwise. Only JJA station days with valid FWI and complete preseason features were retained for subsequent analysis.

## 3.5 Predictor set

For each JJA day in the merged dataset, the predictor vector consisted of calendar information, local preseason climate statistics, and the ENSO index. The calendar information was captured by doy and month. The local preseason climate was represented by the MAM station year features described in Section 3.2, namely the temperature, relative humidity, wind speed, and precipitation summaries. Large-scale forcing was included through the annual spring ENSO index ENSO_MAM. No JJA daily weather variables were used as predictors. The models, therefore, estimate the probability that a given JJA day at a given station is a high FWI day based solely on preseason conditions and the position of the day within the summer.

## 3.6 Train and test split

To evaluate temporal generalization in a way that resembles a forecasting application, the daily dataset was divided into a training period and an independent test period based on year. All station days with year less than 2010 were used for training, and all station days with year greater than or equal to 2010 were reserved for testing. In this way, model parameters were estimated from earlier decades and assessed on more recent summers, which provides a realistic test of performance for future prediction.

## 3.7 Exploratory analysis

Several exploration analyses were performed using the JJA dataset before fitting the classification models. First, a timeseries of daily mean FWI over all stations during JJA was constructed in order to examine interannual variability and the overall temporal behavior of summer fire weather. A 30-day moving average and a simple linear trend were added to this series to highlight seasonal structure and any long-term tendencies. Second, the fraction of JJA days with FWI $\geq$ 20 was computed for each year, producing a time series of the annual frequency of high fire danger days. Third, Pearson correlation coefficients were calculated between daily JJA FWI and each of the preseason MAM features and ENSO_MAM, and likewise between the binary indicator of high FWI and the same set of predictors. Finally, the relationship between ENSO_MAM and the yearly fraction of high FWI JJA days was examined by plotting one point per year and fitting a simple linear regression line. These exploratory steps provide statistical and physical context for the subsequent classification experiments.

## 3.8 Classification models

Four classification models were applied to predict daily high FWI using the predictor set described above. The first model was a stratified dummy classifier, which predicts class labels according to the class frequencies in the training data and serves as a baseline with no real skill. The second model was logistic regression implemented in a pipeline with standardization of the predictors using Standard Scaler and with class weight set to "balanced" to account for class imbalance. The maximum number of iterations was set to 1000 to ensure convergence. The third model was a random forest classifier with 300 trees and class_weight set to "balanced_subsample", which allows for nonlinear decision boundaries and interactions among the predictors. The fourth model was a gradient boosting classifier based on decision trees, which builds an ensemble sequentially to improve the fit. Each model produces an estimated probability that $y = 1$ for each JJA day. In the main comparison, a probability threshold of 0.5 was applied to convert these probabilities into binary class predictions.

# 4 Results

## 4.1 Temporal behavior of summer FWI

The time series of daily mean JJA FWI averaged over all Manitoba stations shows strong variability at both daily and interannual scales (Figure 2). The 30-day moving average highlights the seasonal evolution within each summer, while a fitted linear trend line suggests only a weak tendency compared with the large year-to-year fluctuations. A complementary plot of the annual fraction of JJA days with FWI greater than or equal to 20 (Figure 3) confirms that the frequency of high fire danger days varies substantially between summers, with some years showing many higher FWI days than others.

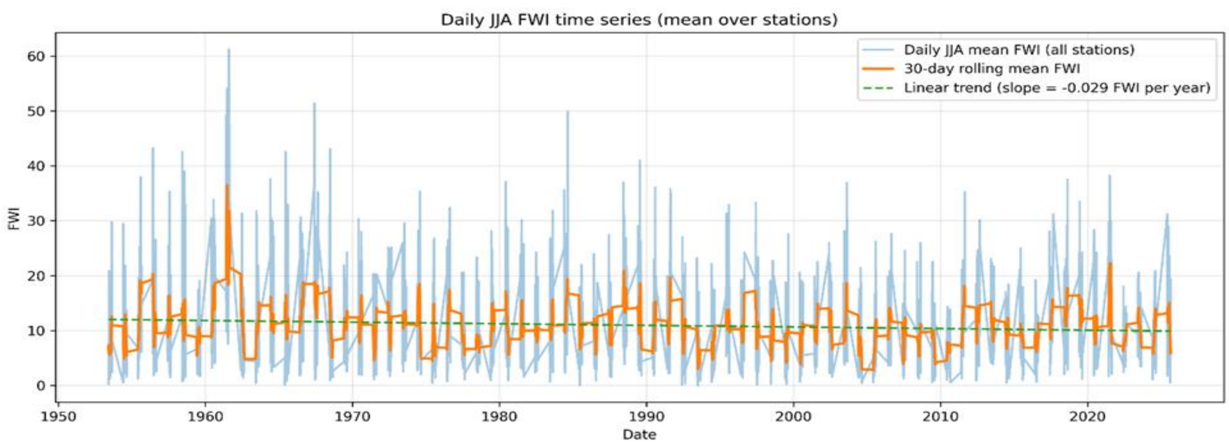


*Figure 2: Daily summer FWI timeseries*

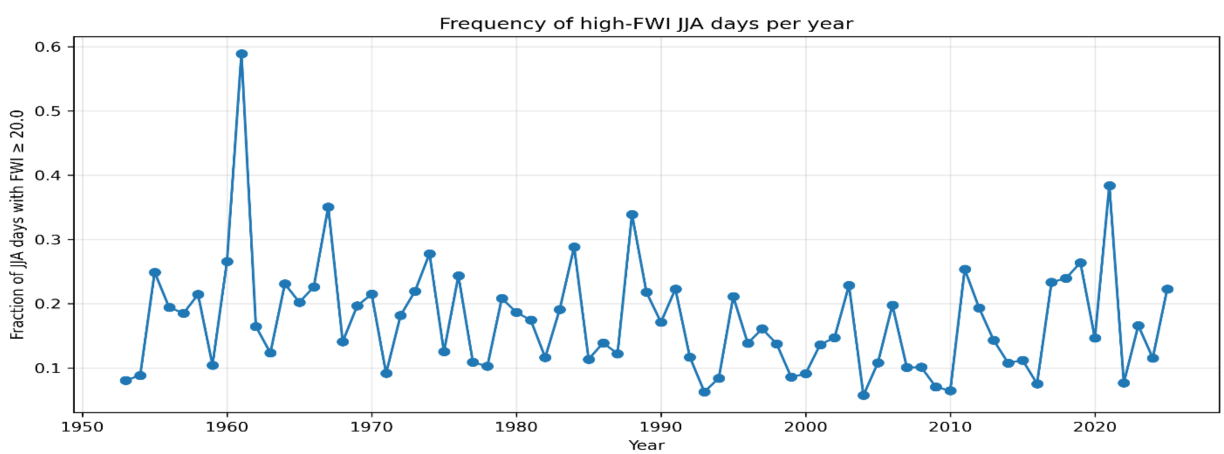


*Figure 3: Frequency of High-FWI summer days per year*

## 4.2 Relationship between preseason conditions, ENSO, and FWI

The correlation plots summarizing the link between preseason MAM features and JJA FWI (Figure 4) indicate that warmer and drier springs are associated with higher summer fire weather, while wetter springs are associated with lower FWI. MAM temperature statistics show weak positive correlations with JJA FWI, while MAM relative humidity, and total MAM precipitation show weak negative correlations, and MAM wind measures have small positive correlations. These relationships are modest in magnitude but physically consistent. When the spring ENSO index ENSO_MAM is added, its direct correlation with daily JJA FWI and with the binary high FWI indicator is small, and the scatter plot of ENSO_MAM versus the yearly fraction of high FWI days (Figure 5) shows a large spread for any given ENSO value. ENSO therefore appears to modify local preseason climate to some extent, but has only a weak direct linear relationship with daily FWI in Manitoba.

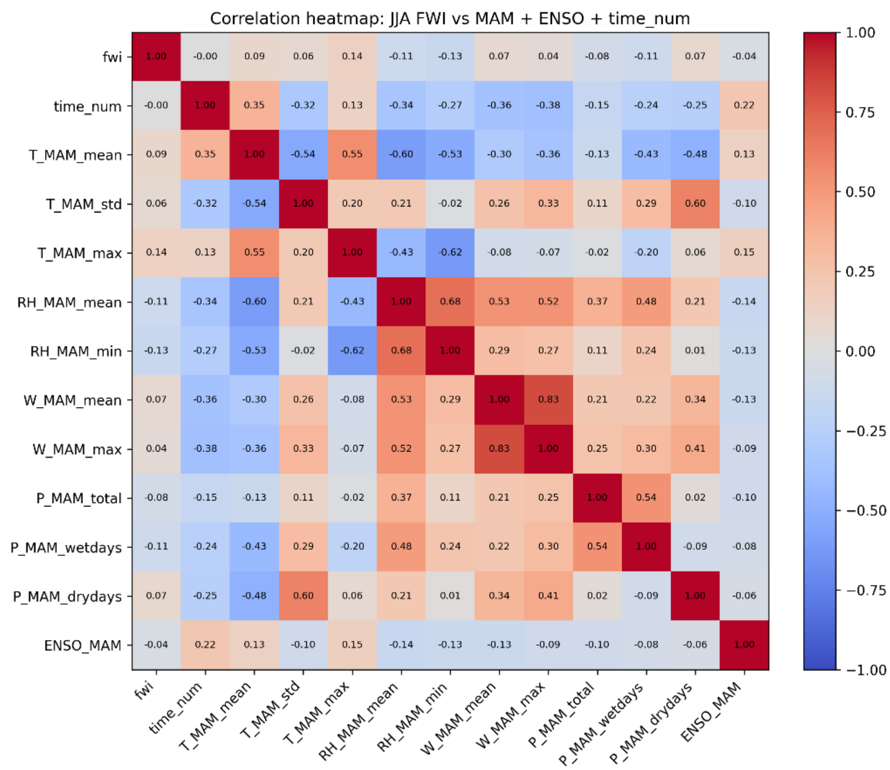


*Figure 4: Correlation Heatmap Summer FWI vs Spring Climate variables and ENSO*

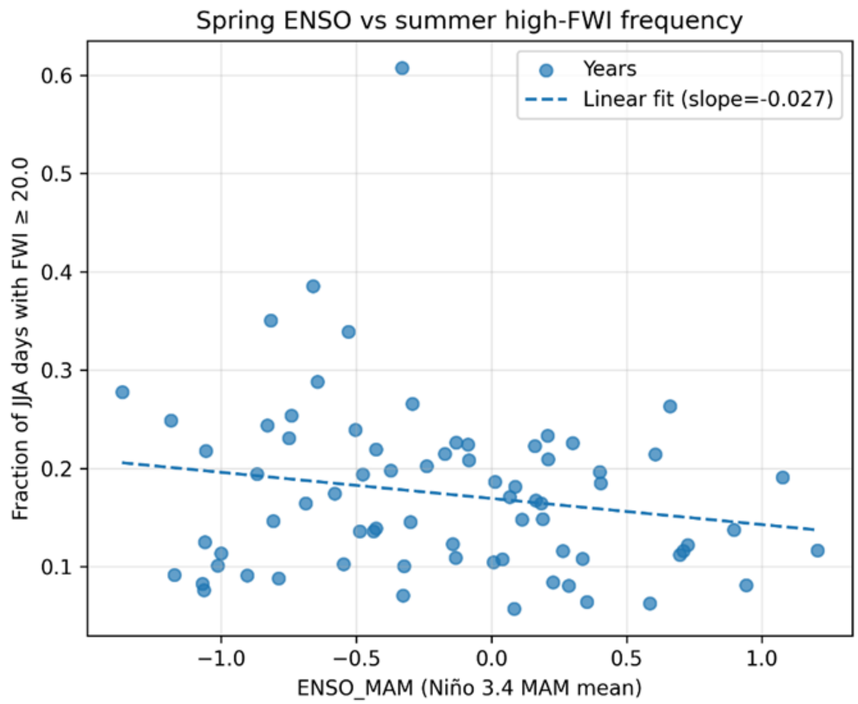


*Figure 5:Scatter plot of ENSO_MAM versus the yearly fraction of high FWI days*

## 4.3 Classification using MAM features only

Using only MAM preseason features and calendar information, the four classifiers behave quite differently on the 2010-2025 test period (Table 1). The stratified dummy classifier provides a baseline test accuracy of about 0.72, with precision around 0.17, recall 0.16, an F1 score of about 0.17, and a Brier score near 0.28. As expected, this baseline neither strongly favors nor strongly discriminates high-FWI days.

The logistic regression model sacrifices overall accuracy (about 0.57) in order to detect more high-FWI days. Its precision for high FWI increases to about 0.23, recall rises to about 0.59, and the F1 score reaches roughly 0.33, with an improved Brier score of about 0.24. In other words, logistic regression deliberately accepts more false alarms but correctly identifies a much larger fraction of high-risk days, which is desirable in a fire-danger early-warning context.

The two tree-based models, random forest and gradient boosting, achieve the highest test accuracy (around 0.81-0.83) and the lowest Brier scores (about 0.14 - 0.15). However, their recall for high-

FWI days is almost zero (≈0.01-0.02), and their F1 scores for the high-FWI class are correspondingly close to zero.

| Model | Accuracy | Precision | Recall | F1 Score | Brier Score |
|---|---|---|---|---|---|
| **Dummy Stratified** | 0.722213 | 0.184842 | 0.154126 | 0.168093 | 0.277787 |
| **Logistic Regression** | 0.567824 | 0.230295 | 0.586382 | 0.330708 | 0.244461 |
| **Random Forest** | 0.815570 | 0.333874 | 0.012928 | 0.024891 | 0.149573 |
| **Gradient Boosting** | 0.811491 | 0.263069 | 0.019580 | 0.036446 | 0.149250 |

*Table 1: Summary of Model Performance (MAM)*

The confusion matrices in Figures 6 to 9 show that these models classify nearly all days as "low" FWI, exploiting the strong class imbalance to maximize accuracy but providing almost no useful detection of high-danger days.

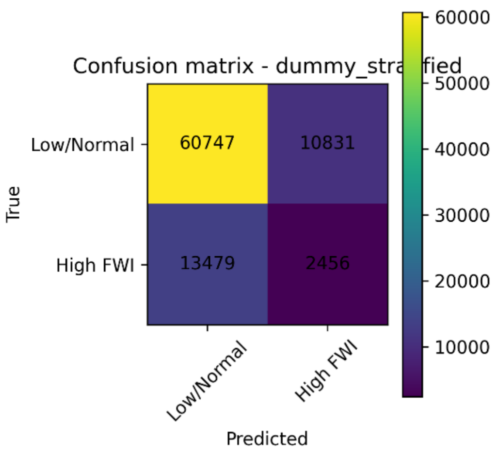


*Figure 8: Confusion matrix dummy stratified (MAM)*

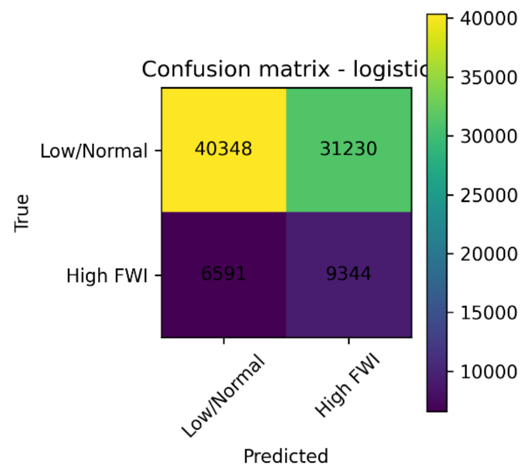


*Figure 9:Confusion matrix Logistic (MAM)*

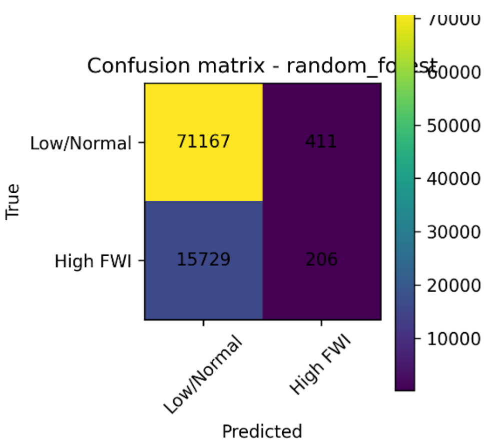


*Figure 7: Confusion matrix Random Forest (MAM)*

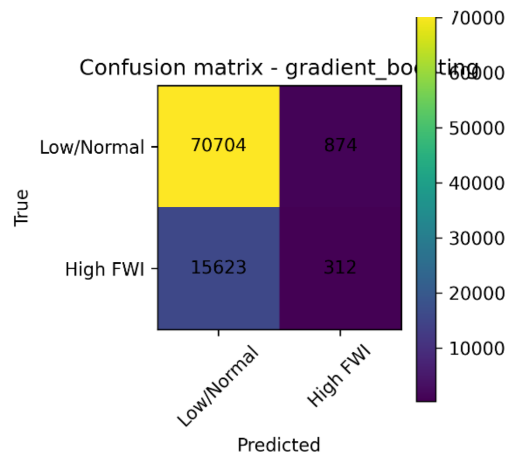


*Figure 6: Confusion matrix Gradient boosting (MAM)*

The bar plots in Figures 10 and 11 summarize these trade-offs. Logistic regression has the lowest overall accuracy but the highest recall for high FWI, while the tree-based models appear superior in terms of accuracy alone but effectively fail to identify high-risk days. This illustrates the accuracy paradox in imbalanced classification and supports the choice of logistic regression as the more useful model for operational high-FWI detection when only MAM features are available.

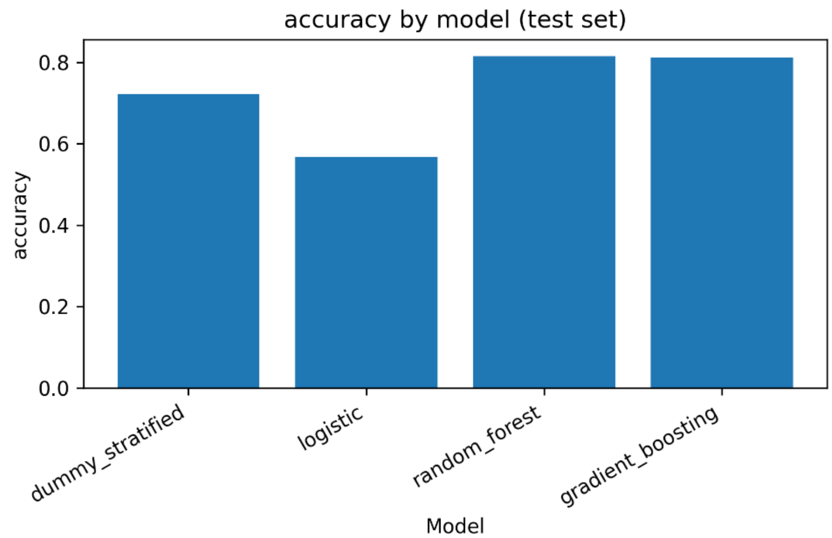


*Figure 10: Accuracy by model bar plot*

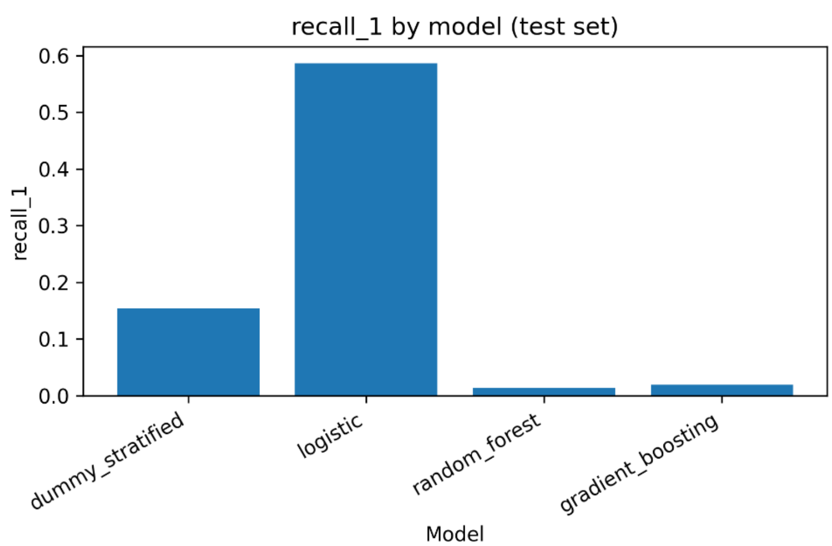


*Figure 11: Recall by model bar plot (MAM)*

## 4.4 Classification using MAM and ENSO features

When the spring ENSO index (ENSO_MAM) is added to the preseason feature set, the overall patterns remain broadly similar (Table 2). The stratified dummy classifier performs almost identically to the MAM-only case, as expected, since it does not use any predictors. Logistic regression shows a small change in performance: test accuracy changes from about 0.567 to 0.573, recall for high FWI changes from about 0.586 to 0.582, and the F1 score from about 0.330 to 0.332, with a Brier score of 0.241. These differences indicate that ENSO_MAM provides at most modest additional information beyond the local MAM climate for this station-based prediction problem.

| Model | Accuracy | Precision | Recall | F1 Score | Brier Score |
|---|---|---|---|---|---|
| **Dummy Stratified** | 0.722213 | 0.184842 | 0.154126 | 0.168093 | 0.277787 |
| **Logistic** | 0.573172 | 0.232128 | 0.582366 | 0.331944 | 0.241928 |
| **Random Forest** | 0.817216 | 0.376518 | 0.005836 | 0.011494 | 0.147240 |
| **Gradient Boosting** | 0.814028 | 0.334630 | 0.021588 | 0.040559 | 0.145559 |

*Table 2: Summary of Model Performance (MAM+ ENSO)*

For the random forest and gradient boosting models, adding ENSO_MAM has little effect on their tendency to classify nearly all days as low FWI. Their accuracy and Brier scores remain high and low, respectively, but recall for high-FWI days stay near zero, and F1 scores remain close to zero. The bar plot in Figure 12 and 13(F1 comparison between MAM-only and MAM+ENSO) shows that ENSO does not fundamentally change the ranking of models: logistic regression continues to provide the best balance between detecting high-FWI days and avoiding excessive false alarms, while the tree-based models remain dominated by the strong class imbalance.

Overall, these results suggest that, at least in this setup, ENSO_MAM is not a dominant predictor at the individual station-day scale compared with local MAM climate statistics and calendar information. ENSO may still be useful for coarser-scale seasonal assessments (e.g., total number of high-FWI days per year), but its added value for daily high-FWI classification at station level appears limited.

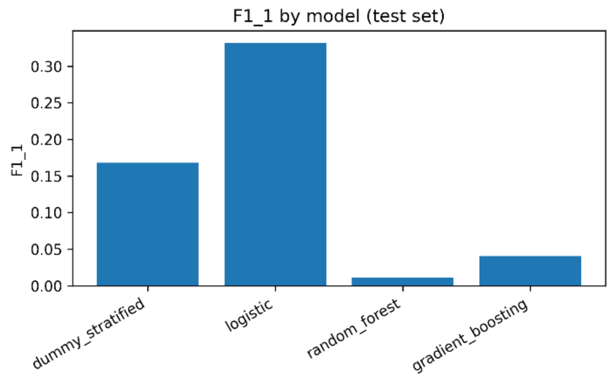


*Figure 12: F1 Score by model bar plot (MAM)*

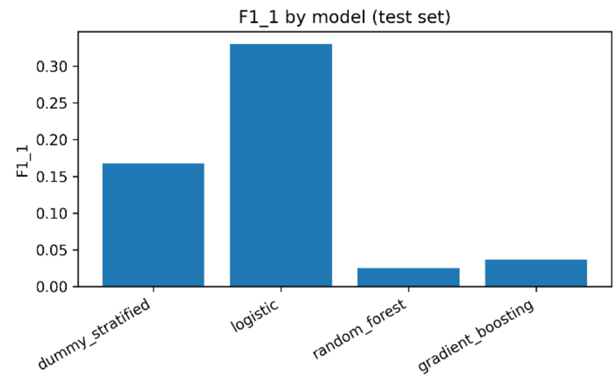


*Figure 13: F1 Score by model bar plot (MAM+ ENSO)*

# 5 Conclusions

This study examined whether spring climate conditions and a simple large-scale climate index can provide useful information about summer fire weather in Manitoba. Daily Canadian Forest Fire Weather Index (FWI) data and associated station-level meteorological variables (temperature, relative humidity, wind speed, and precipitation) from CWFIS were used to construct preseason (MAM) features at the station-year scale. A spring ENSO index (Niño 3.4 MAM mean) was added as a large-scale predictor. These preseason features were then related to both the temporal behavior of summer (JJA) FWI and the probability of high FWI days (FWI ≥ 20).

The temporal analysis shows substantial interannual and multi-decadal variability in Manitoba JJA FWI, with some indication of an upward tendency in mean summer FWI and in the frequency of high FWI days in recent decades. Correlations between preseason MAM climate and JJA FWI are physically plausible but modest: warmer and drier springs, and to a lesser extent windier springs, are associated with slightly higher summer FWI and a higher fraction of high FWI days, but these relationships explain only a small portion of the variance at the station-day level. ENSO_MAM shows, at most, a weak relationship with summer high-FWI frequency in Manitoba, consistent with the idea that ENSO acts mainly through broad circulation anomalies rather than deterministic daily effects at specific stations.

The classification experiments further confirm that preseason information alone has limited skill for predicting individual high-FWI days. Using only MAM features and calendar information, a stratified dummy classifier reflects the strong class imbalance. A class-weighted logistic regression model deliberately trades overall accuracy for improved recall and F1 for high FWI days, which is more relevant for risk-oriented applications. In contrast, random forest and gradient boosting achieve higher overall accuracy and lower Brier scores, but almost never identify high-FWI days and therefore have limited value for early warning. Including ENSO_MAM as an additional predictor does not materially improve this situation. Overall, the results suggest that preseason local climate and a single ENSO index do contain some information about the general level of seasonal fire danger, but are not sufficient on their own to support skillful daily prediction of high FWI at individual stations.

# 6 Future work

This study shows that preseason MAM climate and a simple ENSO index contain some information about summer fire danger in Manitoba, but also highlights important limitations. A natural next step is to relate the predicted high-FWI days to observed fire occurrence and burned area, to assess how well seasonal fire-danger predictions translate into outcomes that matter operationally.

Model performance also varies across space and time. The Manitoba station network is uneven, especially in earlier decades, and some stations have uncertain locations. Future work should therefore compute accuracy and skill per station, to identify where models perform well or poorly and to diagnose whether errors are driven by local data quality, microclimate, or structural model limitations.

On the predictor side, this project only used basic fire-weather variables and a single ENSO index. A key extension is to incorporate additional predictors that more directly reflect fuel and climate conditions, such as soil moisture, remote-sensing vegetation indices, and other large-scale climate indices, with the goal of increasing forecast skill for dangerous fire-weather seasons.

Finally, high-FWI days are rare, and our models still struggle with class imbalance. Future experiments should systematically test imbalance-handling techniques (class weights, over-/under-sampling, synthetic data) and combine them with probability, so that probabilistic forecasts of high FWI are both more sensitive to rare events and better calibrated for decision-making.

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