

Preseason Climate Controls on Summer Fire Weather in Manitoba

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Background and Objectives

Wildfire risk is increasing in many parts of Canada, including Manitoba.

Fire Weather Index (FWI)
is a standard index that combines **temperature, wind, humidity, and precipitation** to describe fire danger.

Objectives of this project:

- Analyze seasonal behavior of FWI for spring (MAM) and summer (JJA) in Manitoba.
- Examine correlations between FWI and key meteorological variables.
- Build and compare predictive models of FWI using local climate variables and ENSO.



Figure1 :Manitoba, Canada. 27 May 2025
<https://www.theguardian.com>



Datasets and Variables

Source: Canadian Wildland Fire Information System (**CWFIS**) daily data.

Region: Stations located inside **Manitoba** only.

Time period: 1953- 2025.

Main variables used:

- Fire Weather Index (FWI)
- Air temperature (T, Temp)
- Relative humidity (RH)
- Wind speed (Ws)
- Precipitation (Precip,P)
- ENSO index (Niño 3.4) from global climate databases

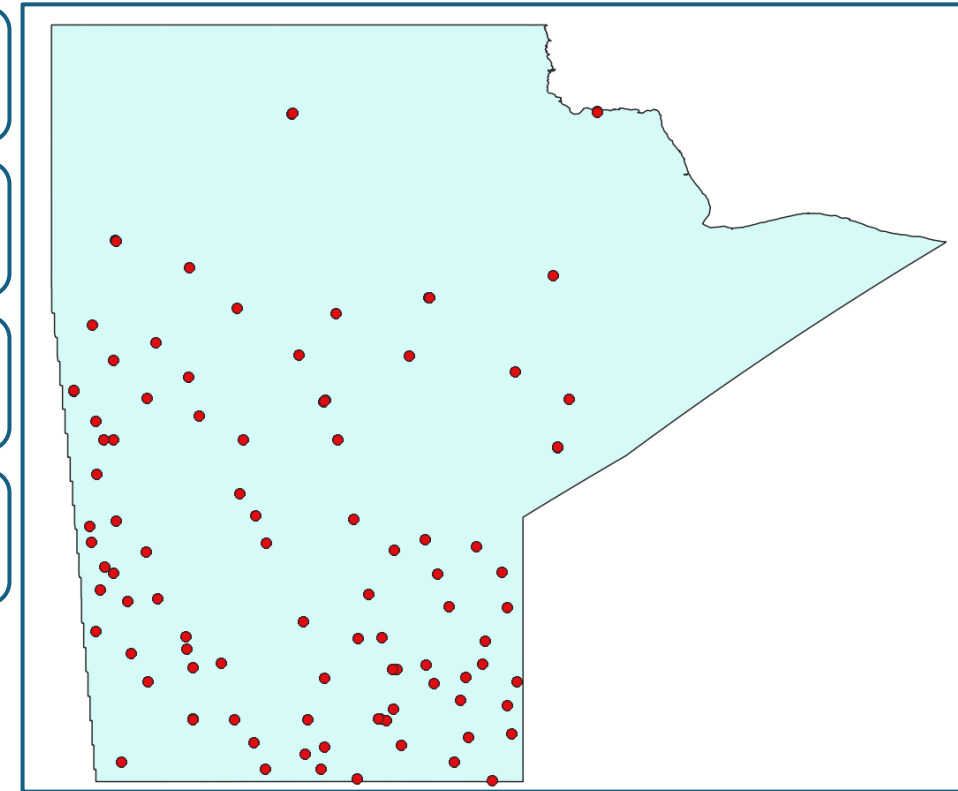


Figure 2: Manitoba Weather Stations



Methods



➤ Pre-processing

- Performed quality control by removing incomplete records and years with substantial missing data.
- Aggregated daily values to **seasonal means** for each **station** and **year**:
 - Spring: March-April-May (MAM)
 - Summer: June-July-August (JJA)
- Converted continuous seasonal FWI into categorical fire-danger classes using predefined FWI thresholds (“High” if $FWI > 20$).

➤ Analysis and modelling

- Quantified relationships between seasonal FWI and predictors using correlation analysis.
- Split the data into training and test sets using 2010 as the cutoff year
- Developed and compared four classification models for seasonal FWI classes:
 - Dummy Stratified Classifier
 - Logistic Regression
 - Random Forest Classifier
 - Gradient Boosting Classifier



Timeseries

- FWI:

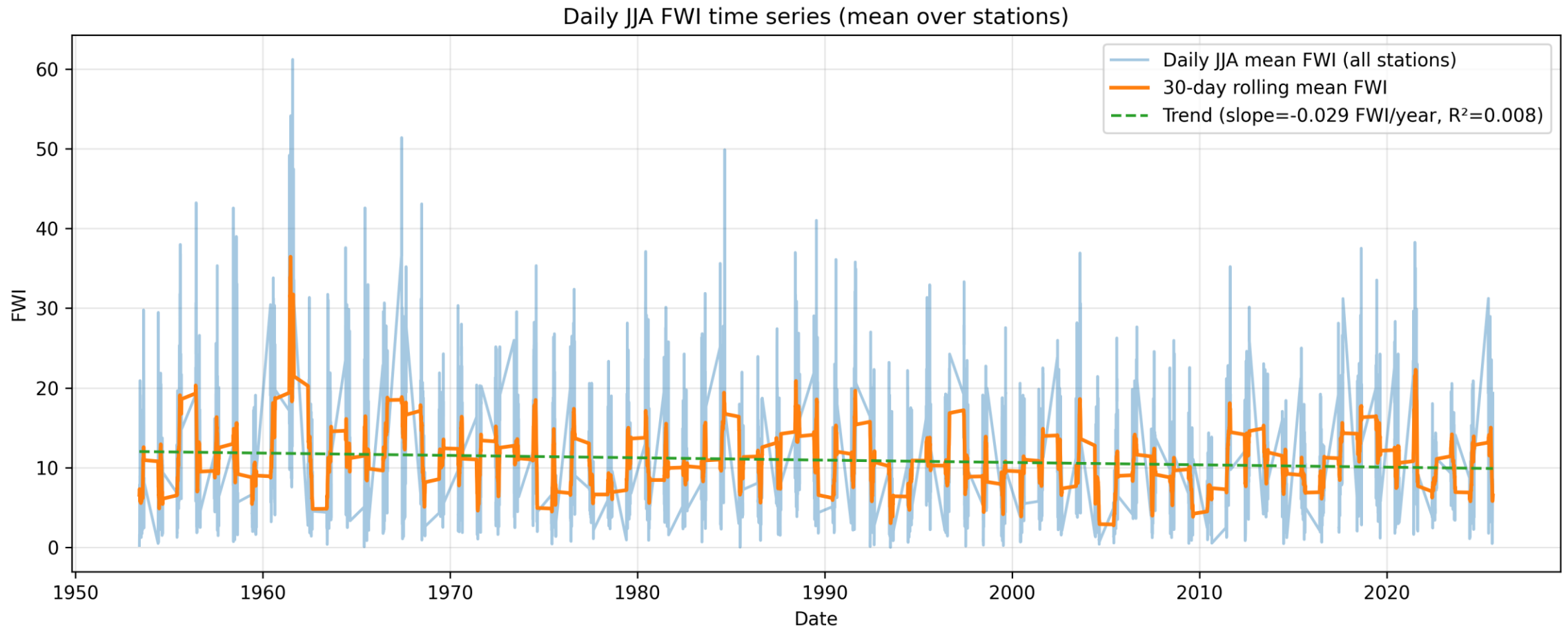


Figure 3: Summer FWI Timeseries



Timeseries

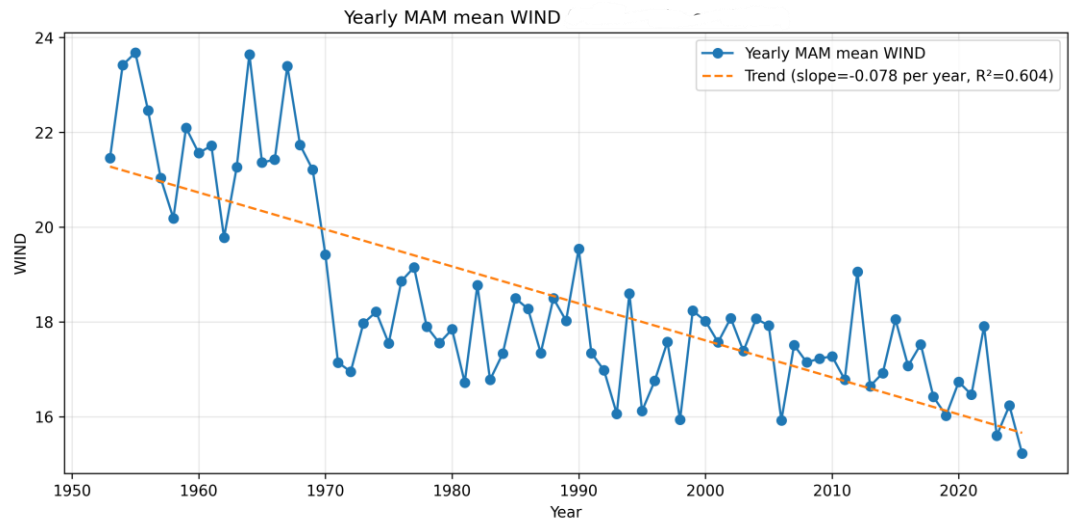
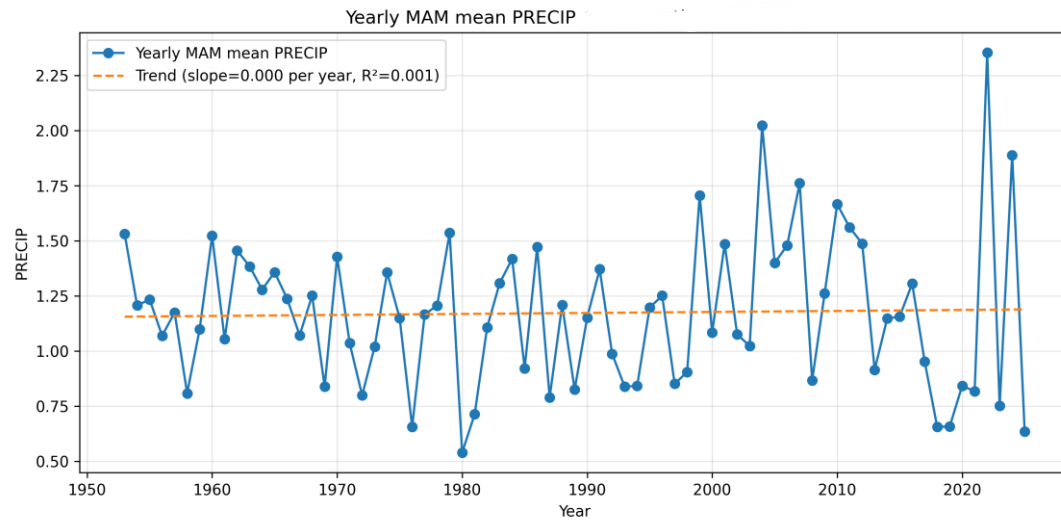
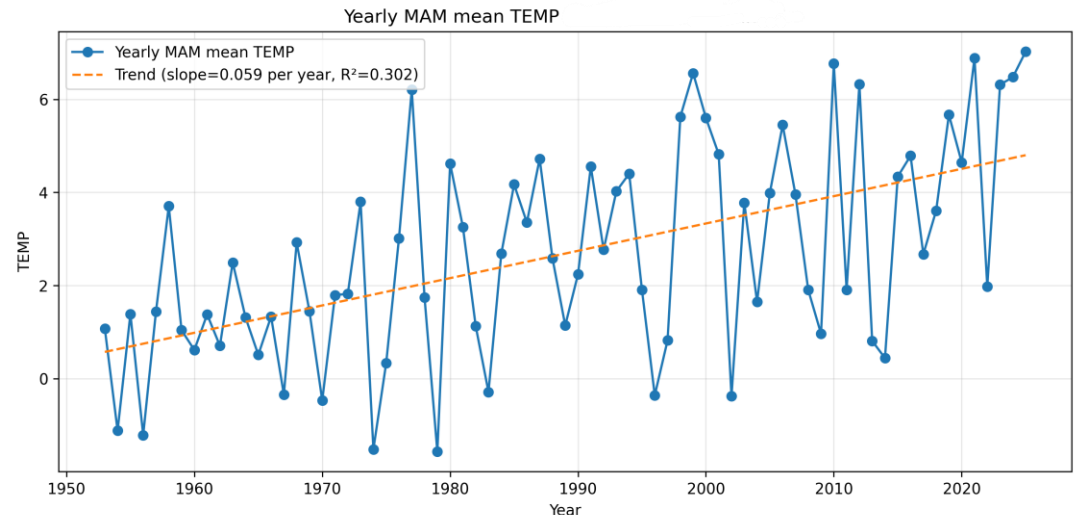
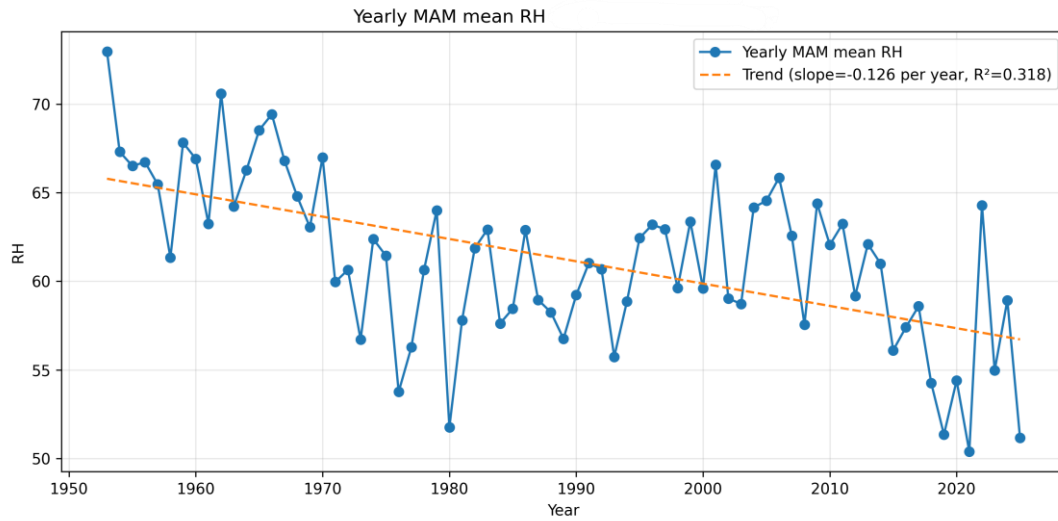


Figure 4: Spring Climate variables Timeseries



Correlation

FWI has weak positive correlation with spring temperature/wind and weak negative correlation with humidity/precipitation

ENSO has near-zero correlation with FWI in MAM.

Predictors are strongly inter-correlated (T vs RH)

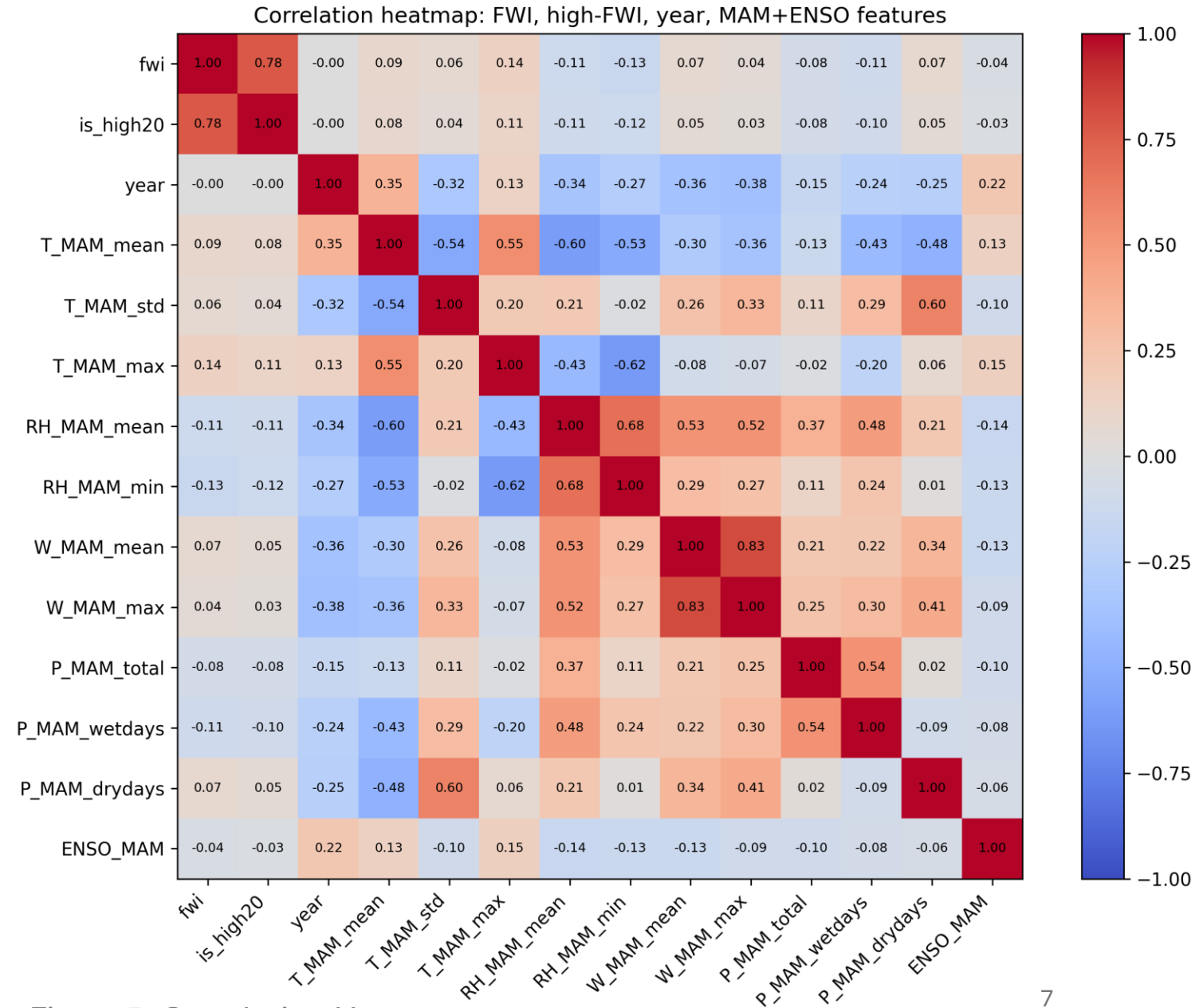


Figure 5: Correlation Heatmap



Model Summary (MAM)

Chosen model: Logistic regression

It has the best recall and F1 for high-FWI cases, so it actually detects dangerous days, even though its overall accuracy is lower than the tree models

- **Accuracy:** Fraction of all days predicted correctly.
- **Precision:** Among days predicted high FWI, how many were actually high.
- **Recall:** Among days that were actually high FWI, how many the model caught.
- **F1-score:** Single number that balances precision and recall (higher = better).
- **Brier score:** Error of predicted probabilities for high FWI (mean squared error; lower = better).

```
===== Summary of model performance (test set) =====
      model  accuracy  precision_1  recall_1    F1_1    Brier
dummy_stratified  0.722213    0.184842  0.154126  0.168093  0.277787
      logistic  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
```

Figure 6: Model Summary table (MAM variables)



Model Summary (MAM+ ENSO)


Adding ENSO gives only a **very small improvement** to the logistic model; most of the predictive power still comes from local spring variables.

```
===== Summary of model performance (test set) =====
      model  accuracy  precision_1  recall_1    F1_1    Brier
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
```

Figure 7: Model summary table (MAM+ ENSO)



Conclusion

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1. Seasonal FWI in Manitoba is **highly variable** long-term trends are weak at the provincial scale.
 2. Spring FWI is slightly higher in warmer, drier, windier springs, but **correlations** with individual variables are **modest**.
 3. Because high-FWI days are rare, **tree models** look good on accuracy but **hardly ever predict** the high class.
 4. **Logistic regression** gives the **best balance** for high-FWI detection
 5. Adding **ENSO** only **slightly changes** model performance



Future Work

Apply imbalance handling techniques (class weights, resampling) and improve probability calibration.

Explore additional predictors such as soil moisture, vegetation indices and other climate indices to increase forecast skill for dangerous fire weather seasons.

Calculate the accuracy per station to investigate the reason and results



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