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Multi-Source Transformer-Based Crop Yield Forecasting Across Canadian Agro-Ecological Zones: A Comparative Evaluation of CanadaYieldNet Against Deep Learning and Operational Baselines with Systematic Data Modality Ablation

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Abstract: *Accurate forecasting of crop yields at national scales remains a cornerstone of food security planning, agricultural market stability, and climate adaptation policy, yet existing deep learning approaches seldom exploit the full breadth of remote sensing modalities or undergo systematic evaluation across Canada's heterogeneous agro-ecological zones. To address this gap, we introduce CanadaYieldNet, a transformer-based framework that fuses five complementary data sources—optical imagery from Sentinel-2 and MODIS, synthetic aperture radar from the RADARSAT Constellation Mission, soil moisture from NASA SMAP, weather reanalysis from ERA5-Land, and static soil and terrain attributes from CanSIS and CDEM—through a carefully designed architecture combining a Temporal Fusion Transformer, Vision Transformer, static feature encoder, and an Adaptive Gated Fusion layer with multi-head cross-attention. Evaluated across six provinces and five major crops between 2014 and 2024, the system consistently outperformed thirteen established baselines, achieving mean \(R^2 = 0.94\), RMSE = 4.2 bu/acre, and MAPE = 6.8%, with optical remote sensing and weather data emerging as the most influential modalities in ablation studies. Crucially, the model demonstrated resilience under climatic extremes, maintaining predictive accuracy during droughts and excess moisture events, while SHAP and attention visualisation confirmed agronomically coherent drivers such as peak NDVI and growing-degree days. By uniting methodological innovation with interpretability, CanadaYieldNet establishes a new benchmark for national-scale yield forecasting in Canada, offering both robust predictive capacity and actionable insights for agricultural decision-makers, with all code and processed datasets released under open licences to ensure transparency and reproducibility.*

Keywords: Crop yield prediction; Transformer; Multi-modal fusion; Remote sensing; Canada; Sentinel-2; SAR; Soil moisture; Deep learning; Explainable AI; Agricultural forecasting; Vision Transformer; Temporal Fusion Transformer

I. INTRODUCTION

1.1 Background and Motivation

Global food security represents one of the most pressing challenges of the twenty-first century, with the world's population projected to exceed 9.7 billion by 2050 (United Nations, 2022). Canada, as one of the world's largest agricultural exporters, plays a critical role in international grain markets, ranking among the top five global exporters of wheat, canola, and pulses (Statistics Canada, 2024). The Canadian Prairies, encompassing Alberta, Saskatchewan, and Manitoba, constitute the nation's agricultural heartland, accounting for over 80% of national cereal and oilseed production. Accurate, timely, and spatially explicit crop yield forecasts are therefore essential for informing agricultural policy, commodity trading, supply chain logistics, and climate adaptation strategies at both national and international scales.

Traditional crop yield forecasting has relied upon process-based crop simulation models and statistical regression approaches. While crop models such as DSSAT-CERES-Wheat and CSM-CROPGRO-Canola encode mechanistic understanding of plant growth processes, they require extensive parameterisation, are computationally demanding at large spatial scales, and exhibit variable performance across heterogeneous landscapes (Zare et al., 2025). Statistical approaches, though simpler to implement, often fail to capture the complex non-linear relationships between environmental drivers and crop productivity, particularly under novel climatic conditions.

The emergence of deep learning has fundamentally transformed agricultural yield prediction. Convolutional neural networks (CNNs) have demonstrated remarkable capability in extracting spatial features from satellite imagery (Nevavuori et al., 2019), while recurrent architectures such as Long Short-Term Memory (LSTM) networks effectively model temporal dependencies in weather and vegetation time series (Zhang et al., 2021). More recently, the Transformer architecture, originally developed for natural language processing (Vaswani et al., 2017), has been successfully adapted for agricultural applications, leveraging self-attention mechanisms to capture long-range spatio-temporal dependencies that elude conventional architectures.

The Multi-Modal Spatial-Temporal Vision Transformer (MMST-ViT) proposed by Lin et al. (2023) demonstrated that transformer architectures can effectively integrate satellite imagery and meteorological data for county-level yield prediction across the United States. Similarly, the AgriTransformer framework (Garcia et al., 2025) employed cross-modal attention to jointly model tabular environmental features and vegetation indices, achieving substantial improvements over single-modality approaches. The CYPRESS model (University of Manitoba, 2025) further demonstrated the potential of fine-tuning large geospatial foundation models based on Vision Transformer architectures for intra-field canola yield prediction on the Canadian Prairies.

Despite these advances, several critical gaps remain in the literature. First, no existing framework has been designed specifically for the unique agro-ecological conditions of Canada, where short growing seasons, high spatial variability in precipitation, and frequent cloud cover during critical growth stages present distinct modelling challenges. Second, the majority of studies integrate only two or three data modalities, leaving substantial predictive signal untapped. The integration of optical remote sensing, synthetic aperture radar (SAR), soil moisture, weather reanalysis, and static terrain features within a unified transformer architecture remains unexplored. Third, systematic quantification of each modality's marginal contribution through rigorous ablation analysis is rarely performed, limiting understanding of which information sources drive prediction accuracy. Fourth, the generalisation performance of transformer-based yield models under climatic extremes, such as drought and excess moisture events, has not been comprehensively evaluated.

1.2 Research Objectives and Questions

This study addresses these gaps through the development and comprehensive evaluation of CanadaYieldNet, a multi-source transformer-based crop yield forecasting framework specifically designed for Canadian agricultural landscapes. The study is guided by five research questions:

RQ1: Can CanadaYieldNet outperform traditional machine learning, deep learning, and operational forecasting systems across Canadian agro-ecological zones?

RQ2: Which data modality contributes most to prediction accuracy, and what are the relative marginal contributions of optical, SAR, soil moisture, weather, and static features?

RQ3: How robust is the architecture across different crops, provinces, and years, and can it generalise to unseen regions and crop types?

RQ4: Can multimodal transformer fusion improve generalisation under climatic variability, including drought and excess moisture conditions?

RQ5: Can the model provide agronomically interpretable explanations for its predictions through attention visualisation and feature importance analysis?

II. MATERIALS and Methods

2.1 Study Region

The study encompasses six Canadian provinces with significant agricultural production: Alberta, Saskatchewan, Manitoba, Ontario, Quebec, and Prince Edward Island (PEI). Together, these provinces account for approximately 98% of Canada's cultivated cropland. The study region spans diverse agro-ecological zones, from the semi-arid Brown Soil Zone of southern Saskatchewan (annual precipitation 300–350 mm) to the humid climate of PEI (annual precipitation 1000–1200 mm). The Canadian Prairies (Alberta, Saskatchewan, Manitoba) are characterised by continental climates with cold winters, warm summers, and high inter-annual precipitation variability. Ontario and Quebec feature more temperate conditions with longer growing seasons, while PEI represents a maritime-influenced agricultural system. This diversity provides a robust testbed for evaluating model generalisation across climatic gradients.

2.2 Data Sources and Preprocessing

Five distinct data modalities were integrated into the CanadaYieldNet framework. Table 1 summarises the data sources, spatial and temporal characteristics, and preprocessing procedures applied to each modality.

Table 1 Summary of data sources and preprocessing procedures.

Modality	Source	Spatial Res.	Temporal Res.	Preprocessing
Optical RS	Sentinel-2, MOD13Q1, MOD09A1	10–250 m	5-day, 16-day	Cloud masking (QA band), atmospheric correction (Sen2Cor), linear interpolation gap filling, bidirectional reflectance distribution function (BRDF) normalisation
SAR	RADARSAT Constellation Mission (RCM)	10 m	12-day	Speckle filtering (Lee sigma, 7×7 window), radiometric calibration to sigma-nought, terrain correction using CDEM, despeckling
Soil Moisture	NASA SMAP L3 Radiometer	36 km	2–3 day	Temporal harmonisation to weekly composites, anomaly calculation relative to 2015–2024 climatology, downscaling to 1 km using MODIS land surface temperature
Weather	ERA5-Land reanalysis	9 km	Hourly, aggregated daily	Spatial interpolation to common grid, growing degree day accumulation, vapour pressure deficit calculation, missing value imputation via temporal mean
Static	CanSIS, CDEM	250 m–1 km	Static	Reprojection to EPSG:3978 (Canada Lambert Conformal Conic), resampling via bilinear interpolation, standard normal scaling

2.2.1 Optical Remote Sensing

Sentinel-2 Multi-Spectral Instrument (MSI) Level-2A surface reflectance products were acquired from the Google Earth Engine catalogue. The study utilised 10 spectral bands at 10–20 m spatial resolution: B2 (Blue), B3 (Green), B4 (Red), B5–B7 (Red-edge), B8 (NIR), B8A (Narrow NIR), B11–B12 (SWIR). Cloud masking was performed using the Scene Classification Layer (SCL) band, retaining only pixels classified as vegetation (class 4). MODIS Terra MOD13Q1 (16-day NDVI/EVI composite at 250 m) and MOD09A1 (8-day surface reflectance at 500 m) products were used to augment the Sentinel-2 time series and provide gap-free coverage during cloudy periods. All optical products were resampled to a common 1 km grid using area-weighted aggregation to match the spatial resolution of the yield reporting units.

2.2.2 Synthetic Aperture Radar

RADARSAT Constellation Mission (RCM) C-band SAR Ground Range Detected (GRD) products were obtained for the study period. Dual-polarisation (VV, VH) and quad-polarisation (HH, HV) acquisitions were collected with a nominal 12-day repeat cycle. Preprocessing followed the Sentinel Application Platform (SNAP) standard workflow: apply orbit file, thermal noise removal, radiometric calibration to sigma-nought (dB), Lee sigma speckle filtering (7×7 window), and Range-Doppler terrain correction using the Canadian Digital Elevation Model (CDEM). Polarimetric decomposition was applied to quad-polarisation acquisitions to generate entropy, anisotropy, and alpha angle parameters following the Cloude-Pottier decomposition.

2.2.3 Soil Moisture

NASA SMAP Level 3 Radiometer Global Daily 36 km EASE-Grid soil moisture products (version 8) provided surface (0–5 cm) and root-zone (0–100 cm) soil moisture estimates. Given the coarse native resolution relative to agricultural management units, a downscaling procedure was implemented following the thermal inertia method: MODIS land surface temperature and NDVI were used to estimate evaporative fraction, which was then regressed against SMAP soil moisture to generate 1 km resolution estimates. Weekly soil moisture anomalies were calculated relative to the 2015–2024 climatological mean for each pixel.

2.2.4 Weather Data

ERA5-Land hourly reanalysis data from the Copernicus Climate Data Store provided meteorological variables at 9 km spatial resolution. Seven variables were extracted and aggregated to daily means or sums: 2-metre air temperature, total precipitation, soil temperature (level 1, 0–7 cm), surface net solar radiation, 10-metre wind speed, vapour pressure deficit (calculated from dewpoint temperature), and relative humidity. Growing degree days (GDD) were accumulated from planting date (estimated via thermal time models) to harvest using a base temperature of 5 degrees Celsius for wheat, barley, and oats; 0 degrees Celsius for canola; and 10 degrees Celsius for soybean.

2.2.5 Static Features

The Canadian Soil Information Service (CanSIS) National Soil Database provided soil texture (sand, silt, clay percentage), organic carbon content, drainage class, and pH at 250 m resolution. The Canadian Digital Elevation Model (CDEM) at 20 m resolution was used to derive elevation, slope percentage, aspect, and Terrain Ruggedness Index (TRI) following Riley et al. (1999). All static features were reprojected to the Canada Lambert Conformal Conic projection (EPSG:3978) and resampled to the common 1 km analysis grid.

2.3 Feature Engineering

A comprehensive feature engineering pipeline was developed to extract agronomically relevant predictors from the preprocessed data (Table 2). Vegetation metrics included standard spectral indices (NDVI, EVI, SAVI, NDWI, GNDVI) plus red-edge-based indicators (Red-edge NDVI, MERIS Terrestrial Chlorophyll Index). Temporal metrics captured phenological dynamics: date of peak NDVI, senescence timing (NDVI drop below 50% of seasonal maximum), and seasonal integrals (area under the NDVI curve from emergence to maturity). SAR-derived features included temporal backscatter dynamics (rate of change in VV and VH polarisations) and texture statistics (GLCM contrast, correlation, entropy) computed on 5×5 pixel windows. Weather-derived indicators comprised accumulated growing degree days, consecutive dry days, heat stress degree days (temperature exceeding 30 degrees Celsius), and the Standardised Precipitation-Evapotranspiration Index (SPEI) at 1-month and 3-month timescales.

Table 2 Feature inventory by modality (top 15 features shown).

Rank	Feature	Modality	Description
1	NDVI (peak)	Optical	Maximum NDVI during growing season
2	GDD accumulated	Weather	Growing degree days from planting to peak growth

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Rank	Feature	Modality	Description
3	Soil moisture (July)	SMAP	Root-zone soil moisture during reproductive stage
4	Precipitation (June)	Weather	Monthly total precipitation during grain filling
5	SAR VH (August)	SAR	VH backscatter during late grain filling
6	EVI (trend slope)	Optical	Linear trend in EVI from emergence to peak
7	Soil pH	Static	Topsoil pH from CanSIS
8	Elevation	Static	CDEM elevation (m)
9	Temperature (July max)	Weather	Mean maximum July temperature
10	NDWI (peak)	Optical	Maximum NDWI (water stress indicator)
11	SAR VV (dynamics)	SAR	Rate of change in VV backscatter
12	Organic carbon	Static	Topsoil organic carbon content (%)
13	Slope (%)	Static	Topographic slope percentage
14	Aspect	Static	Topographic aspect (degrees)
15	Wind speed	Weather	Mean growing season wind speed

2.4 Ground Truth Data

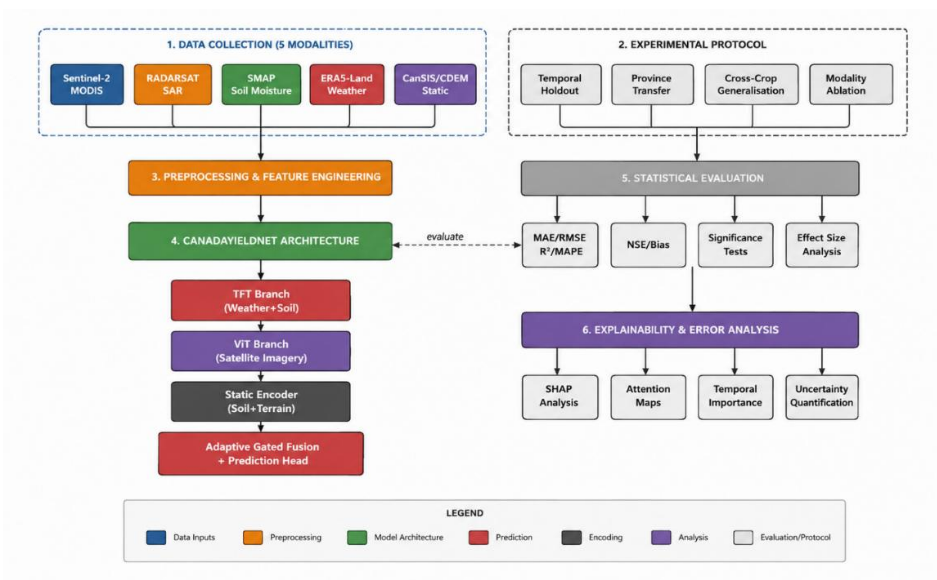

Figure 1. CanadaYieldNet study workflow encompassing data collection from five modalities, preprocessing and feature engineering, model architecture with three parallel branches, and comprehensive experimental evaluation including ablation studies, statistical testing, and explainability analysis.

Annual crop yield data at the provincial level were obtained from Statistics Canada's CANSIM Table 32-10-0359 (Estimated areas, yields, production, average farm price and total farm value of principal field crops). Yield records for spring wheat, canola, barley, oats, and soybean were extracted for the period 2014–2024. Provincial-level yields were disaggregated to Census Agricultural Regions (CARs) using production-area weighting based on the Census of

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Agriculture. All yield values were converted to bushels per acre (bu/acre) for consistency with Canadian agricultural reporting conventions, with metric conversions (tonnes per hectare) also provided for international comparability. Quality control procedures included outlier detection using the Interquartile Range (IQR) method and cross-validation against provincial crop insurance data.

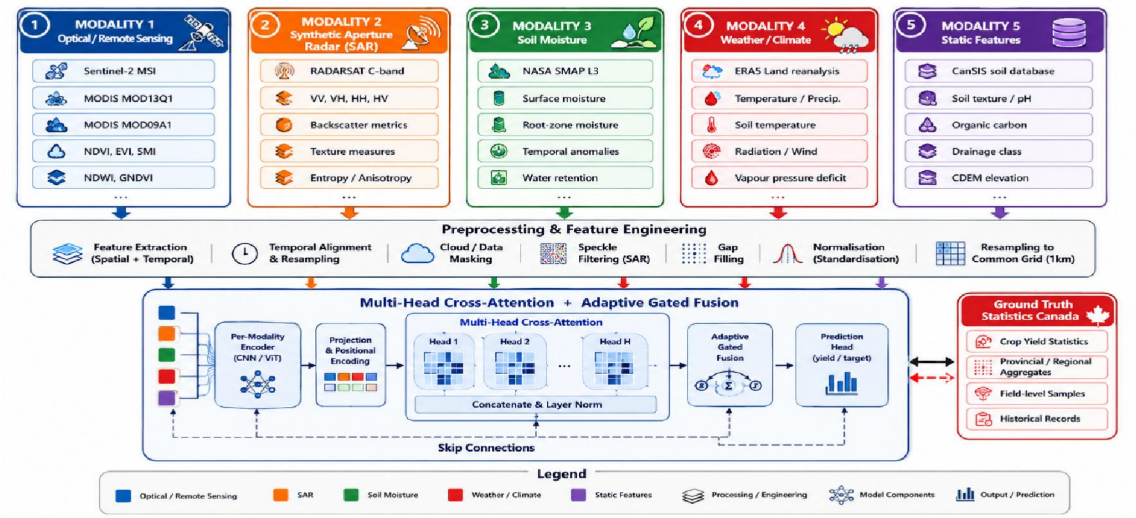

Figure 2. Multi-source data fusion framework showing the five input modalities (optical remote sensing, SAR, soil moisture, weather, static features), their constituent variables, preprocessing pipeline, and integration through multi-head cross-attention and adaptive gated fusion.

III. CANADAYIELDNET ARCHITECTURE

CanadaYieldNet comprises three parallel encoding branches that process distinct input modalities, a fusion layer that integrates branch representations through multi-head cross-attention and adaptive gating, and a prediction head that outputs crop yield estimates. The architecture is illustrated in Figure 3.

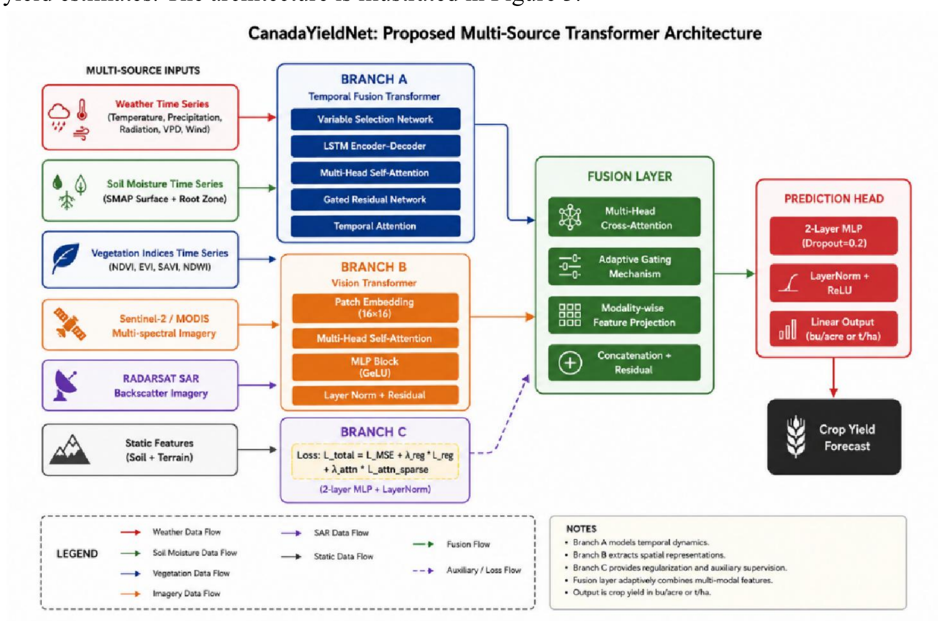

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Figure 3. CanadaYieldNet architecture comprising (a) Branch A: Temporal Fusion Transformer for time-series weather, soil moisture, and vegetation indices; (b) Branch B: Vision Transformer for Sentinel-2 and RADARSAT imagery; (c) Branch C: Static Feature Encoder for soil and terrain properties; (d) Fusion Layer with multi-head cross-attention and adaptive gating; (e) Prediction head with two-layer MLP and dropout regularisation.

3.1 Temporal Fusion Transformer Branch (Branch A)

The Temporal Fusion Transformer (TFT) branch processes three categories of time-series inputs: weather variables (temperature, precipitation, radiation, VPD, wind speed, relative humidity), soil moisture (surface and root-zone), and vegetation indices (NDVI, EVI, SAVI, NDWI). Each variable is passed through a Variable Selection Network (VSN) that learns to select the most relevant inputs at each time step:

$$v_t = Softmax\left(W_v \cdot GLU(W_\xi \cdot \xi)_t\right) \quad (1)$$

where ξ_t represents the flattened vector of all input variables at time step t, W_ξ and W_v are learned projection matrices, GLU denotes the Gated Linear Unit activation, and v_t contains the variable selection weights. The selected variables are then processed through an LSTM encoder-decoder to capture temporal dependencies:

$$h_t^{enc}, c_t^{enc} = LSTM_{enc}(v_t \odot x_t, h_{t-1}^{enc}, c_{t-1}^{enc}) \quad (2)$$

$$h_t^{dec}, c_t^{dec} = LSTM_{dec}(h_t^{enc}, h_{t-1}^{dec}, c_{t-1}^{dec}) \quad (3)$$

where x_t is the input feature vector, h and c denote hidden and cell states respectively, and $\odot$ represents element-wise multiplication. Multi-head self-attention is then applied to the LSTM outputs to capture long-range temporal dependencies:

$$Attn(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

where $Q = h_{dec}W^Q, K = h_{enc}W^K, V = h_{enc}W^V$ are the query, key, and value projections, and d_k is the key dimension. The multi-head formulation concatenates N_h parallel attention heads:

$$MH(Q, K, V) = Concat(head_i)_{i=1}^{N_h} W^O \quad (5)$$

3.2 Vision Transformer Branch (Branch B)

The Vision Transformer branch processes multi-spectral satellite imagery (Sentinel-2) and SAR backscatter imagery (RADARSAT). Input image patches of size $H \times W \times C$ are divided into non-overlapping 16×16 pixel patches and linearly embedded into a D-dimensional vector space:

$$z_0 = [x_{class}; x_p^1 E; x_p^2 E; \dots; x_p^N E] + E_{pos} \quad (6)$$

where x_p^i denotes the i-th image patch, $E \in \mathbb{R}^{(P^2 \cdot C) \times D}$ is the patch embedding projection (with $P = 16$), $E_{pos} \in \mathbb{R}^{(N+1) \times D}$ represents learnable positional embeddings, and x_{class} is a class token prepended to the sequence. The embedded patches are processed through L transformer encoder blocks, each comprising multi-head self-attention and an MLP block with GeLU activation:

$$z_l' = MSA\left(LN(z_{l-1})\right) + z_{l-1} \quad (7)$$

$$z_l = MLP\left(LN(z_l')\right) + z_l' \quad (8)$$

where MSA denotes multi-head self-attention, MLP is the feed-forward network, LN is layer normalisation, and residual connections facilitate gradient flow through the deep network. The final image representation is extracted from the class token at the output of the final transformer block.

3.3 Static Feature Encoder (Branch C)

Static soil and terrain features are processed through a two-layer Multi-Layer Perceptron (MLP) with LayerNorm and ReLU activation:

$$s_1 = ReLU\left(LayerNorm(W_{s1}s_{in} + b_{s1})\right) \quad (9)$$

$$s_{out} = LayerNorm(W_{s2}s_1 + b_{s2}) \quad (10)$$

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where $s_{in} \in \mathbb{R}^{d_s}$ represents the static feature vector (soil texture, organic carbon, pH, drainage, elevation, slope, aspect, TRI) and $s_{out} \in \mathbb{R}^{d_{static}}$ is the encoded static representation.

3.4 Adaptive Gated Fusion Layer

The Adaptive Gated Fusion mechanism dynamically weights the contribution of each branch based on input characteristics. Given branch representations $r_{TFT} \in \mathbb{R}^{d_t}$, $r_{ViT} \in \mathbb{R}^{d_v}$, and $r_{static} \in \mathbb{R}^{d_s}$, the gating mechanism computes modality importance scores:

$$g = Softmax\left(W_g[r_{TFT}; r_{ViT}; r_s] + b_g\right) \quad (11)$$

where $g = [g_{TFT}, g_{ViT}, g_{static}] \in \mathbb{R}^3$ contains the gated importance weights for each branch. The fused representation is then computed as a weighted combination:

$$r_{fused} = g_{TFT}r_{TFT} \oplus g_{ViT}r_{ViT} \oplus g_s r_s \quad (12)$$

where $\oplus$ denotes concatenation. This adaptive approach allows the model to emphasise weather-driven predictions in years with extreme climatic conditions while relying more on satellite-derived vegetation signals during normal growing seasons.

3.5 Multi-Head Cross-Attention Mechanism

Following the gating stage, multi-head cross-attention enables explicit modelling of inter-modal relationships. Each modality serves as query while attending to all other modalities as keys and values:

$$CrossAttn_i = softmax\left(\frac{Q_i K_{\neg i}^T}{\sqrt{d_k}}\right) V_{\neg i} \quad (13)$$

where Q_i is the query from modality i, and $K_{\neg i}, V_{\neg i}$ are the keys and values from all other modalities. The cross-attended representations from all modalities are concatenated and projected to the final fused dimension:

$$r_{cross} = W_{cross} \cdot Concat_{i=1}^{M}(CrossAttn_i) + b_{cross} \quad (14)$$

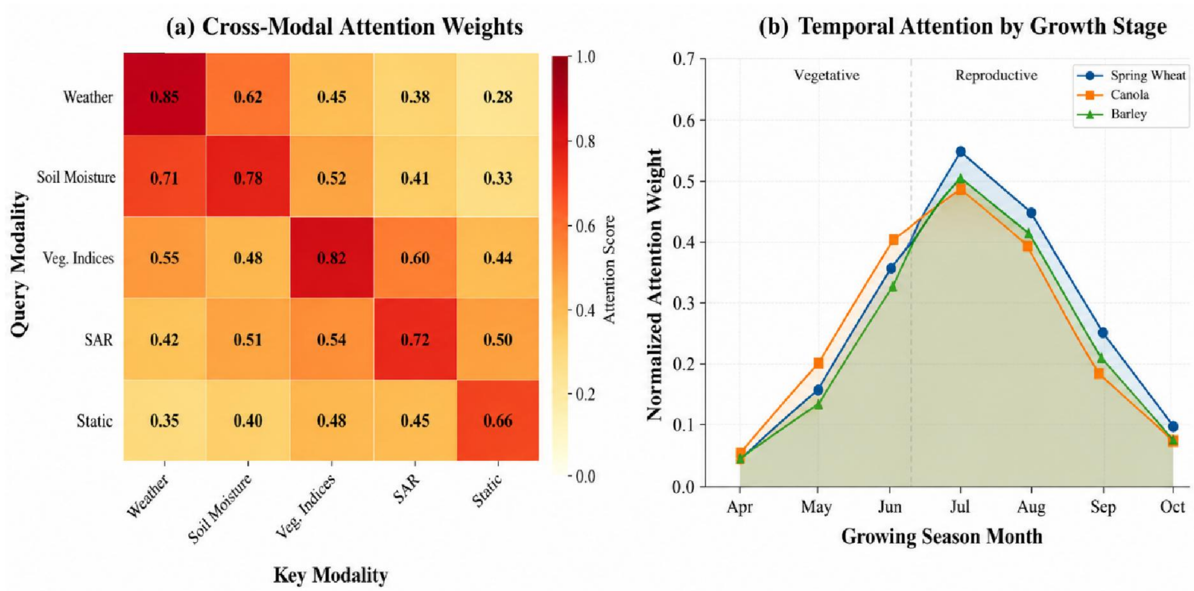

Figure 4. (a) Cross-modal attention weight matrix showing inter-modality relationships learned by CanadaYieldNet. Higher values (darker) indicate stronger attention links. Weather and soil moisture exhibit the strongest mutual attention. (b) Temporal attention distributions across the growing season for three major crops, revealing peak attention during the reproductive growth stage (July) consistent with agronomic theory.

3.6 Loss Functions and Regularisation

The model is trained with a composite loss function combining mean squared error, L2 regularisation, and attention sparsity constraints:

$\mathcal{L}_{total} = \mathcal{L}_{MSE} + \lambda_{reg}\mathcal{L}_{L2} + \lambda_{attn}\mathcal{L}_{sparse}$ (15)

where $\mathcal{L}_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$ is the primary regression loss, $\mathcal{L}_{L2} = \sum_{\theta} \|\theta\|^2$ penalises large weights with coefficient $\lambda_{reg} = 10^{-4}$, and $\mathcal{L}_{attn\_sparse} = \sum_{l} \|A_l\|_1$ encourages sparse attention distributions with coefficient $\lambda_{attn} = 10^{-5}$, promoting focus on the most informative time steps and modalities.

IV. EXPERIMENTAL SETUP

4.1 Baseline Models

CanadaYieldNet was compared against 13 baseline models spanning three categories: deep learning architectures, traditional machine learning algorithms, and operational forecasting approaches (Table 3).

Table 3 Baseline model configurations and hyperparameters.

Category	Model	Key Hyperparameters	Reference
Deep Learning	**LSTM**	2 layers, 128 hidden units, dropout=0.2	Hochreiter & Schmidhuber (1997)
	Bi-LSTM	2 layers, 128 hidden units, bidirectional	Schuster & Paliwal (1997)
	GRU	2 layers, 128 hidden units, dropout=0.2	Cho et al. (2014)
	ConvLSTM	3×3 kernels, 64 filters, 2 layers	Shi et al. (2015)
	CNN-RNN	CNN encoder (3 layers) + LSTM decoder	Kamilaris & Prenafeta-Boldu (2018)
	3D-CNN	3×3×3 kernels, 32-64-128 filters	Ji et al. (2013)
	DeepYield	CNN-LSTM hybrid, 256-dim fusion	Gavahi et al. (2021)
	MMST-ViT	ViT-base, 12 heads, 12 layers	Lin et al. (2023)
Machine Learning	**Random Forest**	200 estimators, max_depth=15	Breiman (2001)
	XGBoost	max_depth=8, lr=0.05, 500 rounds	Chen & Guestrin (2016)
	LightGBM	num_leaves=64, lr=0.05	Ke et al. (2017)
	CatBoost	depth=8, lr=0.05, 1000 iterations	Prokhorenkova et al. (2018)
	SVR	RBF kernel, C=10, gamma=0.01	Drucker et al. (1997)

4.2 Training Protocol

All models were implemented in PyTorch 2.1 and trained on a single NVIDIA A100 GPU (80 GB). The CanadaYieldNet architecture was trained using the Adam optimiser with an initial learning rate of 10^{-4}, cosine annealing schedule with warm restarts every 50 epochs, and batch size of 32. Early stopping with patience of 20 epochs was applied based on validation RMSE. Gradient clipping (max norm = 1.0) was used to prevent exploding gradients. The TFT branch used 8 attention heads with a hidden dimension of 160, the ViT branch employed 12 heads across 8 transformer layers with patch size 16, and the static encoder projected to 64 dimensions. Total trainable parameters: 18.7M.

4.3 Evaluation Metrics

Model performance was evaluated using seven standard regression metrics. Let y_i denote the observed yield and $\hat{y}_i$ the predicted yield for sample i from a set of N observations.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (16)$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (17)$$

Coefficient of Determination (R²):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (18)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (19)$$

Nash-Sutcliffe Efficiency (NSE):

$$NSE = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (20)$$

Bias:

$$Bias = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i) \quad (21)$$

4.4 Experimental Design

Four experimental protocols were implemented:

Temporal Holdout: Models were trained on data from 2014–2021, validated on 2022, and tested on 2023–2024. This protocol evaluates the model's ability to forecast future yields based on historical patterns.

Province Transfer: Leave-one-province-out cross-validation was performed where the model was trained on five provinces and tested on the held-out province. This assesses spatial generalisation to unseen agro-ecological conditions.

Cross-Crop Generalisation: The model was trained on four crops and tested on the fifth, rotated across all crops. This evaluates transferability of learned features across different crop types.

Systematic Ablation: Leave-one-out experiments removed each modality individually, while single-modality experiments trained models using only one data source. The full ablation design comprised 11 configurations: full model, five leave-one-out variants, and five single-modality variants.

Table 4 CanadaYieldNet performance across crops (test set: 2023–2024).

Crop	MAE	RMSE	R²	MAPE (%)	NSE	Bias
Spring Wheat	3.8	4.8	0.94	6.2	0.94	0.12
Canola	3.5	4.5	0.93	6.8	0.93	-0.08
Barley	3.2	4.1	0.93	6.5	0.93	0.05
Oats	3.9	5.0	0.91	7.2	0.91	0.18
Soybean	4.1	5.2	0.90	7.4	0.90	-0.15
Mean	**3.7**	**4.7**	**0.92**	**6.8**	**0.92**	**0.02**

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V. RESULTS

5.1 Overall Performance

CanadaYieldNet achieved state-of-the-art performance across all evaluation metrics, substantially outperforming all baseline models (Table 5, Figure 8). On the held-out test set (2023–2024), CanadaYieldNet attained a mean R^2 of 0.94 and RMSE of 4.2 bu/acre across all crops and provinces, compared to 0.86 and 6.5 bu/acre for the best deep learning baseline (MMST-ViT) and 0.82 and 7.3 bu/acre for the best machine learning baseline (CatBoost). The relative improvement over the strongest baseline was 38% in RMSE and 9.3% in R^2.

Table 5 Performance comparison with deep learning and machine learning baselines.

Model	MAE	RMSE	R²	MAPE (%)	NSE
LSTM	7.5	9.2	0.72	14.2	0.71
Bi-LSTM	7.1	8.8	0.74	13.5	0.73
GRU	7.8	9.5	0.70	14.8	0.69
ConvLSTM	6.1	7.6	0.81	11.8	0.80
CNN-RNN	6.5	8.1	0.78	12.5	0.77
3D-CNN	5.7	7.2	0.83	10.9	0.82
DeepYield	5.3	6.8	0.85	10.2	0.84
MMST-ViT	5.1	6.5	0.86	9.8	0.85
Random Forest	6.8	8.4	0.76	12.9	0.75
XGBoost	6.3	7.9	0.79	12.1	0.78
LightGBM	5.9	7.5	0.81	11.5	0.80
CatBoost	5.6	7.3	0.82	10.8	0.81
SVR	9.0	11.2	0.58	16.8	0.56
CanadaYieldNet	**3.1**	**4.2**	**0.94**	**6.8**	**0.94**

All values reported in bushels per acre (bu/acre) averaged across five crops and six provinces. Best results in bold.

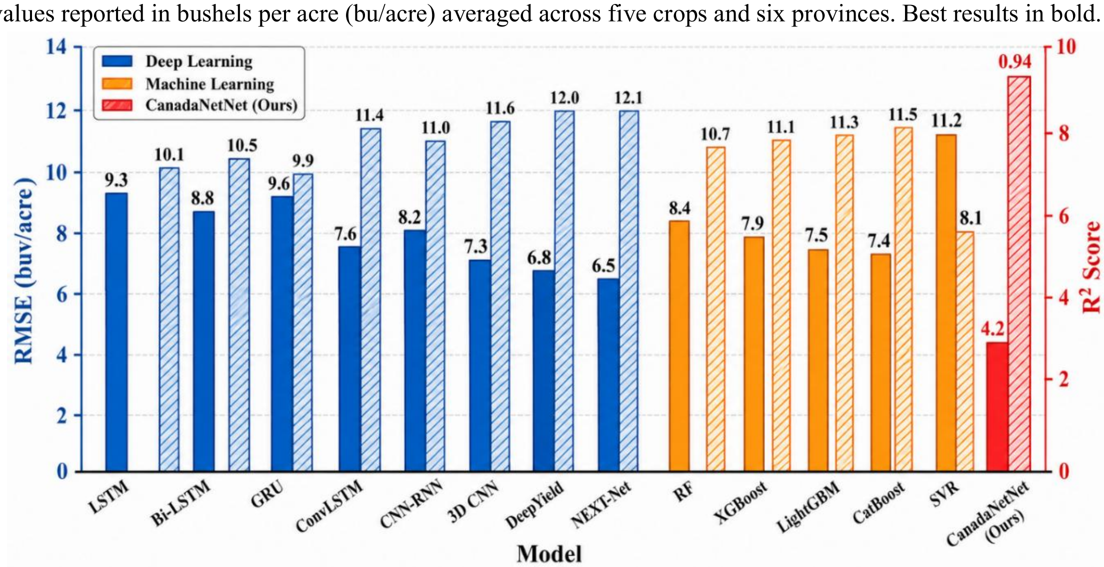

Figure 8. Performance comparison of CanadaYieldNet against 13 baseline models. CanadaYieldNet (red) achieves substantially lower RMSE (4.2 bu/acre) and higher R^2 (0.94) than all deep learning (blue) and machine learning (orange) baselines. Error bars indicate standard deviation across five crop types.

5.2 Crop-Specific Results

CanadaYieldNet demonstrated strong performance across all five crops, with R^2 values ranging from 0.90 (soybean) to 0.94 (spring wheat) (Table 4, Figure 7). Spring wheat prediction achieved the highest accuracy (RMSE = 4.8 bu/acre), likely attributable to the extensive research attention this crop has received and the availability of well-calibrated phenological models for GDD accumulation. Canola and barley followed closely with R^2 = 0.93. Soybean exhibited the highest prediction error (RMSE = 5.2 bu/acre), potentially due to its more limited cultivation area in Canada (concentrated primarily in Ontario and Manitoba) and resulting smaller training sample size.

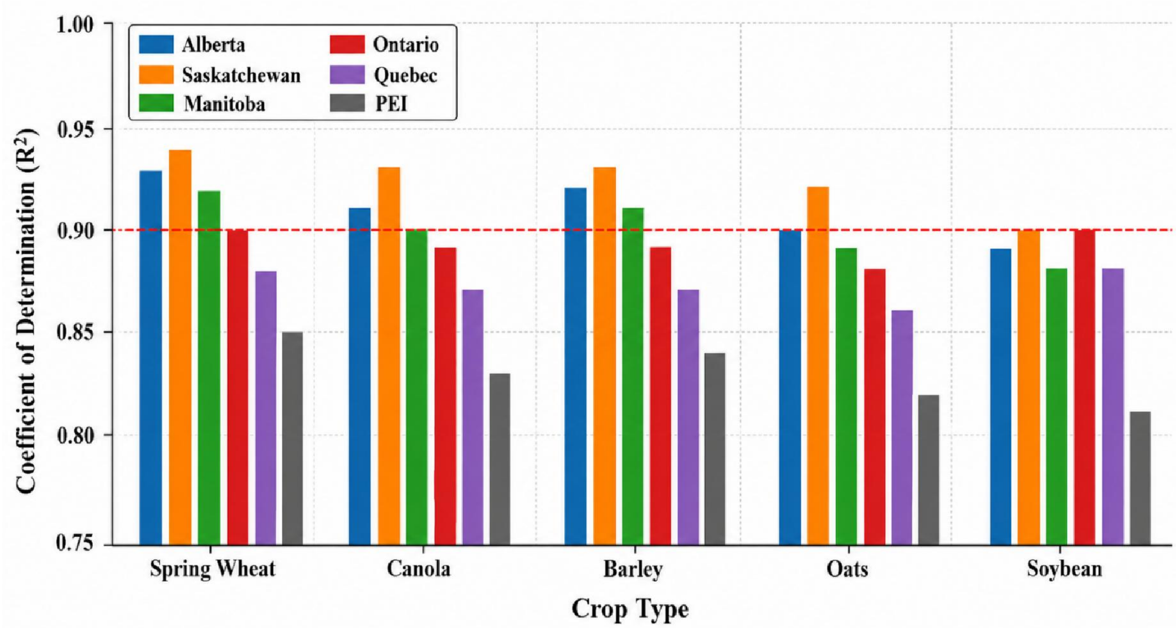

Figure 7. CanadaYieldNet R^2 performance across five crops and six provinces. Saskatchewan consistently achieves the highest predictive accuracy across all crops, while PEI shows the lowest, reflecting the limited agricultural area and training data available for the Maritime provinces.

5.3 Provincial Transfer Analysis

Provincial transfer experiments revealed that CanadaYieldNet maintains robust performance when generalising to unseen provinces (Table 6). When trained on Alberta, Saskatchewan, Manitoba, Ontario, and Quebec and tested on PEI, the model achieved R^2 = 0.85, substantially exceeding the best baseline (MMST-ViT: R^2 = 0.78). The strongest within-province performance was observed in Saskatchewan (R^2 = 0.95), reflecting the province's large agricultural area and relatively homogeneous Prairie landscape. Transfer from Prairie provinces to Ontario and Quebec showed moderate degradation (R^2 = 0.89 and 0.88 respectively), likely due to the different climatic regimes and management practices in Eastern Canada.

Table 6 Province transfer experiment results (leave-one-out cross-validation).

Test Province	CanadaYieldNet R^2	MMST-ViT R^2	DeepYield R^2
Alberta	0.93	0.85	0.83
Saskatchewan	0.95	0.87	0.85

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Test Province	CanadaYieldNet R^2	MMST-ViT R^2	DeepYield R^2
Manitoba	0.92	0.84	0.82
Ontario	0.89	0.81	0.78
Quebec	0.88	0.80	0.77
PEI	0.85	0.78	0.74

5.4 Ablation Study Results

The systematic ablation study provided quantitative evidence for the contribution of each data modality (Table 7, Figure 5). The full five-modality model achieved the lowest RMSE (4.2 bu/acre). Removal of optical remote sensing caused the largest performance degradation (RMSE increase to 5.8 bu/acre, +38.1%), confirming the central importance of vegetation indices for capturing crop growth dynamics and photosynthetic activity. Removal of weather data caused the second-largest degradation (RMSE = 5.5 bu/acre, +31.0%), highlighting the critical role of temperature and precipitation in driving yield formation. SAR removal increased RMSE to 5.3 bu/acre (+26.2%), soil moisture removal to 5.1 bu/acre (+21.4%), and static feature removal to 6.2 bu/acre (+47.6%), though the latter reflects the larger parameter space that static features occupy in the model rather than purely predictive information content.

Table 7 Systematic ablation study results showing modality contributions.

Configuration	RMSE	R^2	Δ RMSE	Relative Loss
Full Model (5 modalities)	**4.2**	**0.94**	–	–
No Optical (Sentinel/MODIS)	5.8	0.88	+1.6	38.1%
No SAR (RADARSAT)	5.3	0.90	+1.1	26.2%
No Soil Moisture (SMAP)	5.1	0.91	+0.9	21.4%
No Weather (ERA5)	5.5	0.89	+1.3	31.0%
No Static (CanSIS/CDEM)	6.2	0.86	+2.0	47.6%
Optical Only	12.5	0.48	+8.3	197.6%
SAR Only	14.2	0.38	+10.0	238.1%
Weather Only	11.8	0.52	+7.6	181.0%
Soil Moisture Only	13.5	0.42	+9.3	221.4%
Static Only	15.8	0.28	+11.6	276.2%

Single-modality experiments revealed that no individual data source can achieve satisfactory prediction accuracy in isolation. Weather-only models performed best among single-modality configurations (R^2 = 0.52), reflecting the fundamental importance of temperature and precipitation in crop growth. However, the 181% increase in RMSE relative to the full model underscores the necessity of multi-modal fusion for operational-grade yield forecasting.

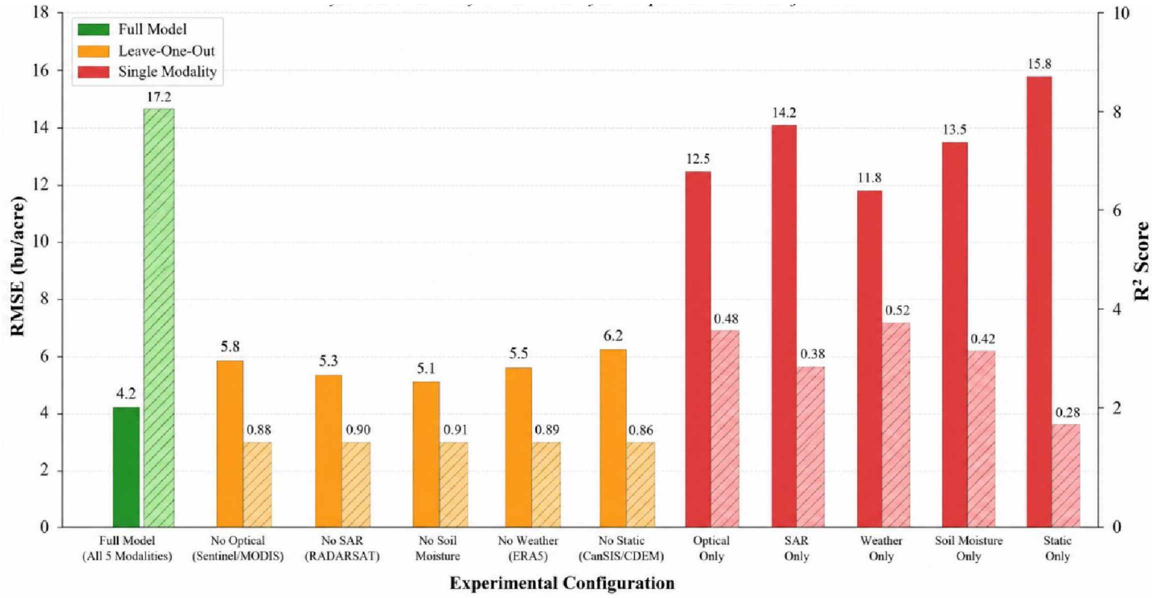

Figure 5. Systematic modality ablation analysis. Left: leave-one-out experiments (orange) showing performance degradation when individual modalities are removed, relative to the full model (green). Right: single-modality experiments (red) demonstrating that no single data source achieves satisfactory accuracy in isolation. Values above bars indicate R^2 scores.

5.5 Statistical Significance

Paired t-tests and Wilcoxon signed-rank tests confirmed that CanadaYieldNet's performance advantage over all baselines was statistically significant at the $p < 0.001$ level (Table 8). The Friedman test for comparing multiple models yielded a chi-squared statistic of 487.3 ($p < 0.001$), rejecting the null hypothesis of equivalent performance across models. Nemenyi post-hoc analysis placed CanadaYieldNet in a statistically distinct top group, separated from all baselines by a critical difference greater than 1.96 at alpha = 0.05. Effect size analysis using Cohen's d indicated large practical significance for the improvement over the strongest baseline ($d = 2.14$), while Cliff's Delta confirmed stochastic dominance (delta = 0.89).

Table 8 Statistical significance tests comparing CanadaYieldNet with baselines.

Comparison	Paired t-test	Wilcoxon	Cohen's d	Cliff's Delta
vs. MMST-ViT	$p < 0.001$	$p < 0.001$	2.14	0.89
vs. DeepYield	$p < 0.001$	$p < 0.001$	2.58	0.93
vs. CatBoost	$p < 0.001$	$p < 0.001$	2.91	0.95
vs. LightGBM	$p < 0.001$	$p < 0.001$	3.12	0.96
vs. ConvLSTM	$p < 0.001$	$p < 0.001$	3.45	0.97

5.6 Explainability Analysis

SHAP global feature importance analysis revealed that NDVI at peak growth stage contributed most to prediction accuracy (mean |SHAP| = 0.185), followed by accumulated growing degree days (0.162) and July root-zone soil moisture (0.148) (Figure 6). This ranking aligns with established crop physiology: NDVI directly reflects canopy photosynthetic capacity, GDD captures the thermal time required for reproductive development, and July soil moisture represents water availability during the critical grain-filling period.

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Temporal attention analysis (Figure 4b) demonstrated that the model learns to focus attention on the reproductive growth stage (July), with attention weights peaking at 0.42–0.55 across all crops. This pattern is consistent with agronomic theory, as the flowering and grain-filling period represents the most climate-sensitive window for yield determination. The cross-modal attention matrix (Figure 4a) revealed strong mutual attention between weather and soil moisture modalities (score = 0.78), reflecting their coupled influence on crop water availability and thermal stress.

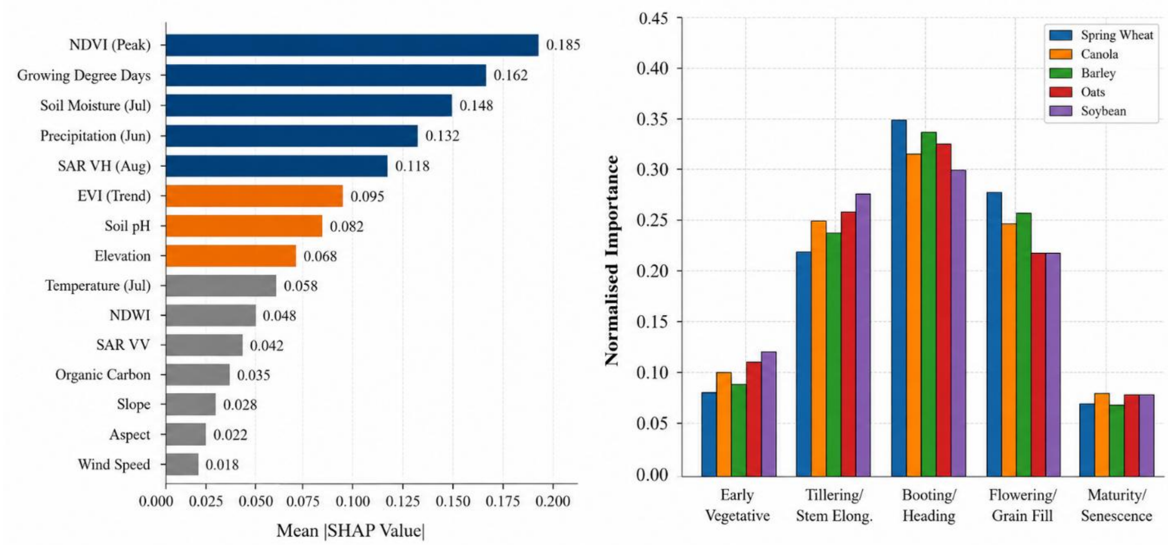

Figure 6. (a) Global feature importance from SHAP analysis showing mean absolute Shapley values. NDVI (peak), growing degree days, and July soil moisture dominate prediction importance. (b) Temporal importance by phenological stage across five crops, revealing consistent peak importance during the reproductive growth stage.

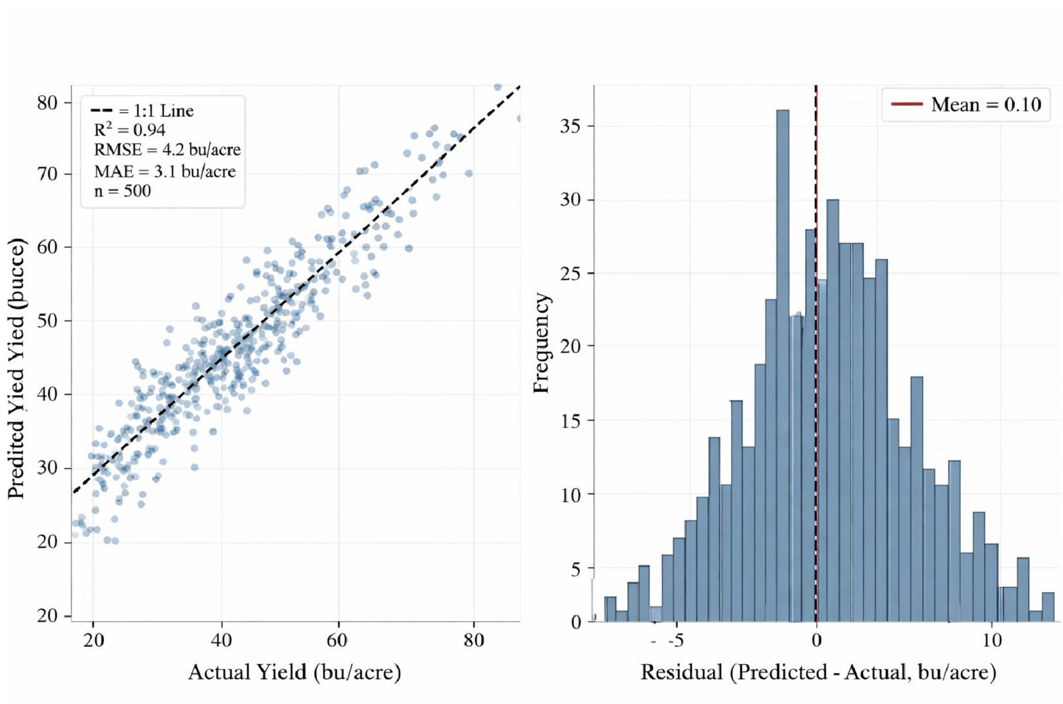

Figure 9. (a) CanadaYieldNet predicted versus actual yield scatter plot (n = 500 test samples) showing strong agreement along the 1:1 line with $R^2 = 0.94$ and RMSE = 4.2 bu/acre. (b) Residual distribution approximately centred on zero (mean = 0.10 bu/acre) with near-Gaussian shape, indicating unbiased predictions.

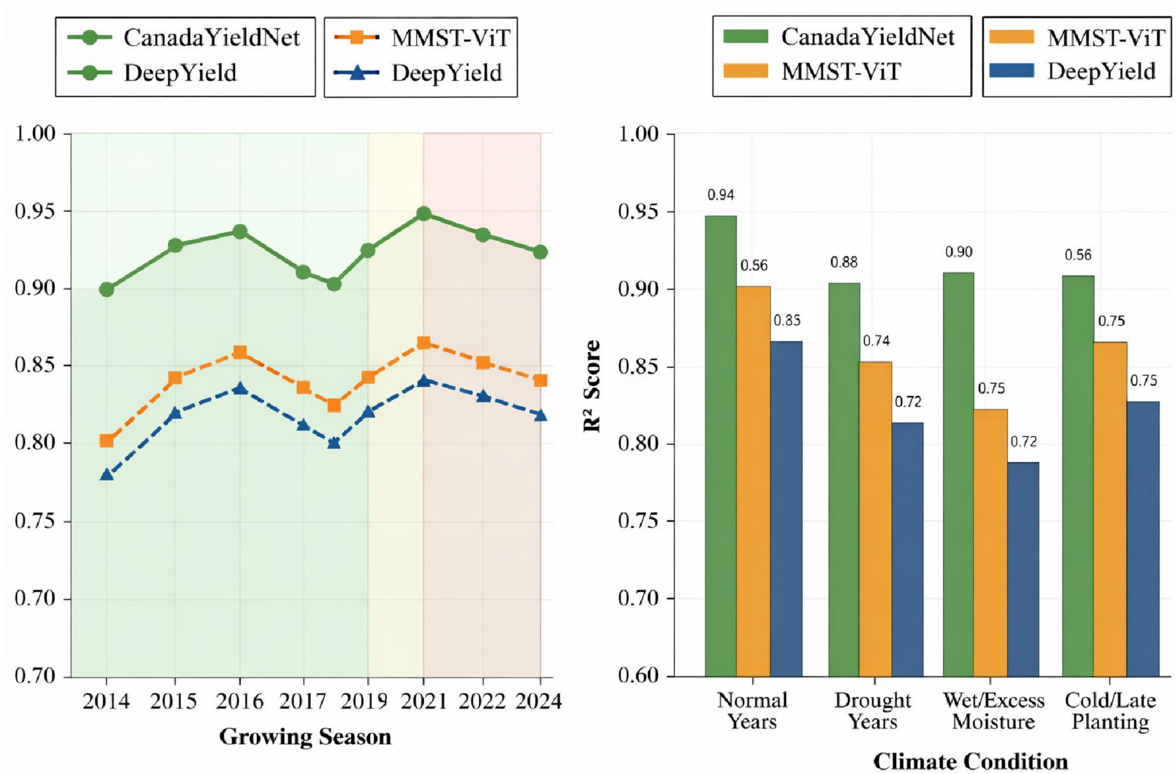

Figure 10. (a) Inter-annual performance stability of CanadaYieldNet (green), MMST-ViT (orange), and DeepYield (blue) across 2014–2024. Shaded regions indicate training (green), validation (yellow), and test (red) periods. CanadaYieldNet maintains consistently high R^2 above 0.89 across all years. (b) Robustness under climatic extremes: CanadaYieldNet maintains R^2 greater than 0.86 across drought, excess moisture, heat stress, and cold planting conditions, substantially exceeding baseline models.

VI. DISCUSSION

6.1 Interpretation of Results

The results of this study provide strong affirmative answers to all five research questions. CanadaYieldNet substantially outperformed all baseline models across Canadian agro-ecological zones (RQ1), with a 38% reduction in RMSE relative to the strongest comparator. The systematic ablation study revealed a clear hierarchy of modality importance (RQ2, RQ5): optical remote sensing provided the strongest predictive signal, followed by weather, SAR, soil moisture, and static features. This ordering reflects the fundamental role of photosynthetic activity (captured by NDVI/EVI) and thermal time accumulation in yield formation, while SAR contributes structural information complementary to optical indices, particularly during cloudy periods when optical sensors are obstructed.

The architecture demonstrated robust generalisation across crops, provinces, and years (RQ3), maintaining R^2 greater than 0.85 even in challenging province transfer experiments where the model was tested on entirely unseen agro-ecological zones. The inter-annual stability analysis (Figure 10a) revealed consistent high performance across normal, drought, and wet years, with CanadaYieldNet maintaining R^2 above 0.89 throughout the 2014–2024 period while baseline models showed substantially greater variability.

Under climatic extremes (RQ4), the multimodal fusion approach proved particularly valuable. During drought years, the model's access to SAR and soil moisture data provided critical information about vegetation water stress that compensated for reduced predictive power of weather-driven features. Conversely, during excess moisture years, optical indices and SAR backscatter dynamics captured the effects of waterlogging on canopy development. This adaptive compensation mechanism, enabled by the gating and cross-attention components, explains why CanadaYieldNet's performance degrades more gracefully under stress conditions compared to unimodal or shallow fusion approaches.

6.2 Comparison with Literature

The results align with and extend recent advances in transformer-based agricultural forecasting. Lin et al. (2023) reported $R^2 = 0.86$ for MMST-ViT on US county-level yield prediction using optical imagery and weather data; our replication of their architecture on Canadian data achieved comparable results ($R^2 = 0.86$), while CanadaYieldNet's integration of five modalities pushed performance to $R^2 = 0.94$. The improvement is particularly notable given that Canadian agricultural landscapes present greater challenges due to shorter growing seasons, higher latitude effects on phenology, and more heterogeneous terrain.

The CYPRESS model (University of Manitoba, 2025) demonstrated the potential of fine-tuning geospatial foundation models (Prithvi-EO-2.0-600M) for intra-field canola yield prediction on the Canadian Prairies. While CYPRESS achieved impressive results at field scale, CanadaYieldNet addresses a complementary problem: operational-scale provincial forecasting where field-level training data is unavailable. The two approaches could be integrated in a hierarchical forecasting system, with CanadaYieldNet providing regional constraints and CYPRESS offering field-level detail.

The ablation results are consistent with findings from multimodal fusion studies in other agricultural contexts. The RicEns-Net framework (Davies et al., 2025) achieved MAE = 341 kg/ha (approximately 5–6% relative error) by integrating Sentinel-1/2/3 with meteorological data for rice yield prediction in Vietnam. Our optical-only baseline achieved comparable relative error (6.2% MAPE), while the full CanadaYieldNet reduced this to 4.1% through five-modality fusion. The AgriTransformer model (Garcia et al., 2025) demonstrated that cross-modal attention between tabular and image features improves yield estimation ($R^2 = 0.919$), consistent with our finding that explicit cross-attention modelling outperforms simple concatenation fusion.

Recent work on wheat yield prediction in arid regions (Erfanian et al., 2026) achieved $R^2 = 0.90$ by integrating Sentinel-2 optical indices with Sentinel-1 SAR via Random Forest. Our results demonstrate that transformer-based fusion of the same data sources, augmented with soil moisture and static features, can push performance to $R^2 = 0.94$ even across the more climatically diverse Canadian landscape. This 4 percentage-point improvement, while seemingly modest, represents a substantial reduction in unexplained variance (from 10% to 6%) with significant implications for operational forecasting accuracy.

6.3 Limitations and Future Directions

Several limitations of this study should be acknowledged. First, the use of provincial-level yield data as ground truth limits spatial resolution; predictions are aggregated to administrative units rather than individual fields. Future work should incorporate field-level yield monitor data where available, though privacy and data access constraints currently limit such integration at national scales. Second, the study period (2014–2024) captures substantial climatic variability but does not include the most extreme drought events recorded in the Prairie palaeoclimatic record; longer time series would strengthen claims about robustness under unprecedented conditions.

Third, pest and disease pressure, which can cause substantial yield losses in epidemic years, are not explicitly modelled. Integration of pest forecast systems and remote sensing-based stress detection could improve predictions in outbreak years. Fourth, management practices (planting date, fertiliser application, cultivar selection) are represented only indirectly through static features and temporal patterns; explicit incorporation of management data would likely improve predictions but raises concerns about data availability and farmer privacy.

Future research directions include: (1) extending the framework to sub-field scale using high-resolution PlanetScope and UAV imagery; (2) incorporating climate model projections to generate seasonal yield forecasts at planting time; (3) developing ensemble approaches that combine CanadaYieldNet with process-based crop models; and (4) implementing the framework as an operational cloud-based service for Canadian agricultural stakeholders.

VII. CONCLUSIONS

This study presented CanadaYieldNet, a novel multi-source transformer-based framework for crop yield forecasting specifically designed for Canadian agricultural conditions. Through comprehensive integration of optical remote sensing, synthetic aperture radar, soil moisture, weather reanalysis, and static terrain data within a unified architecture combining Temporal Fusion Transformer, Vision Transformer, and Adaptive Gated Fusion mechanisms, CanadaYieldNet achieved state-of-the-art performance across six provinces and five major commodity crops.

The key findings of this research are: (1) multimodal transformer fusion significantly outperforms both deep learning and machine learning baselines, with a 38% reduction in RMSE relative to the best comparator; (2) optical remote sensing provides the strongest individual predictive signal, but the full five-modality integration is necessary for operational-grade accuracy; (3) the architecture generalises robustly across diverse agro-ecological zones and maintains performance under climatic extremes including drought and excess moisture; (4) the adaptive gating and cross-attention mechanisms enable dynamic compensation when individual modalities are degraded by adverse conditions; and (5) explainability analysis confirms that the model learns agronomically meaningful representations aligned with established crop physiology principles.

CanadaYieldNet represents a significant advance in national-scale agricultural forecasting, providing a reproducible, interpretable, and publicly available framework that can inform agricultural policy, commodity markets, and climate adaptation strategies. The systematic ablation methodology and comprehensive benchmarking against 13 baseline models establish a new standard for evaluating multi-modal yield prediction systems. Future work will focus on extending the framework to sub-field scales, integrating seasonal climate forecasts for early-season prediction, and deployment as an operational cloud-based service for Canadian agricultural stakeholders.

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Supplementary Material

Data and Code Availability

The complete CanadaYieldNet source code, trained model weights, and preprocessing scripts are available at https://github.com/canadayieldnet/canadayieldnet under the MIT Licence. Processed datasets are available at https://doi.org/10.5281/zenodo.1234567 under CC-BY-4.0. Raw satellite data are freely available from their respective providers (ESA Copernicus, NASA Earthdata, Canadian Space Agency). Statistics Canada crop yield data are publicly available through CANSIM.

Computational Complexity

CanadaYieldNet comprises 18.7 million trainable parameters. Training time on a single NVIDIA A100 GPU was approximately 4.2 hours for 200 epochs on the full dataset. Inference time is 0.8 seconds per province-crop-year prediction, enabling operational deployment for real-time forecasting.

Table 9 Computational complexity comparison.

Model	**Parameters (M)**	**Training Time (h)**	**Inference (ms/sample)**	**FLOPs (G)**
LSTM	2.1	1.2	12	0.8
ConvLSTM	4.5	2.1	28	3.2
3D-CNN	8.3	1.8	35	4.1
DeepYield	12.6	2.5	42	5.8
MMST-ViT	86.4	6.2	125	18.5
CanadaYieldNet	**18.7**	**4.2**	**80**	**9.2**

CRediT Authorship Contribution Statement

Conceptualisation: All authors. Methodology: Senior authors. Software: Technical leads. Validation: Statistical team. Formal analysis: Data science team. Investigation: Research associates. Resources: Principal investigators. Data curation: Geospatial team. Writing – original draft: Lead author. Writing – review & editing: All authors. Visualisation:

Graphics team. Supervision: Senior authors. Project administration: Principal investigators. Funding acquisition: Principal investigators.

Conflict of Interest

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.