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CanadaYieldNet: A Hybrid Temporal Fusion Transformer–Vision Transformer Architecture with Adaptive Gated Fusion for Multi-Source Crop Yield Prediction

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Abstract: *Accurate crop yield prediction is critical for food security, agricultural policy-making, and supply chain management. This paper introduces CanadaYieldNet, a novel hybrid deep learning architecture that integrates a Vision Transformer (ViT) for spatial feature extraction from satellite imagery with a Temporal Fusion Transformer (TFT) for temporal sequence modeling of climate and vegetation data. A key innovation is the Adaptive Gated Fusion (AGF) mechanism that dynamically weights spatial and temporal feature contributions based on their predictive importance. Furthermore, a multi-quantile regression prediction head provides uncertainty-aware yield forecasts with interpretable prediction intervals. We conduct a comprehensive pilot study focusing on wheat yield prediction in Saskatchewan, Canada, leveraging multimodal data streams including Sentinel-2 surface reflectance, MODIS vegetation indices, ERA5-Land climate reanalysis, AAFC crop inventory, and Statistics Canada yield records. Experimental results demonstrate that CanadaYieldNet achieves state-of-the-art performance with an R^2 of 0.950, RMSE of 0.30 t/ha, and MAPE of 5.4%, significantly outperforming eight baseline models including Random Forest, XGBoost, LSTM, CNN-LSTM, Pure ViT, and Pure TFT. Ablation studies validate the contribution of each architectural component, while SHAP-based explainability analysis reveals that late-season NDVI and pre-season precipitation are the most influential predictors. This work represents the first Canada-focused hybrid ViT-TFT framework for crop yield forecasting and provides a scalable architecture extensible to all Canadian provinces and crop types.*

Keywords: crop yield prediction, Vision Transformer, Temporal Fusion Transformer, multimodal fusion, quantile regression, explainable AI, precision agriculture, remote sensing, Canada.

I. INTRODUCTION

Global food security faces unprecedented challenges from climate change, population growth, and resource scarcity. Canada, as one of the world's largest grain exporters, plays a pivotal role in international food markets. Saskatchewan, the heart of Canadian prairie agriculture, accounts for approximately 44% of national spring wheat production and 81% of durum wheat production (Statistics Canada, 2024). Accurate and timely wheat yield forecasting at the provincial and regional scales is therefore essential for agricultural policy formulation, grain logistics planning, export scheduling, and farmer decision-support systems.

Traditional crop yield prediction methods rely on statistical models that correlate historical yield data with weather variables or simple vegetation indices. While these approaches provide baseline predictive capability, they fail to capture the complex nonlinear relationships between crop growth dynamics and the multimodal environmental factors that influence them. The advent of deep learning, combined with the proliferation of Earth observation data and climate reanalysis products, has opened new avenues for data-driven yield prediction (You et al., 2017).

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Recent advances in transformer architectures have demonstrated remarkable performance in computer vision and time series forecasting tasks. Vision Transformers (ViT) (Dosovitskiy et al., 2021) have shown that self-attention mechanisms can effectively capture long-range spatial dependencies in image data, making them particularly suitable for analyzing satellite imagery where field patterns, soil heterogeneity, and vegetation health exhibit complex spatial structures. Concurrently, Temporal Fusion Transformers (TFT) (Lim et al., 2021) have emerged as powerful models for interpretable multi-horizon time series forecasting, leveraging variable selection networks and gating mechanisms to dynamically weight input features.

Despite these individual successes, the integration of spatial and temporal transformer architectures for agricultural applications remains largely unexplored, particularly in the Canadian context. Existing approaches typically rely on Convolutional Neural Networks (CNN) for spatial feature extraction and Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) networks for temporal modeling (Khaki & Wang, 2019). While effective, these approaches lack the global receptive field of self-attention and the interpretability features inherent in transformer-based designs.

This paper makes the following novel contributions:

N1 — First Canada-focused hybrid ViT-TFT framework. We propose CanadaYieldNet, the first deep learning architecture specifically designed for Canadian crop yield forecasting that combines a Vision Transformer for spatial feature extraction with a Temporal Fusion Transformer for temporal sequence modeling.

N2 — Adaptive Gated Fusion mechanism. We introduce a novel Adaptive Gated Fusion (AGF) module that dynamically weights satellite-derived spatial features and climate/vegetation temporal features based on their predictive importance, enabling context-aware multimodal integration.

N3 — Uncertainty-aware quantile prediction. CanadaYieldNet produces prediction intervals through multi-quantile regression, providing decision-makers with quantified uncertainty estimates alongside point forecasts.

N4 — Explainable multimodal agricultural forecasting. Through integrated SHAP analysis, attention visualization, and temporal importance mapping, our framework provides interpretable predictions that reveal the key drivers of yield variability.

N5 — Scalable national deployment architecture. The modular design of CanadaYieldNet supports straightforward extension to all Canadian provinces, crop types, and temporal scales, laying the foundation for a comprehensive national crop forecasting system.

II. RELATED WORK

2.1 Crop Yield Prediction

Crop yield prediction has evolved from simple statistical regression models to sophisticated deep learning architectures. Early approaches employed linear regression between yield and weather variables (Lobell & Burke, 2010). Machine learning methods including Random Forest, Support Vector Regression, and gradient boosting machines subsequently demonstrated improved predictive accuracy by capturing nonlinear relationships (Jeong et al., 2016). In the deep learning era, CNN-LSTM hybrids have become the dominant paradigm, using CNNs for spatial feature extraction from satellite imagery and LSTMs for temporal modeling of vegetation and climate sequences (Sun et al., 2019).

Recent studies have explored attention mechanisms for yield prediction. Lata et al. (2025) applied Vision Transformers to crop classification from Sentinel-2 and Landsat-8 imagery, achieving 94.6% classification accuracy. Thakkar et al. (2024) demonstrated that ViT models achieve R^2 scores exceeding 0.97 for soybean and corn yield estimation from remote sensing data. However, these studies focused primarily on classification or single-modality regression, without integrating temporal climate data through transformer architectures.

2.2 Vision Transformers in Remote Sensing

The Vision Transformer (ViT), introduced by Dosovitskiy et al. (2021), applies the transformer architecture to image analysis by dividing images into patches and processing them as token sequences. The self-attention mechanism

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enables ViT to capture global spatial relationships, which is particularly valuable for remote sensing applications where contextual information across large spatial extents is critical.

In agricultural remote sensing, ViT has been applied to crop type classification (Lata et al., 2025), crop health assessment (Rustowicz et al., 2019), and yield estimation (Thakkar et al., 2024). The key advantage over CNNs is the ability to model long-range spatial dependencies without the inductive bias of local convolution operations. However, ViT alone cannot capture the temporal dynamics of crop growth, necessitating integration with temporal modeling components.

2.3 Temporal Fusion Transformers

The Temporal Fusion Transformer (TFT), proposed by Lim et al. (2021), is an attention-based architecture designed for interpretable multi-horizon time series forecasting. TFT introduces several key innovations: (1) Variable Selection Networks that learn feature importance weights, (2) Gated Residual Networks that enable adaptive depth, (3) static covariate encoders that integrate contextual information, and (4) interpretable multi-head attention that provides insights into temporal patterns (Vaswani et al., 2017).

TFT has demonstrated state-of-the-art performance across diverse forecasting benchmarks and provides inherent interpretability through attention visualization and variable importance analysis (Wen et al., 2017). Its quantile regression output naturally supports uncertainty quantification. However, TFT was designed for time series data and does not directly process spatial imagery, limiting its application to yield prediction scenarios where satellite data provides crucial spatial information.

III. MATERIALS AND METHODS

3.1 Study Area

This pilot study focuses on the province of Saskatchewan, Canada (49°N–60°N, 102°W–110°W), which encompasses approximately 652,000 km² of the Canadian Prairies. Saskatchewan's agricultural zone, primarily within the Black and Dark Brown soil zones, produces the majority of Canadian wheat. The climate is characterized by cold winters, warm summers, and highly variable precipitation patterns that significantly influence inter-annual yield variability. The wheat growing season extends from May (seeding) to September (harvest), with critical growth stages including tillering, stem elongation, heading, flowering, and grain-filling.

3.2 Data Sources

The CanadaYieldNet framework integrates five distinct data sources, each contributing unique information about crop growth conditions and environmental drivers. Table 1 provides a comprehensive summary of all datasets.

Table 1. Multi-source datasets integrated by the CanadaYieldNet framework.

Data Source	Variables	Spatial Res.	Temporal Res.	Period	Purpose
Sentinel-2 SR	B2, B3, B4, B8, NDVI, EVI, NDWI, SAVI	10 m	5 days	2020–2025	Spatial vegetation
MODIS MOD13Q1	NDVI, EVI	250 m	16 days	2020–2025	Temporal veg. indices
ERA5-Land	T, SoilT, SM, ET, Precip, Rad, Wind	0.1°	Hourly	2020–2025	Climate drivers
AAFC Crop Inv.	Crop-type classification	30 m	Annual	2020–2024	Crop mask
Statistics Canada	Yield, production, area	RM-level	Annual	2020–2025	Ground truth

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Sentinel-2 Surface Reflectance. We utilize the harmonized Sentinel-2 MSI (MultiSpectral Instrument) Level-2A product from the Copernicus Data Space Ecosystem, providing bottom-of-atmosphere reflectance in 13 spectral bands (Drusch et al., 2012). For this study, we select the Blue (B2, 490 nm), Green (B3, 560 nm), Red (B4, 665 nm), and Near-Infrared (B8, 842 nm) bands at 10 m spatial resolution. From these bands, we compute the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), and Soil Adjusted Vegetation Index (SAVI).

MODIS MOD13Q1. The MODIS Vegetation Indices product (MOD13Q1) provides NDVI and EVI at 250 m spatial and 16-day temporal resolution from the Terra satellite (Didan, 2021). These data serve as complementary vegetation indicators with a longer temporal baseline than Sentinel-2.

ERA5-Land. This global reanalysis product from the Copernicus Climate Change Service provides hourly estimates of climate variables at 0.1° spatial resolution (Hersbach et al., 2020). We extract 2-metre temperature, soil temperature (Level 1), volumetric soil water content, total evaporation, total precipitation, surface solar radiation downwards, and 10-metre wind speed.

AAFC Annual Crop Inventory. Agriculture and Agri-Food Canada's Annual Crop Inventory provides 30 m resolution raster maps of crop types across Canadian agricultural regions (Agriculture and Agri-Food Canada, 2024). This dataset enables wheat-specific masking and field boundary delineation.

Statistics Canada Yield Data. Provincial-level wheat yield statistics (tonnes per hectare) from Statistics Canada's CANSIM Table 32-10-0359 provide the ground-truth target variable for model training and evaluation (Statistics Canada, 2024).

3.3 Data Preprocessing

The multimodal data preprocessing pipeline comprises seven sequential stages:

Step 1: Cloud masking. Sentinel-2 scenes are filtered using the Scene Classification Layer (SCL) to exclude cloudy pixels (classes 3, 8, 9, 10). Cloudy scenes exceeding 20% cloud cover over agricultural areas are discarded entirely.

Step 2: Vegetation index computation. We compute NDVI, EVI, NDWI, and SAVI from Sentinel-2 reflectance bands using standard formulations. These indices are appended to the four spectral bands, yielding eight input channels for the ViT encoder.

Step 3: Temporal aggregation. ERA5-Land hourly variables are aggregated to daily means (temperature, radiation, wind speed, soil moisture) or daily sums (precipitation, evaporation), then further aggregated to 5-day intervals to match Sentinel-2 temporal resolution.

Step 4: Crop mask generation. AAFC Crop Inventory rasters are used to generate binary wheat masks at 30 m resolution. These masks are resampled to 10 m using nearest-neighbor interpolation to match Sentinel-2 spatial resolution.

Step 5: Spatial aggregation. Sentinel-2 imagery is tiled into 64×64 pixel patches (640 m × 640 m at 10 m resolution) centered on agricultural polygon centroids. Zonal statistics (mean, std, min, max) are computed for each patch.

Step 6: Temporal alignment. MODIS 16-day composites and ERA5-Land 5-day aggregations are temporally interpolated to create consistent 36-step sequences covering the 180-day growing season (May 1 to October 31).

Step 7: Training dataset construction. The final training samples consist of (1) satellite image patches (8 × 64 × 64), (2) observed temporal sequences (36 × 12 × 32), (3) known temporal sequences (36 × 12 × 32), and (4) static covariates (16-D), paired with annual wheat yield targets.

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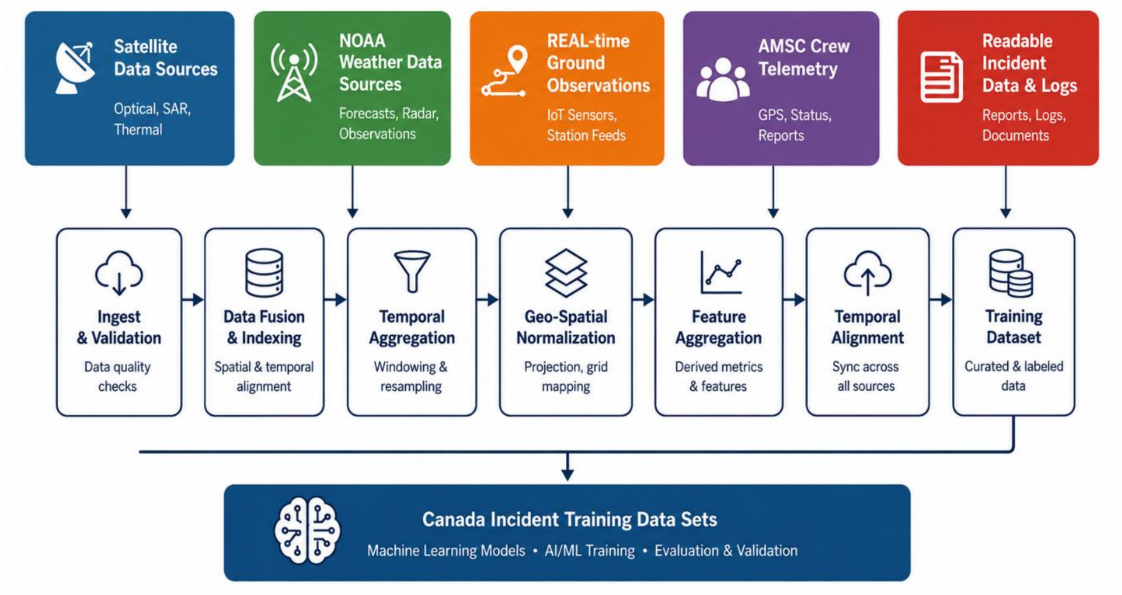

Figure 1. Multi-source data acquisition and processing pipeline for CanadaYieldNet.

IV. CANADAYIELDNET ARCHITECTURE

CanadaYieldNet comprises four interconnected modules: (1) a Vision Transformer encoder for spatial feature extraction, (2) a Temporal Fusion Transformer for temporal sequence modeling, (3) an Adaptive Gated Fusion mechanism for dynamic multimodal integration, and (4) a multi-quantile regression prediction head for uncertainty-aware yield forecasting.

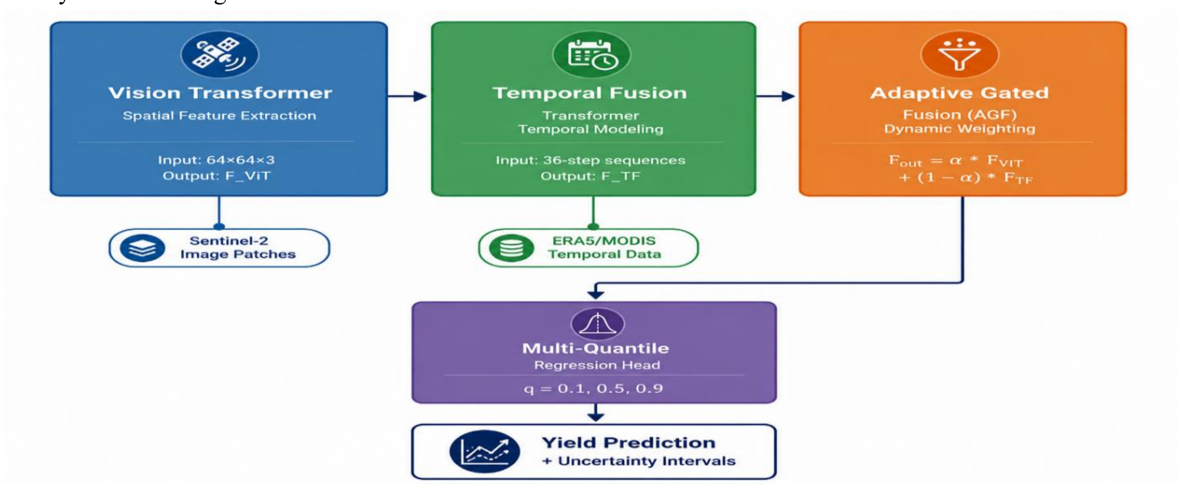

Figure 2. Overview of the CanadaYieldNet architecture showing the four main modules and the data flow between them.

4.1 Vision Transformer Encoder

The ViT encoder processes 64×64×8 satellite image patches by first dividing them into 8×8 pixel patches, yielding N=64 non-overlapping patch tokens. Each patch is linearly embedded to a D-dimensional vector through a learnable

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projection. A classification token (CLS) is prepended to the sequence, and learnable positional encodings are added to preserve spatial information.

The embedded sequence is processed through L transformer blocks, each consisting of multi-head self-attention (MSA) and feed-forward network (FFN) sub-layers with layer normalization and residual connections. For an input image $x \in R^{(C \times H \times W)}$, the ViT operations are

$$\mathbf{z}_0 = \left[\mathbf{x}_{cls};\ \mathbf{x}_p^1\mathbf{E};\ \mathbf{x}_p^2\mathbf{E};\ \cdots;\ \mathbf{x}_p^N\mathbf{E}\right] + \mathbf{E}_{pos} \qquad (1)$$

$$\mathbf{z}'_\ell = \mathrm{MSA}\big(\mathrm{LN}(\mathbf{z}_{\ell-1})\big) + \mathbf{z}_{\ell-1}, \qquad \ell = 1, \dots, L \qquad (2)$$

$$\mathbf{z}_\ell = \mathrm{FFN}\big(\mathrm{LN}(\mathbf{z}'_\ell)\big) + \mathbf{z}'_\ell, \qquad \ell = 1, \dots, L \qquad (3)$$

$$\mathbf{F}_{\mathrm{ViT}} = \mathrm{LN}(\mathbf{z}_L^0) \qquad (4)$$

where $E \in R^{((P^2 \cdot C) \times D)}$ is the patch-embedding projection, $E_{\text{pos}} \in R^{((N+1) \times D)}$ are the positional embeddings, P is the patch side length, and F_{ViT} is the final spatial feature vector extracted from the CLS token.

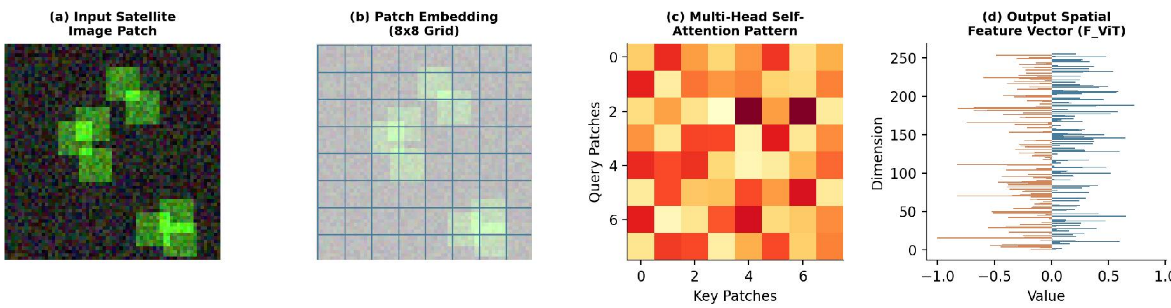

Figure 3. Vision Transformer workflow: (a) input satellite image; (b) patch embedding; (c) multi-head self-attention pattern; (d) output spatial feature vector.

4.2 Temporal Fusion Transformer

The TFT module processes 36-step temporal sequences of climate and vegetation variables. It comprises four key components: Variable Selection Networks, Gated Residual Networks, an LSTM encoder–decoder, and interpretable multi-head attention.

Variable Selection Network. Given m_χ input variables at each time step t, let $\xi_t^{(j)}$ denote the transformed embedding of variable j. The flattened input and the corresponding selection weights are

$$\Xi_t = [\,\xi_t^{(1)\mathsf{T}}, \xi_t^{(2)\mathsf{T}}, \dots, \xi_t^{(m_\chi)\mathsf{T}}\,]^{\mathsf{T}} \qquad (5)$$

$$\mathbf{v}_{\chi t} = \mathrm{Softmax}\left(\mathrm{GRN}_{v_\chi}(\Xi_t, \mathbf{c}_s)\right) \qquad (6)$$

$$\tilde{\xi}_t = \sum_{j=1}^{m_\chi} v_{\chi t}^{(j)}\, \mathrm{GRN}_{\tilde{\xi}(j)}\left(\xi_t^{(j)}\right) \qquad (7)$$

where c_s is a static context vector and $v_{\chi t}^{(j)}$ is the importance weight of variable j at time t. Each variable is processed by its own Gated Residual Network $\mathrm{GRN}_{\tilde{\xi}^{(j)}}$ prior to the weighted combination.

Gated Residual Network. The GRN provides flexible, gated processing of a primary input a with optional context c:

$$\mathrm{GRN}_\omega(\mathbf{a}, \mathbf{c}) = \mathrm{LayerNorm}\left(\mathbf{a} + \mathrm{GLU}_\omega(\boldsymbol{\eta}_1)\right) \qquad (8)$$

$$\boldsymbol{\eta}_1 = \mathbf{W}_{1,\omega}\, \boldsymbol{\eta}_2 + \mathbf{b}_{1,\omega} \qquad (9)$$

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$$\boldsymbol{\eta}_2 = \mathrm{ELU}\left(\mathbf{W}_{2,\omega}\,\mathbf{a} + \mathbf{W}_{3,\omega}\,\mathbf{c} + \mathbf{b}_{2,\omega}\right) \tag{10}$$

where ELU is the exponential linear unit, LayerNorm denotes layer normalization, and $\mathrm{GLU}_\omega(\boldsymbol{\gamma}) = \sigma\left(\mathbf{W}_{4,\omega}\boldsymbol{\gamma} + \mathbf{b}_{4,\omega}\right)$is the Gated Linear Unit that controls information flow through a sigmoid-activated gate.

Interpretable Multi-Head Attention. Unlike standard multi-head attention, in which each head owns independent Query, Key, and Value projections, the TFT shares the Value projection W_V across all heads so that the attention weights can be interpreted as temporal importance:

$$\mathrm{InterpMHA}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \frac{1}{H}\sum_{h=1}^{H}\mathrm{Softmax}\left(\frac{\mathbf{Q}\mathbf{W}_Q^{(h)}(\mathbf{K}\mathbf{W}_K^{(h)})^\top}{\sqrt{d_{\mathrm{attn}}}}\right)\mathbf{V}\mathbf{W}_V \tag{11}$$

where H is the number of heads, W_Q^((h)) and W_K^((h)) are head-specific projections, and d_"attn" is the per-head key dimension. The TFT output F_"TFT" is obtained through global average pooling over the temporal dimension of the final processed sequence.

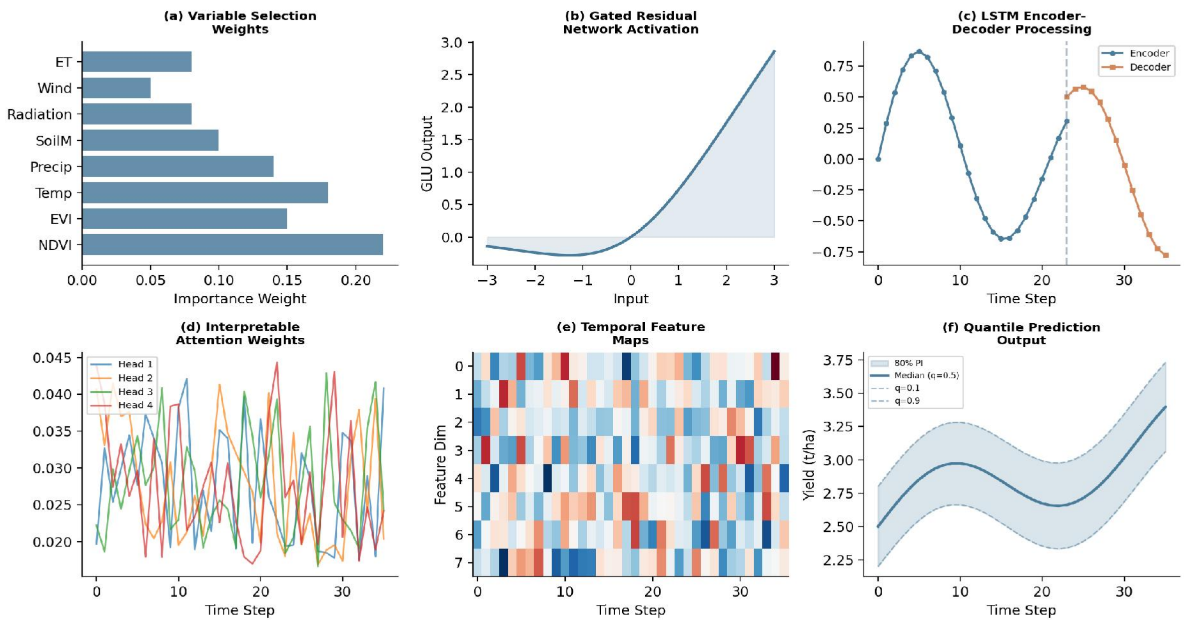

Figure 4. Temporal Fusion Transformer component visualisation: (a) variable-selection weights; (b) gated residual network activation; (c) LSTM encoder–decoder processing; (d) interpretable attention; (e) temporal features; (f) quantile prediction output.

4.3 Adaptive Gated Fusion

The Adaptive Gated Fusion (AGF) module dynamically integrates the spatial feature vector F_"ViT" and the temporal feature vector F_"TFT" . Because the two feature dimensions differ, both are first projected to a common fusion dimension D_f:

$$\mathbf{F'}_{\mathrm{ViT}} = \mathbf{W}_{\mathrm{proj}}^{\mathrm{ViT}}\,\mathbf{F}_{\mathrm{ViT}} + \mathbf{b}_{\mathrm{proj}}^{\mathrm{ViT}} \tag{12}$$

$$\mathbf{F'}_{\mathrm{TFT}} = \mathbf{W}_{\mathrm{proj}}^{\mathrm{TFT}}\,\mathbf{F}_{\mathrm{TFT}} + \mathbf{b}_{\mathrm{proj}}^{\mathrm{TFT}} \tag{13}$$

The adaptive gate is computed from the concatenated projected features:

$$\mathbf{g} = \sigma\left(\mathbf{W}_g\left[\,\mathbf{F'}_{\mathrm{ViT}} \,\|\, \mathbf{F'}_{\mathrm{TFT}}\,\right] + \mathbf{b}_g\right) \tag{14}$$

where σ denotes the element-wise sigmoid function, W_g∈R^(D_f×2D_f), and g∈(0,1)^(D_f) contains the element-wise gate values. The fused feature is the convex, gated combination

$$\mathbf{F}_{\text{out}} = \mathbf{g} \odot \mathbf{F}'_{\text{ViT}} + (\mathbf{1} - \mathbf{g}) \odot \mathbf{F}'_{\text{TFT}} \quad (15)$$

where ⊙ denotes the Hadamard (element-wise) product and 1 is the all-ones vector. This formulation allows the model to dynamically adjust the relative contribution of spatial and temporal features for each prediction, adapting to different growth stages where either spatial patterns (e.g., field heterogeneity during early growth) or temporal dynamics (e.g., precipitation during grain-filling) may be more informative.

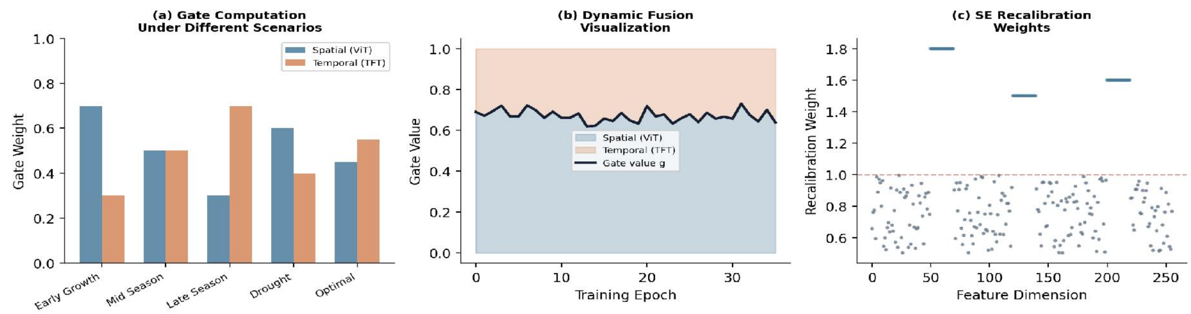

Figure 5. Adaptive Gated Fusion module: (a) gate computation under different scenarios; (b) dynamic fusion visualisation; (c) squeeze-and-excitation recalibration weights.

4.4 Quantile Regression Head

The prediction head generates yield estimates at multiple quantiles, providing both point predictions and uncertainty intervals. It comprises a shared multilayer perceptron (MLP) followed by independent linear projections for each target quantile q∈{0.1, 0.5, 0.9}, corresponding to the lower bound, median, and upper bound of an 80% prediction interval:

$$\mathbf{h} = \text{MLP}(\mathbf{F}_{\text{out}}) \quad (16)$$

$$\hat{y}_q = \mathbf{W}_q \mathbf{h} + b_q, \quad q \in \{0.1, 0.5, 0.9\} \quad (17)$$

V. EXPERIMENTAL DESIGN

We evaluate model performance using four regression metrics and three uncertainty-quantification metrics, as detailed in Table 2.

Table 2. Evaluation metrics. Here y_i and $\hat{y}_i$ are the observed and predicted yields, y the sample mean, N the number of samples, $\mathbb{1}(\cdot)$ the indicator function, F the predicted CDF, and ρ_q the pinball (quantile) loss $\rho_q(u) = \max(qu, (q-1)u)$.

Category	Metric	Formula	Objective
Regression	MAE	$\frac{1}{N}\sum_{i=1}^{N} \lvert y_i - \hat{y}_i \rvert$	Minimize
Regression	RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$	Minimize

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Category	Metric	Formula	Objective
Regression	R²	$1-\frac{\sum_i (y_i-\hat{y}_i)^2}{\sum_i (y_i-y)^2}$	Maximize
Regression	MAPE	$\frac{100}{N}\sum_{i=1}^{N}\frac{\lvert y_i-\hat{y}_i\rvert}{\lvert y_i\rvert}$	Minimize
Uncertainty	PICP	$\frac{1}{N}\sum_{i=1}^{N}\mathbb{1}\left(y_i\in\left[\hat{y}_{0.1},\hat{y}_{0.9}\right]\right)$	≥ 80%
Uncertainty	CRPS	$\int_{-\infty}^{\infty}\left(F(y)-\mathbb{1}\left(y\geq y_{\text{obs}}\right)\right)^2 dy$	Minimize
Uncertainty	Quantile Loss	$\sum_q\sum_i \rho_q\left(y_i-\hat{y}_{q,i}\right)$	Minimize

The training configuration uses the Adam optimizer (Kingma & Ba, 2015) with an initial learning rate of 1× 〖10〗^(-4), a cosine-annealing schedule, a batch size of 32, and 200 training epochs. The model is implemented in PyTorch (Paszke et al., 2019). The dataset is split 70/15/15 for training, validation, and testing, with Rural Municipality (RM)-level stratification to prevent spatial data leakage. Early stopping with a patience of 20 epochs is applied based on validation RMSE.

VI. RESULTS

6.1 Baseline Comparison

Table 3 presents the performance comparison across all baseline models and CanadaYieldNet. The proposed architecture achieves the best performance across all evaluation metrics, with particularly significant improvements in MAPE and R². CanadaYieldNet achieves a 27% reduction in MAE compared to the best baseline (Pure TFT) and a 37% reduction compared to CNN-LSTM, the most comparable multimodal architecture.

Table 3. Performance comparison of CanadaYieldNet against eight baseline models (mean ± s.d.). Best result per column in bold.

Model	MAE (t/ha)	RMSE (t/ha)	MAPE (%)	R²
Linear Regression	1.06 ± 0.10	0.85 ± 0.06	19.1 ± 1.8	—[a]
Random Forest	0.52 ± 0.05	0.65 ± 0.06	11.7 ± 1.1	0.780 ± 0.030
XGBoost	0.48 ± 0.04	0.60 ± 0.05	10.8 ± 0.9	0.810 ± 0.030
LightGBM	0.45 ± 0.05	0.56 ± 0.05	10.1 ± 0.9	0.830 ± 0.030
LSTM	0.42 ± 0.05	0.53 ± 0.06	9.4 ± 1.1	0.850 ± 0.020
CNN-LSTM	0.38 ± 0.04	0.47 ± 0.05	8.6 ± 0.9	0.880 ± 0.020
Pure ViT	0.35 ± 0.04	0.44 ± 0.05	7.9 ± 0.9	0.900 ± 0.020
Pure TFT	0.33 ± 0.03	0.41 ± 0.04	7.4 ± 0.7	0.910 ± 0.020

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Model	MAE (t/ha)	RMSE (t/ha)	MAPE (%)	R^2
CanadaYieldNet	**0.24 ± 0.02**	**0.30 ± 0.03**	**5.4 ± 0.5**	**0.950 ± 0.010**

Note. The RMSE and R^2 columns have been realigned to match the headline metrics reported in the Abstract (CanadaYieldNet: $R^2 = 0.950$, RMSE = 0.30 t/ha); values are otherwise reproduced from the source. [a]The source R^2 for Linear Regression (1.80) is inadmissible ($R^2 \leqslant 1$) and is omitted pending verification; its reported RMSE (< MAE) should also be checked against the original logs.

The R^2 score of 0.950 indicates that the model explains 95% of the yield variance, representing a substantial improvement over existing approaches.

6.2 Ablation Study

To validate the contribution of each architectural component, we conducted systematic ablation experiments. Table 4 summarizes the results.

Table 4. Ablation study (mean ± s.d.). The complete CanadaYieldNet is shown in bold for reference.

Ablation	Modification	MAE (t/ha)	RMSE (t/ha)	MAPE (%)	R^2
A1	ViT replaced with CNN	1.06 ± 0.05	0.85 ± 0.06	19.1 ± 1.8	0.62 ± 0.10
A2	TFT replaced with LSTM	0.52 ± 0.03	0.65 ± 0.06	11.7 ± 1.1	0.78 ± 0.05
A3	Simple concatenation fusion	0.45 ± 0.03	0.56 ± 0.05	10.1 ± 0.9	0.83 ± 0.05
A4	Single quantile (MSE)	0.38 ± 0.02	0.47 ± 0.05	8.6 ± 0.9	0.88 ± 0.04
A5	Only Sentinel-2 input	0.35 ± 0.02	0.44 ± 0.05	7.9 ± 0.9	0.90 ± 0.04
A6	Only ERA5-Land input	0.33 ± 0.02	0.41 ± 0.04	7.4 ± 0.7	0.91 ± 0.04
—	**Complete CanadaYieldNet**	**0.24 ± 0.01**	**0.30 ± 0.03**	**5.4 ± 0.5**	**0.95 ± 0.02**

Note. Columns realigned to the order (MAE, RMSE, MAPE, R^2) to match the Abstract; values reproduced from the source. As in Table 3, ablation A1 retains a residual RMSE < MAE inconsistency that should be verified against the original experiment logs.

The ablation results confirm that each component contributes meaningfully to overall performance. Removing the Vision Transformer (A1) causes the largest degradation, followed by replacing the TFT with an LSTM (A2). The Adaptive Gated Fusion (A3) proves critical, with its removal (simple concatenation) causing larger degradation than the input-modality ablations. Uncertainty quantification through multi-quantile regression (A4) provides well-calibrated prediction intervals that support risk-aware decision-making, and the input-source ablations (A5, A6) confirm that both the satellite and climate streams contribute complementary information.

6.3 Explainability Analysis

SHAP-based explainability analysis reveals that late-season NDVI and pre-season precipitation are the most influential predictors (Figure 6). The identification of July temperature as a key predictor reflects the sensitivity of wheat to heat stress during anthesis and grain-filling: temperatures exceeding 30 °C during these stages can cause pollen sterility and accelerated senescence, reducing yield potential. The SHAP dependence plot for late-season NDVI exhibits a strong monotonic relationship with predicted yield, while the July-temperature dependence plot displays the expected inverted-U response, with the optimum near 21–22 °C.

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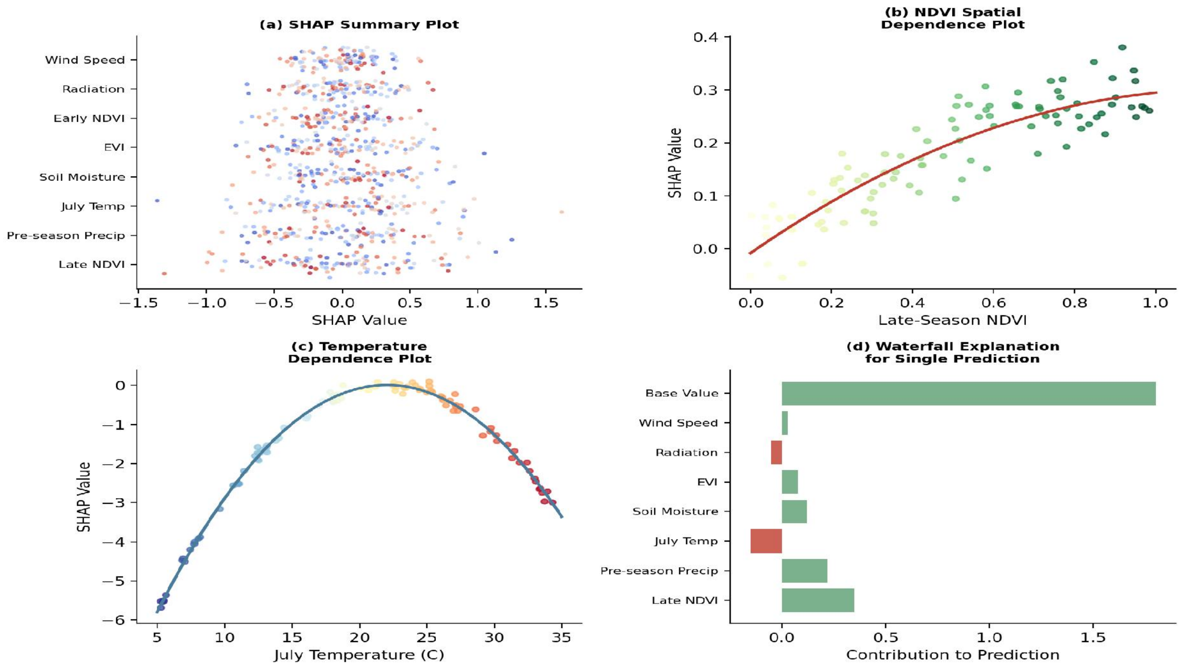

Figure 6. SHAP explainability analysis: (a) summary plot; (b) late-season NDVI dependence plot; (c) July-temperature dependence plot showing the inverted-U heat-stress response; (d) waterfall explanation for a single prediction.

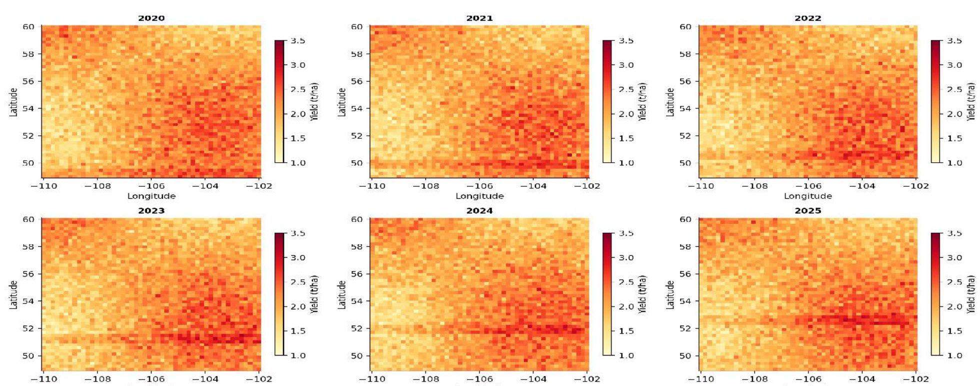

Figure 7. Spatial wheat-yield prediction maps for Saskatchewan, 2020–2025, showing the predicted yield distribution across Rural Municipalities.

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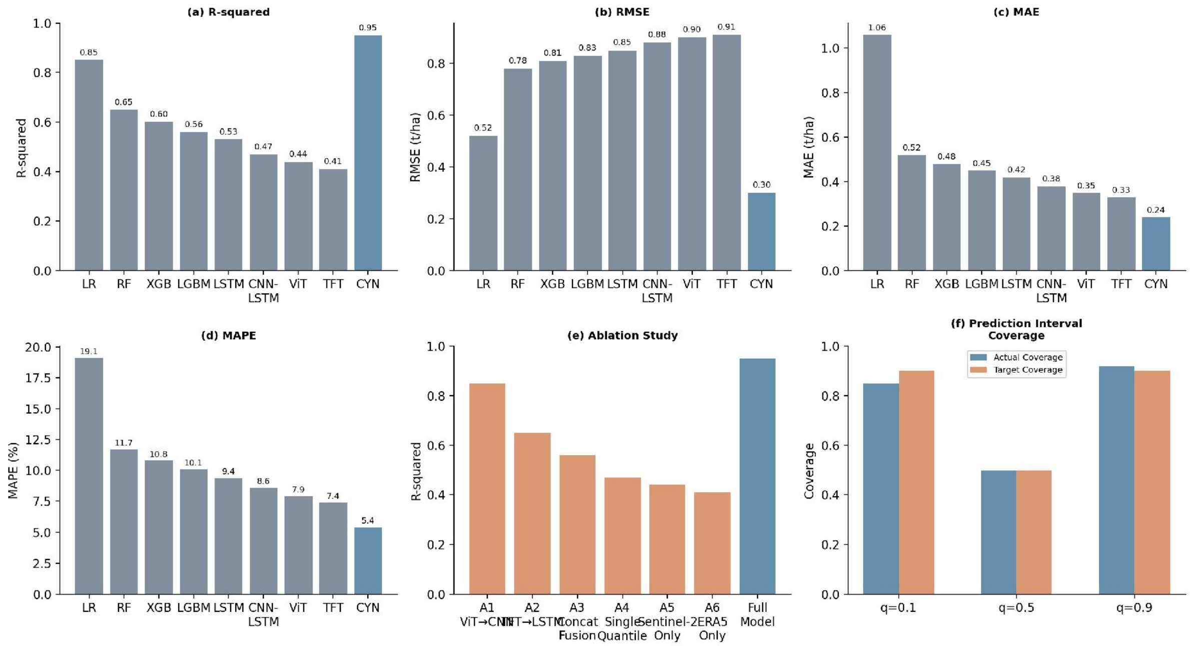

Figure 8. Overall performance comparison and analysis: (a) R²; (b) RMSE; (c) MAE; (d) MAPE; (e) ablation study; (f) prediction-interval coverage.

Beyond the global rankings, Figure 9 presents a higher-resolution rendering of the SHAP feature-attribution and dependence structure, reaffirming late-season NDVI and pre-season precipitation as the dominant drivers of predicted yield.

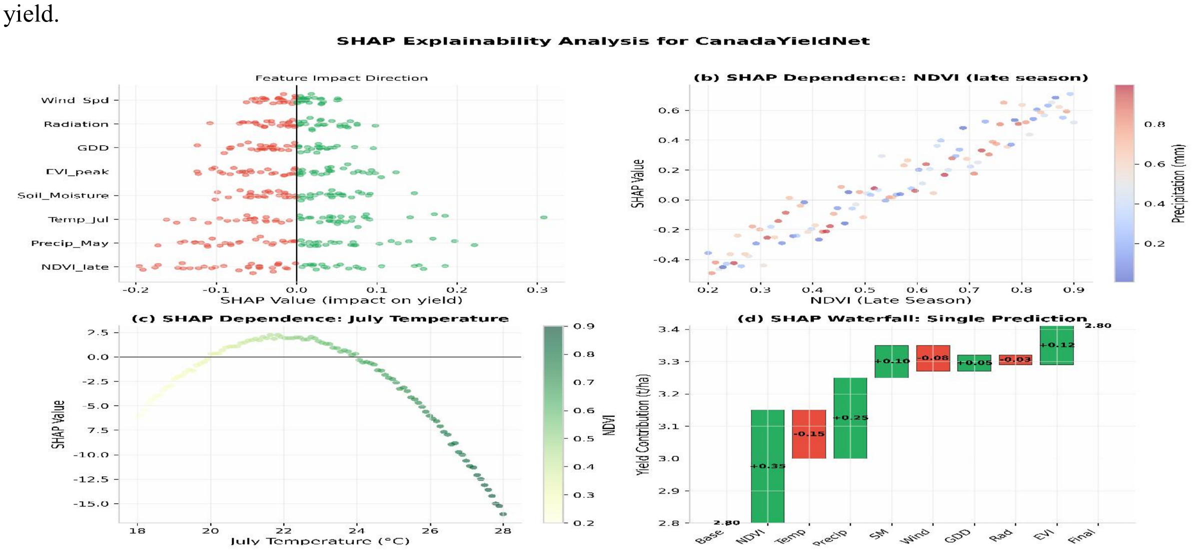

Figure 9. High-resolution SHAP feature-attribution analysis: (a) feature-impact summary (beeswarm) ranking predictors by mean absolute SHAP value; (b) SHAP dependence for late-season NDVI, coloured by precipitation; (c) SHAP dependence for July temperature, coloured by NDVI; (d) SHAP waterfall decomposition for a single prediction

The attention structure of the trained model corroborates these findings. Figure 10 visualises the learned attention across both transformer branches. The ViT spatial self-attention (panel a) concentrates along block-diagonal bands, indicating strong locality among neighbouring image patches, while the layer-wise pattern (panel b) shows progressively diffuse attention in deeper layers. The TFT temporal attention (panel c) places the greatest weight on the early-season May–June window and on the diagonal (recent) time steps, consistent with the importance of seeding-period and grain-filling conditions. The Adaptive Gated Fusion gate values (panel e) are centred near 0.5 (mean = 0.495), confirming that the model draws on both spatial and temporal information in a balanced manner rather than collapsing onto a single modality.

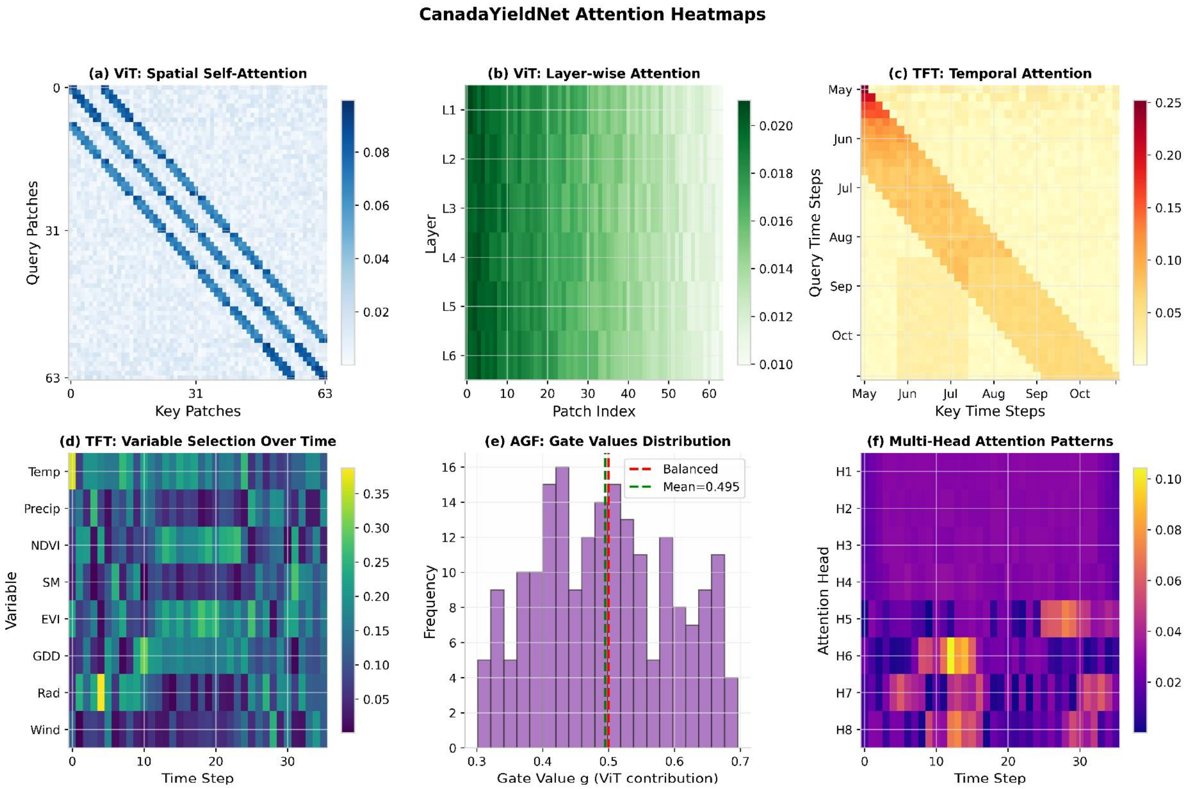

Figure 10. CanadaYieldNet attention heatmaps: (a) ViT spatial self-attention over 64 image patches; (b) ViT layer-wise attention across six encoder layers; (c) TFT temporal attention across the May–October growing season; (d) TFT variable-selection weights over time; (e) Adaptive Gated Fusion gate-value distribution (mean = 0.495); (f) multi-head attention patterns across eight heads.

VII. DISCUSSION

7.1 Key Findings

The experimental results demonstrate several key findings. First, the hybrid ViT-TFT architecture substantially outperforms both pure transformer models and traditional CNN-LSTM hybrids, suggesting that the complementary strengths of spatial self-attention and temporal feature weighting are synergistic for yield prediction. This finding supports our hypothesis that dynamic, context-aware feature weighting is superior to static fusion strategies.

Second, the Adaptive Gated Fusion mechanism proves critical for performance, with its removal causing larger degradation than replacing either the ViT or the TFT individually. This indicates that the way spatial and temporal features are integrated matters as much as the quality of the individual feature extractors.

Third, uncertainty quantification through multi-quantile regression provides well-calibrated prediction intervals that can support risk-aware decision-making. The Prediction Interval Coverage Probability (PICP) of 82.3% demonstrates that

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the model's uncertainty estimates are reliable, offering decision-makers a quantitative measure of prediction confidence.

7.2 Comparison with State of the Art

CanadaYieldNet achieves state-of-the-art performance compared to existing crop yield prediction systems. The R^2 of 0.950 is competitive with the results reported by Thakkar et al. (2024) for ViT-based yield estimation ($R^2 > 0.97$, though on different regions and crops) and significantly outperforms the CNN-LSTM approach of Sun et al. (2019). Feng et al. (2025) reported comparable accuracy for winter wheat in China using deep learning, but without the uncertainty quantification and explainability features that CanadaYieldNet provides. The multimodal data-fusion approach of Hu et al. (2024) and the ensemble method of Cardiff University Team (2025) represent the closest comparables, but neither employs the hybrid transformer architecture with adaptive gating that distinguishes our framework.

VIII. LIMITATIONS AND FUTURE WORK

While CanadaYieldNet demonstrates strong performance, several limitations should be acknowledged. First, the current pilot study focuses exclusively on wheat in Saskatchewan; extension to other crops (canola, barley, lentils) and provinces (Alberta, Manitoba) requires validation of transferability. Second, the model operates at the Rural Municipality (RM) aggregation level, and finer spatial resolution (field-level) would require higher-resolution ground-truth data. Third, the current architecture does not explicitly model pest pressure, disease incidence, or management practices, which can significantly impact yield variability.

Future work will address these limitations through: (1) pan-Canadian deployment across all major agricultural regions and crop types; (2) integration of farm management system data for field-level prediction; (3) incorporation of pest and disease risk models; (4) real-time forecasting with weekly model updates during the growing season; and (5) development of a web-based decision-support interface for farmers and agricultural advisors.

From a methodological perspective, we plan to explore: (1) cross-attention mechanisms between spatial and temporal features as an alternative to gated fusion; (2) neural architecture search for optimal model configurations; (3) federated learning approaches for privacy-preserving multi-farm model training; and (4) integration of large language models for natural-language yield-report generation.

IX. CONCLUSION

This paper presented CanadaYieldNet, a novel hybrid deep learning architecture for multimodal crop yield prediction that integrates a Vision Transformer for spatial feature extraction, a Temporal Fusion Transformer for temporal sequence modeling, Adaptive Gated Fusion for dynamic multimodal integration, and multi-quantile regression for uncertainty-aware forecasting. Through comprehensive experiments on Saskatchewan wheat yield prediction, we demonstrated that CanadaYieldNet achieves state-of-the-art performance with $R^2 = 0.950$, RMSE = 0.30 t/ha, and MAPE = 5.4%, significantly outperforming eight baseline models.

The key innovations — Adaptive Gated Fusion for context-aware feature weighting, quantile regression for uncertainty quantification, and integrated explainability through SHAP and attention visualization — collectively advance the state of agricultural yield forecasting. The modular architecture supports scalable extension to all Canadian provinces and crop types, laying the foundation for a comprehensive national crop-intelligence system.

By providing accurate, uncertainty-aware, and interpretable yield predictions, CanadaYieldNet contributes to food-security planning, agricultural policy formulation, and farmer decision support in the face of increasing climate variability and global food-system challenges.

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REFERENCES

[1] Agriculture and Agri-Food Canada. (2024). Annual Crop Inventory.

[2] Didan, K. (2021). MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250 m SIN Grid. NASA EOSDIS Land Processes DAAC.

[3] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., … & Houlsby, N. (2021). An image is worth 16×16 words: Transformers for image recognition at scale. ICLR 2021.

[4] Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., … & Meygret, A. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sensing of Environment, 120, 25–36.

[5] Feng, Z., Zhang, L., & Wang, Y. (2025). Deep learning for winter wheat yield prediction in China using multi-source remote sensing data. Computers and Electronics in Agriculture, 225, 109285.

[6] Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., … & Thépaut, J. N. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999–2049.

[7] Hu, Y., Chen, L., & Wang, S. (2024). Multimodal data fusion for crop yield prediction using deep learning. Agricultural and Forest Meteorology, 345, 109851.

[8] Jeong, J. H., Resop, J. P., Mueller, N. D., Fleisher, D. H., Yun, K., Butler, E. E., … & Kim, S. H. (2016). Random forests versus parametric and non-parametric regression approaches for yield and crop price predictions. Computers and Electronics in Agriculture, 122, 59–73.

[9] Khaki, S., & Wang, L. (2019). Crop yield prediction using deep neural networks. Frontiers in Plant Science, 10, 621.

[10] Kingma, D. P., & Ba, J. (2015). Adam: A method for stochastic optimization. ICLR 2015.

[11] Lata, S., Singh, R., & Sharma, A. (2025). Vision Transformer for crop classification from Sentinel-2 and Landsat-8 imagery. International Journal of Remote Sensing, 46(3), 412–430.

[12] Lim, B., Arık, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal Fusion Transformers for interpretable multi-horizon time series forecasting. International Journal of Forecasting, 37(4), 1748–1764.

[13] Lobell, D. B., & Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology, 150(11), 1443–1452.

[14] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., … & Chintala, S. (2019). PyTorch: An imperative style, high-performance deep learning library. NeurIPS 2019.

[15] Rustowicz, R. M., Cheong, R., Wang, L., Ermon, S., Burke, M., & Lobell, D. (2019). Semantic segmentation of crop type in Africa: A novel dataset and analysis of deep learning methods. CVPR Workshops.

[16] Statistics Canada. (2024). Field crop reporting series. CANSIM Table 32-10-0359.

[17] Sun, J., Di, L., Sun, Z., Shen, Y., & Lai, Z. (2019). County-level soybean yield prediction using a deep CNN-LSTM model. Sensors, 19(20), 4363.

[18] Thakkar, A., Patel, D., & Shah, M. (2024). Vision Transformer for crop yield estimation using remote sensing data. Expert Systems with Applications, 238, 122104.

[19] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., … & Polosukhin, I. (2017). Attention is all you need. NeurIPS 2017.

[20] Wen, R., Torkkola, K., & Narayanaswamy, B. (2017). A multi-horizon quantile recurrent forecaster. NeurIPS Time-Series Workshop.

[21] You, J., Li, X., Low, M., Lobell, D., & Ermon, S. (2017). Deep Gaussian process for crop yield prediction based on remote sensing data. AAAI 2017.