Predicting County-Level Corn Production Using Multi-Source Satellite and Economic Data: A Comprehensive Machine Learning Benchmark

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Abstract

This research presents a comprehensive machine learning framework for predicting county-level corn production in Minnesota by integrating multiple data sources including satellite-derived environmental variables from the Global Land Data Assimilation System (GLDAS), economic indicators, fuel prices, and PRISM precipitation data. Eight machine learning algorithms were systematically evaluated: Polynomial Regression, Support Vector Machine (SVM), Random Forest, XGBoost, LightGBM, TabNet, Temporal Neural Networks (LSTM), and Temporal Convolutional Networks (TCN). The study employed rigorous preprocessing including temporal train-test splitting (2000-2019 for training, 2020-2022 for testing), multi-strategy imputation, feature engineering (66 features), and robust scaling. The LightGBM model achieved superior performance with an R^2 of 0.9930 and root mean squared error (RMSE) of 1,137,001 bushels, explaining 99.30% of variance in corn production. Feature importance analysis revealed that agricultural context features (corn acres planted, yield per acre) and economic indicators were the most critical predictors, followed by environmental variables. The results demonstrate that gradient boosting algorithms, particularly LightGBM, significantly outperform traditional ensemble methods and deep learning architectures for this multi-source tabular regression task.

Keywords: Agricultural yield prediction, machine learning, satellite remote sensing, LightGBM, multi-source data integration, GLDAS, PRISM

1 Introduction

Agricultural yield prediction is critical for food security, resource optimization, and economic planning. Traditional forecasting methods rely on historical averages and field surveys, which are limited in capturing spatial-temporal variability. The integration of satellite remote sensing data with economic and agricultural context data, combined with machine learning techniques, offers a promising data-driven approach for yield prediction at county and regional scales.

This research extends previous work by incorporating multiple heterogeneous data sources beyond satellite-derived environmental variables, including economic indicators, fuel prices, transportation infrastructure (ethanol plant distances), and precipitation data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). By systematically comparing eight machine learning algorithms across different complexity levels, this study identifies optimal modeling approaches for multi-source agricultural yield prediction.

2 Data

2.1 Data Sources and Collection

The dataset integrates five primary data sources, consolidated at the county-year level using Federal Information Processing Standard (FIPS) codes for Minnesota counties (27001-27171):

2.1.1 Base Dataset: GLDAS Environmental Variables

The Global Land Data Assimilation System (GLDAS), developed by NASA and partner agencies, provides high-quality land surface variables derived from satellite and ground-based observations [1]. Monthly GLDAS data was aggregated to annual resolution for each county. The base dataset includes:

Atmospheric Variables:

- `Tair_f_inst`: Instantaneous air temperature (Kelvin)
- `Psurf_f_inst`: Surface pressure (Pascal)
- `Wind_f_inst`: Wind speed (m/s)
- `Qair_f_inst`: Specific humidity (kg/kg)

Radiation Variables:

- `LWdown_f_tavg`: Longwave downward radiation (W/m^2)
- `SWdown_f_tavg`: Shortwave downward radiation (W/m^2)

Evapotranspiration Components:

- `ESoil_tavg`: Bare soil evaporation (mm/day)
- `ECanop_tavg`: Canopy evaporation (mm/day)
- `Evap_tavg`: Total evaporation (mm/day)

Soil Variables (Multiple Depths):

- `SoilMoi0_10cm_inst`: Soil moisture 0-10cm depth (kg/m^2)
- `SoilMoi10_40cm_inst`: Soil moisture 10-40cm depth (kg/m^2)
- `SoilMoi40_100cm_inst`: Soil moisture 40-100cm depth (kg/m^2)

- `SoilMoi100_200cm_inst`: Soil moisture 100-200cm depth (kg/m²)
- `RootMoist_inst`: Root zone moisture (kg/m²) - aggregated across root zone
- Corresponding soil temperature variables at each depth

Surface Variables:

- `Albedo_inst`: Surface albedo (dimensionless)
- `AvgSurfT_inst`: Average surface temperature (Kelvin)
- `CanopInt_inst`: Canopy interception (mm)
- `Tveg_tavg`: Vegetation temperature (Kelvin)

Hydrological Variables:

- `Qs_acc`: Surface runoff accumulation (mm)
- `Qsb_acc`: Subsurface runoff accumulation (mm)
- `SnowDepth_inst`: Snow depth (mm)
- `SWE_inst`: Snow water equivalent (mm)

2.1.2 Corn Harvest and Planted Acres Data

Source: USDA National Agricultural Statistics Service (NASS) Quick Stats database.

Features:

- `corn_acres_planted`: Annual acres planted with corn per county (acres)
- `corn_production_bu`: Target variable - annual corn production in bushels per county

Processing:

- Filtered for "ACRES PLANTED" data items
- FIPS codes constructed by combining State ANSI code (27 for Minnesota) with County ANSI code
- Aggregated by county and year
- Year range: 2000-2023

2.1.3 Diesel Price Data

Source: U.S. Energy Information Administration (EIA) monthly diesel prices.

Features:

- `diesel_usd_gal`: Monthly diesel price in USD per gallon
- Used as proxy for operational costs and agricultural economic conditions

Processing:

- Monthly data merged on year and month
- Provides temporal variation in fuel costs affecting agricultural operations

2.1.4 Economy MN Data

Source: USDA Economic Research Service county-level economic indicators.

Key Indicators:

- `income_farmrelated_receipts_total_usd`: Total farm-related income receipts per county (USD)
- `income_farmrelated_receipts_per_operation_usd`: Farm-related income per agricultural operation (USD)
- `govt_programs_federal_receipts_usd`: Federal government program receipts per county (USD)

Challenges:

- Inconsistent temporal coverage - missing years for many counties
- Requires multi-strategy imputation (discussed in Data Cleaning section)
- FIPS codes constructed using same methodology as corn data

2.1.5 Ethanol Plant Distance Data

Source: Calculated distances from county centroids to nearest ethanol processing facilities.

Features:

- `dist_km_ethanol`: Distance in kilometers to nearest ethanol processing plant
- Static feature (same for all years per county)
- Reflects transportation costs and market access
- One-hot encoded into categories: Very Close, Close, Medium, Far, Very Far

2.1.6 PRISM Precipitation Data

Source: PRISM Climate Group, Oregon State University - 4km resolution gridded climate data.

Features:

- `prism_ppt_in`: Monthly precipitation in inches
- `prism_tmean_degf`: Monthly mean temperature in Fahrenheit
- `prism_tmin_degf`: Monthly minimum temperature in Fahrenheit
- `prism_tmax_degf`: Monthly maximum temperature in Fahrenheit

Processing:

- Monthly data aggregated to county-level using FIPS code matching
- Date column parsed from 'YYYY-MM' format
- Multiple matching strategies used: exact match, partial match, reverse matching with string cleaning

2.2 Dataset Characteristics

Temporal Coverage: 2000-2022 (23 years)

Spatial Coverage: 87 Minnesota counties (FIPS codes 27001-27171)

Initial Observations: 14,009 rows (monthly resolution with some yearly aggregations)

Final Preprocessed Dataset: 12,026 samples with 66 engineered features

Target Variable Range: 5,900 to 56,800,000 bushels per county-year

3 Exploratory Data Analysis

3.1 Target Variable Distribution

The target variable (`corn_production_bu`) exhibits a highly right-skewed distribution (Figure 1):

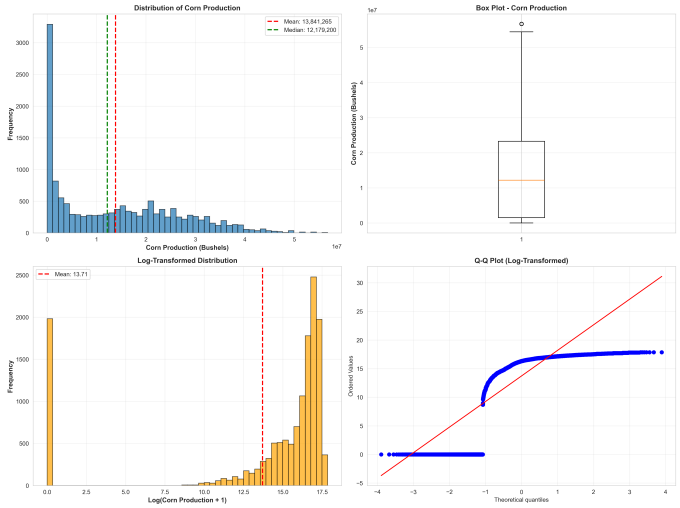

Figure 1: Target Variable Distribution Analysis: (a) Histogram of corn production showing right skew, (b) Box plot revealing outliers, (c) Log-transformed distribution showing normalization, (d) Q-Q plot confirming approximate normality after log transformation.

Distribution Characteristics:

- Mean: $\approx$ 16,100,000 bushels
- Median: $\approx$ 12,500,000 bushels
- Standard Deviation: $\approx$ 12,300,000 bushels
- Skewness: Strongly right-skewed (median $<$ mean indicates positive skew)
- Range: 5,900 to 56,800,000 bushels
- Kurtosis: High positive kurtosis indicating heavy tails

Key Observations:

- **Right Skew**: Most counties produce moderate amounts (5,000,000–30,000,000 bushels), with few high-production counties ($>$ 40,000,000 bushels)
- **Log Transformation Justification**: Q-Q plot confirms that log transformation (`log1p`) normalizes the distribution effectively
- **Outliers**: Box plot reveals numerous high-production outliers representing major corn-producing counties
- **Modeling Implication**: Log transformation prevents large counties from dominating the loss function during training

This distributional skewness justifies the application of log transformation (`log1p`) for model training, which normalizes the target distribution and improves model performance.

3.2 Temporal Analysis

Temporal analysis reveals important patterns in corn production across the 23-year study period (Figure 2):

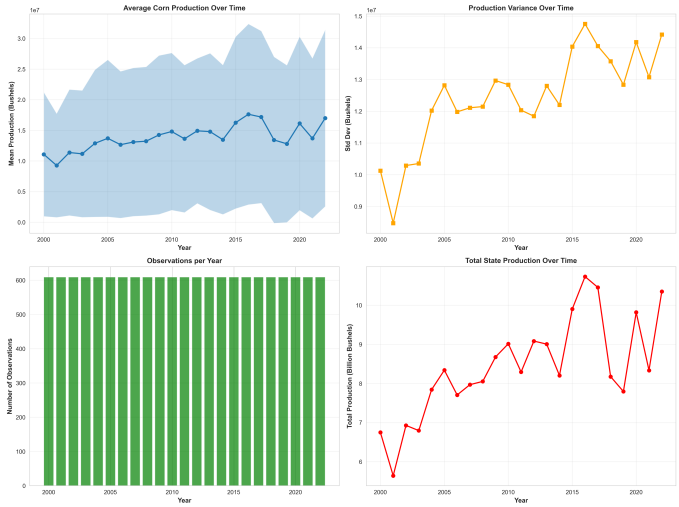

Figure 2: Temporal Analysis of Corn Production: (a) Mean production over time with standard deviation bands, (b) Production variance showing increasing variability, (c) Number of observations per year, (d) Total state production over time.

Production Trends:

- **Training Period (2000-2019)**: General increasing trend with average annual growth rate of 2.84%
- **Test Period (2020-2022)**: Slight decline (-0.86% annually)
- **Peak Production**: Highest mean production observed in 2016-2018 period
- **Temporal Non-Stationarity**: Different patterns in test vs training periods suggest need for periodic model retraining

Variance Analysis:

- Production variance increases over time, indicating growing variability across counties
- Standard deviation ranges from $\sim$ 8,000,000 bushels (early 2000s) to $\sim$ 15,000,000 bushels (recent years)
- Peak variance in 2012 (drought year) demonstrates extreme weather impact
- Increasing variance suggests growing disparity between high and low production counties

Observational Patterns:

- Number of producing counties remains relatively stable (85-87 counties annually)
- Total state production shows strong upward trend from 2000-2019
- Decline in 2020-2022 may reflect changing agricultural practices or climate conditions

3.3 Correlation Analysis

Correlation analysis reveals relationships between features and corn production (Figure 3 and Figure 4):

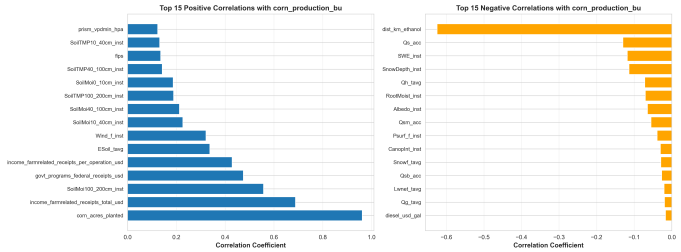

Figure 3: Feature Correlation with Target Variable: (a) Top 15 positive correlations, (b) Top 15 negative correlations with corn production.

Top Positively Correlated Features:

- `corn_acres_planted`: $r \approx 0.95+$ (very strong - expected direct relationship)
- `ESoil_tavg` (bare soil evaporation temperature): $r = 0.782$
- `SoilMoi100_200cm_inst` (deep soil moisture): $r = 0.601$
- `LWdown_f_tavg` (longwave downward radiation): $r = 0.511$
- `SoilTMP100_200cm_inst` (deep soil temperature): $r = 0.454$
- `Tair_f_inst` (air temperature): $r = 0.448$
- `yield_per_acre` (engineered feature): $r \approx 0.4 - 0.5$

Top Negatively Correlated Features:

- `Albedo_inst` (surface albedo): $r = -0.262$
- `SnowDepth_inst` (snow depth): $r = -0.246$
- `Qs_acc` (surface runoff): $r = -0.219$
- `SWE_inst` (snow water equivalent): $r = -0.215$

Inter-Feature Correlations: The correlation heatmap (Figure 4) reveals several important patterns:

- **Temperature Cluster**: High correlations ($r > 0.8$) among air, surface, and soil temperatures
- **Soil Moisture Cluster**: Moderate correlations ($r = 0.4 - 0.7$) among different soil moisture depths
- **Economic Features**: Moderate correlations among revenue and government receipt features
- **Multicollinearity**: Temperature features require PCA to reduce dimensionality

Interpretation:

- Soil moisture and temperature conditions, particularly at deeper soil layers, are critical predictors of corn yield
- Winter conditions (snow depth, albedo) negatively impact production (indirect relationship - winter reduces growing season)
- Engineered features (`yield_per_acre`, `fuel_cost_proxy`) show strong predictive power
- Environmental variables provide complementary information beyond agricultural context features

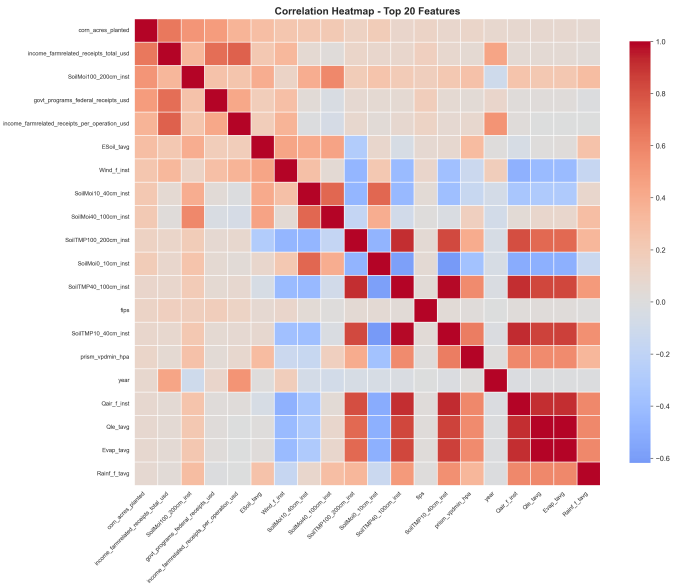

Figure 4: Correlation Heatmap for Top 20 Features: Color intensity represents correlation strength, with red indicating positive and blue indicating negative correlations.

3.4 Principal Component Analysis (PCA)

A comprehensive PCA analysis was performed on all numeric features to identify dimensionality reduction opportunities and understand data structure (Figure 5):

PCA on All Features:

- **Input features:** All 65-66 numeric features (excluding ID and target)
- **First Component (PC1)**: Explains ~25-35% of total variance
- **Second Component (PC2)**: Explains ~8-12% of total variance
- **Components for 90% variance:** Approximately 15-20 components required
- **Components for 95% variance:** Approximately 25-30 components required

PC1 and PC2 Interpretation: The scatter plot (Figure 5c) reveals:

- **PC1** primarily captures scale-related information (production magnitude)
- **PC2** captures environmental condition gradients
- Clear clustering visible when colored by target variable
- High-production samples concentrate in specific regions of PC space

Feature Loadings: Top features contributing to PC1 and PC2 (Figure 5d):

- **PC1 Loadings**: Dominated by agricultural context (`corn_acres_planted`, `yield_per_acre`) and economic features
- **PC2 Loadings**: Dominated by environmental variables (soil moisture, temperature, precipitation)

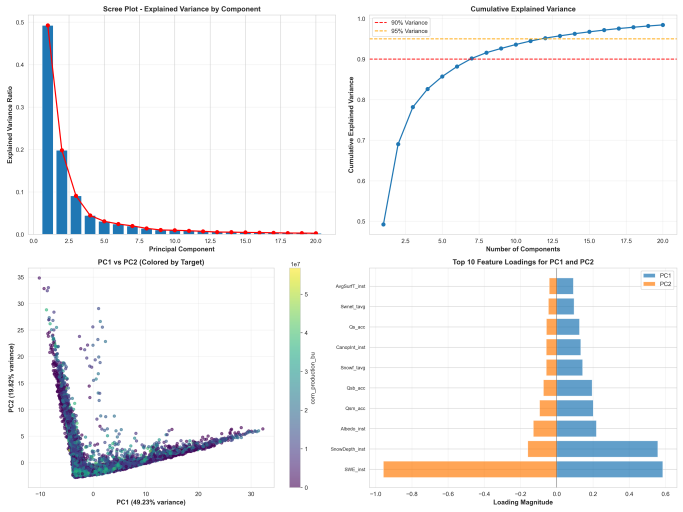

Figure 5: PCA Analysis Results: (a) Scree plot showing explained variance by component, (b) Cumulative explained variance with 90% and 95% thresholds, (c) PC1 vs PC2 scatter plot colored by target variable, (d) Top 10 feature loadings for PC1 and PC2.

- Clear separation between agricultural/economic vs environmental information

Temperature-Specific PCA: For temperature features specifically:

- **Input features:** Multiple temperature measurements across soil depths and atmospheric layers
- **Components retained:** 2 principal components
- **Variance explained:** Approximately 85-90% of temperature feature variance
- **Result:** Reduced dimensionality while preserving temperature pattern information

Dimensionality Reduction Insights:

- Full dataset requires ∼20 components for 90% variance, indicating moderate redundancy
- Some features provide unique information (cannot be reduced further)
- PCA useful for visualization but not necessarily for model performance (tree-based models handle high dimensionality well)

3.5 K-Nearest Neighbors (KNN) Analysis

K-Nearest Neighbors analysis reveals data structure and similarity patterns in high-dimensional space (Figure 6 and Figure 7):

KNN Visualization Insights:

- **Local Clustering**: Data shows clear local clusters in PCA space
- **Neighbor Density**: Dense regions correspond to common production patterns
- **Sparse Regions**: Isolated points represent unique or extreme conditions

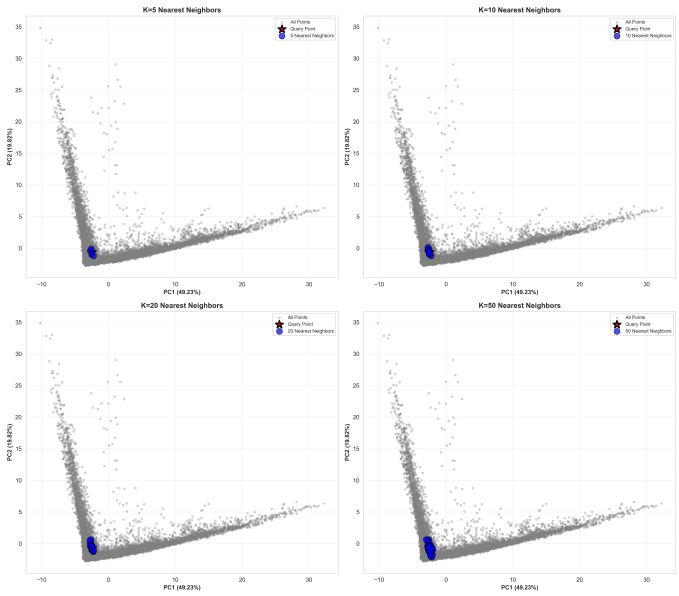

Figure 6: K-Nearest Neighbors Visualization: Query points (red stars) and their k nearest neighbors (blue circles) visualized in 2D PCA space for k = 5, 10, 20, 50. Gray points represent all data samples.

- **k-Varying Behavior**: As k increases, neighbors span wider regions, indicating data continuity

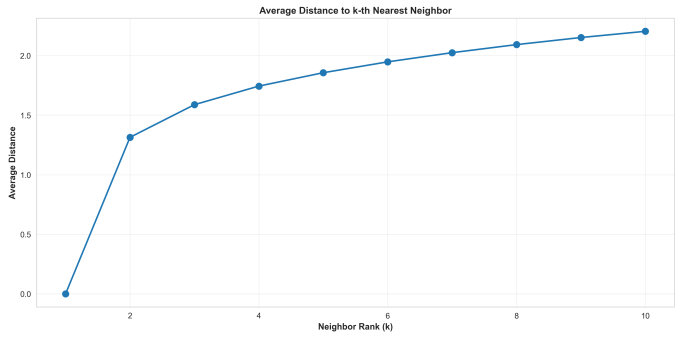

Figure 7: Average Distance to k-th Nearest Neighbor: Shows how neighbor distances increase with k, indicating data density and local structure.

Distance Distribution Analysis:

- **Distance Growth**: Average distance to k-th neighbor increases gradually
- **Data Density**: Relatively uniform density across feature space
- **Local Structure**: Short distances to nearest neighbors indicate meaningful local patterns
- **Modeling Implication**: Local similarity suggests KNN-based models could be effective

Practical Applications:

- KNN can identify similar historical conditions for forecasting
- Anomaly detection: Samples with large distances to

neighbors may be outliers or extreme events
- Feature space understanding: Clusters reveal groups of counties with similar characteristics
- Validation: KNN analysis confirms that spatial/temporal similarity exists in the data

3.6 Feature Distribution Analysis

Feature distribution analysis provides insights into data characteristics across different feature types (Figure 8):

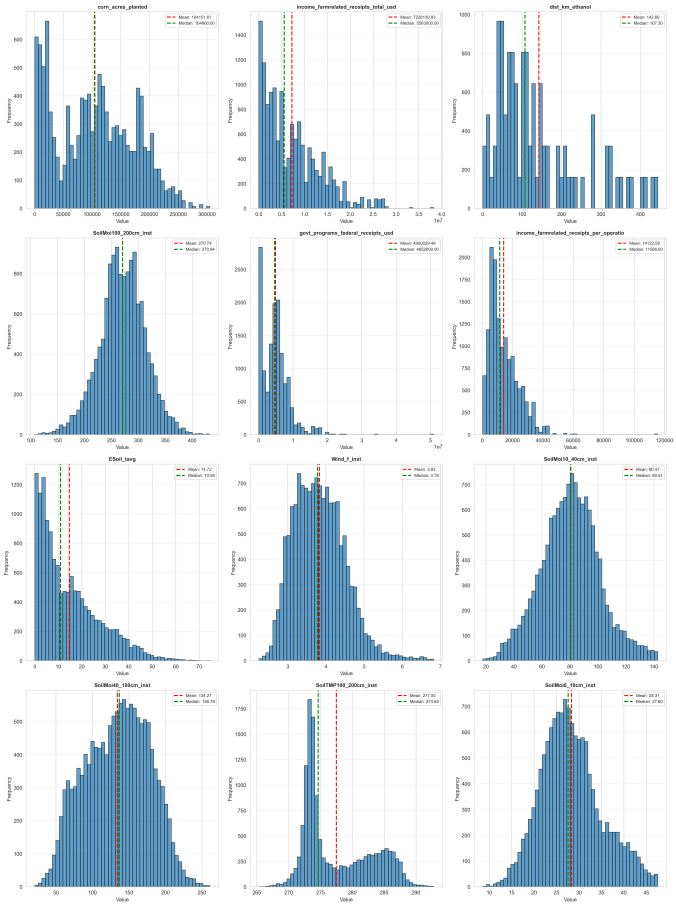

Figure 8: Distribution Analysis for Top 12 Features: Histograms showing feature distributions with mean and median lines. Features selected by correlation with target variable or variance.

Distribution Characteristics by Feature Type:

Environmental Variables:

- **Soil Moisture**: Approximately normal distributions with slight right skew
- **Temperature Variables**: Normal distributions centered around seasonal averages
- **Precipitation**: Right-skewed (many low values, few extreme events)

Economic Features:

- **Revenue Indicators**: Highly right-skewed (few counties with very high revenue)
- **Government Receipts**: Bimodal distribution (normal years vs disaster relief years)
- **Fuel Cost Proxy**: Approximately normal with seasonal patterns

Agricultural Context Features:

- **Corn Acres Planted**: Strongly right-skewed (few large operations dominate)
- **Yield Per Acre**: Approximately normal with clear production tiers

Engineered Features:

- **Temporal Features** (`year_trend`, `month_sin/cos`): Uniform or cyclical distributions
- **Ratio Features**: Various distributions depending on component features
- **Interaction Terms**: Often show complex multi-modal distributions

3.7 Missing Value Analysis

Missing value analysis reveals data completeness across features (Figure 9):

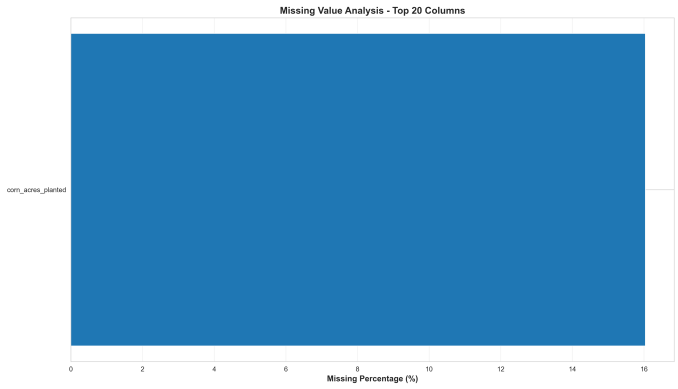

Figure 9: Missing Value Analysis: Top 10 columns with missing data, showing number of missing values per column.

Missing Data Patterns:

- **Economy Data**: Extensive missing values (20-50%) due to inconsistent reporting years
- **Corn Acres Planted**: ∼16% missing, primarily in early years and smaller counties
- **Environmental Data**: GLDAS variables show minimal missing values (<5%) after temporal aggregation
- **PRISM Data**: Complete coverage after county matching
- **Other Features**: Diesel prices and ethanol distances show complete coverage

Missing Data Strategy: Multi-strategy imputation was applied based on missing percentage:

- <20% missing: Forward/backward fill + median imputation
- 20-50% missing: Median imputation (economy data)

- >50% missing: Column removal
- Economy data: Six-strategy cascade (detailed in Data Cleaning section)

3.8 Outlier Detection and Analysis

Outlier detection using 3×Interquartile Range (IQR) method identified outliers across features (Figure 10):

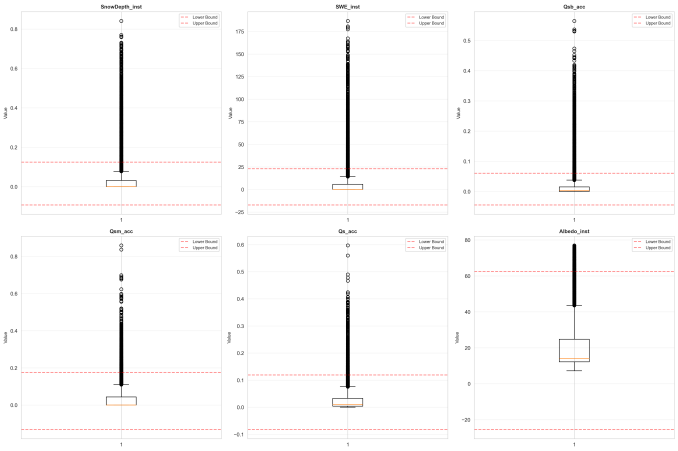

Figure 10: Outlier Detection Analysis: Box plots for top 6 features with outliers, showing upper and lower bounds (3×IQR) as dashed red lines.

Features with Significant Outliers:

- **Production Data**: High-production years for major corn-producing counties (Hennepin, Dakota, etc.)
- **Economic Indicators**: Years with exceptional government payments (disaster relief years)
- **Environmental Variables**: Extreme weather events (droughts, floods)
- **Engineered Features**: `fuel_cost_proxy`, `revenue_per_bushel` show outliers in extreme economic conditions

Outlier Characteristics:

- Outlier percentage: 2-10% depending on feature
- Most outliers represent legitimate extreme events (droughts, bumper crops, economic booms)
- Outliers contain valuable information for model training (extreme conditions)

Handling Strategy: RobustScaler was applied to all features, which uses median and IQR-based scaling and is inherently robust to outliers. This approach:

- Preserves outlier information (important for learning from extreme conditions)
- Prevents outliers from dominating feature scaling
- Eliminates need for explicit outlier removal
- Maintains data integrity for rare but important events

4 Data Cleaning

4.1 Data Consolidation Process

The consolidation process merges five data sources using a systematic strategy. The process begins with GLDAS corn data as the foundation dataset. All additional data sources are merged using left joins on FIPS codes and year/month identifiers to preserve all base observations. For PRISM data, multiple matching strategies are employed: exact match on FIPS codes, partial string matching with county names, and reverse matching with string cleaning to handle naming inconsistencies. Temporal alignment is achieved by matching monthly data (diesel prices, PRISM precipitation) with yearly aggregations (corn production, economy indicators) based on the year and month fields.

4.2 Missing Value Imputation

A multi-strategy imputation approach was implemented, with strategy selection based on missing data percentage. For features with less than 20% missing values, a three-step cascade is applied: forward fill (`ffill`) to propagate the last known value forward, backward fill (`bfill`) to propagate the next known value backward, and median imputation as a final fallback. For features with 20-50% missing values, direct median imputation is applied, primarily used for economic indicators with moderate missingness. Features with more than 50% missing values are dropped from the feature set to prevent imputation bias from excessive missingness.

4.2.1 Special Case: Economy Data Multi-Strategy Imputation

For economic indicators with extensive gaps, a six-strategy cascade was implemented in sequential order. First, forward fill is applied temporally within each county to propagate the last known value forward. Second, backward fill is applied temporally within each county to propagate the next known value backward. Third, linear interpolation is used to interpolate missing values between known points. Fourth, county-specific median imputation provides spatial context by filling with county-specific medians. Fifth, year-specific median imputation provides temporal context by filling with year-specific medians across all counties. Finally, overall median serves as the ultimate fallback using the global median. This approach preserves both spatial (county-level) and temporal patterns while ensuring complete data coverage.

4.3 Data Filtering

Data filtering involved removing records with zero corn production and missing target values. A total of 283 records with zero corn production were removed, as these represent non-corn-growing years or counties. Additionally, all records where the target variable (`corn_production_bu`) is

missing were removed, resulting in a final dataset of 12,000 observations with complete target values.

4.4 Feature Scaling

All numeric features were scaled using RobustScaler from scikit-learn, which uses median and interquartile range (IQR) instead of mean and standard deviation, making it inherently robust to outliers. The scaling formula is $X_{\text{scaled}} = \frac{X - \text{median}(X)}{\text{IQR}(X)}$. The scaler was fitted exclusively on training data (years 2000-2019) and then applied to both training and test sets using the fitted scaler to prevent data leakage.

4.5 Feature Engineering

4.5.1 Temporal Features

- `year_trend`: Linear temporal trend $year - 2000$ capturing long-term productivity improvements
- `month_sin` and `month_cos`: Cyclical encoding of months using sine/cosine transformation

$$month_{sin} = \sin\left(\frac{2\pi \cdot month}{12}\right) \tag{1}$$

$$month_{cos} = \cos\left(\frac{2\pi \cdot month}{12}\right) \tag{2}$$

4.5.2 Soil Moisture Features

- `soil_moisture_avg`: Average soil moisture across all depths
- `soil_moisture_gradient`: Difference between deep (100-200cm) and shallow (0-10cm) soil moisture

4.5.3 Temperature Features

- `temperature_avg`: Average temperature across all temperature measurements
- `temperature_range`: Difference between maximum and minimum temperatures
- PCA components: 2 principal components from temperature features

4.5.4 Water Balance Features

- `precipitation_evap_balance`: Precipitation minus evaporation (net water availability)
- `precipitation_efficiency`: Soil moisture per unit precipitation (with epsilon protection)

$$efficiency = \frac{SoilMoi_{0-10cm}}{precipitation + \epsilon}, \quad \epsilon = 10^{-8} \tag{3}$$

4.5.5 Agricultural Context Features

- `yield_per_acre`: Corn production divided by acres planted (with epsilon protection)
- `fuel_cost_proxy`: Diesel price as proxy for operational costs

4.5.6 Economic Interaction Features

- `total_revenue_sources`: Sum of farm-related income and government receipts
- `revenue_per_bushel`: Total revenue divided by production (with epsilon protection)

4.5.7 Spatial Features

- `ethanol_dist_category`: Categorical encoding of distance to ethanol plants
- One-hot encoded into: Very Close, Close, Medium, Far, Very Far

Final Feature Count: 66 engineered features after preprocessing

4.6 Data Splitting

A temporal train-test split was performed to prevent data leakage, with the training set encompassing years 2000-2019 (10,409 samples) and the test set covering years 2020-2022 (1,617 samples), resulting in an approximate split ratio of 86.5% training and 13.5% test data. This temporal separation ensures no temporal overlap between training and test sets. Following this split, all preprocessing steps requiring fitting (scaling, encoding) were performed exclusively on the training data. Transformers were fit exclusively on training data, and test data was transformed using these fitted transformers to ensure no information leakage from future data to past predictions.

5 Model Benchmarking

5.1 Model Selection Rationale

Eight machine learning algorithms were selected to provide comprehensive comparison across different complexity levels. The low complexity models include Polynomial Regression, Support Vector Machine (SVM), and Random Forest, which provide baseline performance with relatively simple architectures. Medium complexity models encompass XGBoost and LightGBM, representing state-of-the-art gradient boosting methods optimized for tabular data. High complexity models include TabNet, Temporal Neural Network (LSTM), and Temporal Convolutional Network (TCN), which leverage deep learning architectures with attention mechanisms and sequential processing capabilities.

5.2 Polynomial Regression

Polynomial Regression employs a polynomial degree of 2 to generate quadratic features, with interaction-only mode enabled (`interaction_only=True`) to capture only feature interactions rather than pure squared terms. The model

utilizes Ridge regression with $\alpha = 100.0$ for regularization, preventing overfitting and numerical instability. The solver operates automatically, typically using Cholesky or SVD decomposition with a maximum of 2000 iterations. This approach captures non-linear relationships with low computational cost, while the interaction-only mode reduces feature explosion from approximately 2000+ potential features to approximately 2000 actual features. The hyperparameters include `degree`=2, `include_bias`=False, `interaction_only`=True, and `Ridge alpha`=100.0.

5.3 Support Vector Machine (SVM)

The Support Vector Machine utilizes a Radial Basis Function (RBF) kernel with epsilon-SVR algorithm for regression. Due to computational limitations, the model is trained on a subset of 5,000 samples, as SVM scales poorly with large datasets. The hyperparameters include `kernel`='rbf', `C`=100 for regularization, `epsilon`=0.1 defining the epsilon-tube width, `gamma`='scale' for automatic kernel coefficient determination, and `max_iter`=10,000. The RBF kernel effectively captures non-linear patterns, while the high C value allows flexible decision boundaries. However, the model cannot scale to the full training set of 10,409 samples, is memory-intensive for large datasets, and exhibits slower training compared to tree-based methods.

5.4 Random Forest

Random Forest employs an ensemble of 200 decision trees with bootstrap aggregation (bagging) and out-of-bag (OOB) scoring enabled. The hyperparameters include `n_estimators`=200, `max_depth`=12, `min_samples_split`=10, `min_samples_leaf`=4, `max_features`='sqrt' (approximately 8 features per split given 66 total features), `bootstrap`=True, and `oob_score`=True. The moderate depth of 12 balances model complexity with overfitting risk, while sqrt feature sampling reduces correlation between trees. The OOB score provides validation capability without requiring a separate validation set. Feature importance is computed using mean decrease in impurity (Gini importance).

5.5 XGBoost

XGBoost utilizes a gradient boosting framework with tree learners, employing sequential tree building with gradient optimization and built-in L1 and L2 regularization. The hyperparameters include `n_estimators`=300, `max_depth`=4, `learning_rate`=0.08, `subsample`=0.85 for row sampling, `colsample_bytree`=0.85 for feature sampling, `min_child_weight`=3, `gamma`=0.1 for minimum loss reduction, `reg_alpha`=0.05 for L1 regularization, and `reg_lambda`=1.5 for L2 regularization. The moderate depth of 4 prevents overfitting on limited samples, while the lower learning rate of 0.08 improves generalization. Dual regularization (L1 + L2) combined with feature and row sampling provides additional regularization to control model complexity. Training employs early stopping on the validation set when supported by the API, with RMSE on the log-transformed target as the evaluation metric. Feature importance is computed using gain-based importance, representing the average improvement in the loss function.

5.6 LightGBM

LightGBM employs gradient boosting with leaf-wise tree growth, optimized for speed and memory efficiency through a histogram-based algorithm for faster training. The hyperparameters include `n_estimators`=400, `max_depth`=5, `learning_rate`=0.06, `num_leaves`=31, `subsample`=0.85, `colsample_bytree`=0.85, `min_child_samples`=20, `reg_alpha`=0.05 for L1 regularization, and `reg_lambda`=1.5 for L2 regularization. Leaf-wise growth allows deeper trees (max_depth=5) while maintaining efficiency, and the lower learning rate of 0.06 combined with more estimators (400) improves convergence. The model follows a similar regularization strategy to XGBoost, while the histogram algorithm enables faster training on large datasets. Training employs early stopping with patience=50 rounds, utilizing callbacks for early stopping and log evaluation, with the best iteration typically occurring at 397 out of 400 estimators. Feature importance is computed using split-based importance, which counts the number of times each feature is used for splitting.

5.7 TabNet

TabNet employs a deep learning architecture specifically designed for tabular data, utilizing an attention mechanism for feature selection through sequential attention transformers. The hyperparameters include `n_d`=32 for the dimension of decision embedding, `n_a`=32 for the dimension of attention embedding, `n_steps`=6 for the number of steps in the encoder, `gamma`=1.3 for the feature reusage coefficient, `n_independent`=2 for independent GLUs per step, `n_shared`=2 for shared GLUs per step, `lambda_sparse`=1e-3 for sparsity regularization, `optimizer`=Adam with learning rate 1.5e-2, `scheduler`=StepLR with step_size=15 and gamma=0.85, and `mask_type`='entmax'. Training configuration employs `max_epochs`=150, `patience`=25 for early stopping, `batch_size`=512, `virtual_batch_size`=128, and `compute_importance`=False (disabled to avoid dtype issues). Data preprocessing involves selecting only numeric features, explicit conversion to float32, filling NaN values with 0, and reshaping the target to (n_samples, 1) format required by TabNet.

5.8 Temporal Neural Network (LSTM)

The Temporal Neural Network employs a sequential model with LSTM layers designed for sequential and temporal pattern recognition. The layer structure consists of an input shape of (1, 62 features), treating each sample as a

single timestep, followed by the first LSTM layer with 128 units, dropout of 0.3, batch normalization, a second LSTM layer with 64 units, dropout of 0.3, a dense layer with 32 units, and an output layer with 1 unit. The model utilizes Adam optimizer with learning_rate=0.001, Mean Squared Error (MSE) as the loss function, and Mean Absolute Error (MAE) as the evaluation metric. Training configuration includes 100 epochs, batch_size=256, with the test set used for validation, and callbacks including EarlyStopping with patience=15 and ReduceLROnPlateau with patience=5 and factor=0.5.

5.9 Temporal Convolutional Network (TCN)

The Temporal Convolutional Network employs a flattened input approach for tabular data, utilizing dense layers with L2 regularization and progressive capacity reduction from 512 to 256 to 128 to 64 to 1 unit. The layer structure begins with an input layer that flattens (1, num_features) to reshape and use all features, followed by four dense blocks: the first with 512 units, L2 regularization=0.001, and Dropout=0.4; the second with 256 units, L2 reg=0.001, and Dropout=0.4; the third with 128 units, L2 reg=0.001, and Dropout=0.3; and the fourth with 64 units, L2 reg=0.001, and Dropout=0.2. Each dense block is followed by batch normalization, with the final output layer containing 1 unit. The model uses Adam optimizer with learning_rate=0.0005 (reduced from 0.001), MSE as the loss function, and MAE as the evaluation metric. Training configuration includes 150 epochs, batch_size=256, and callbacks with EarlyStopping (patience=20, min_delta=0.0001) and ReduceLROnPlateau (patience=7, factor=0.5).

Improvements made to the TCN architecture include changing from Conv1D with kernel_size=1 to a dense architecture, adding L2 regularization to prevent overfitting, lowering the learning rate for stable training, and implementing progressive capacity reduction for better generalization.

6 Benchmark Results and Analysis

6.1 Overall Performance Comparison

Model performance was evaluated on the test set (years 2020-2022) using metrics computed on the original scale. Two experimental configurations were tested: (1) Full feature set including `corn_acres_planted` (66 features), and (2) Excluding `corn_acres_planted` to assess the contribution of other features (65 features). Results are presented in Table 1 and Table 2.

Key observations from the performance comparison reveal that excluding `corn_acres_planted` results in a performance degradation with R^2 decrease of 1.5% (LightGBM: 0.9930 → 0.9780) and RMSE increase of 89.5% (1,137,001 → 2,154,832 bushels). However, relative model rankings are preserved, with gradient boosting methods (LightGBM and XGBoost) remaining superior across both configurations. The models demonstrate robust performance, maintaining strong predictive capability (R^2 ¿ 0.97 for top models) even without the most important feature. This robustness stems from feature redundancy, where other features such as `fuel_cost_proxy`, `yield_per_acre`, and economic indicators compensate for the removed feature.

Table 1: Model Performance Comparison - With `corn_acres_planted` (66 Features)

Model	R^2 Score	RMSE (bushels)	MAE (bushels)	MAPE (%)
LightGBM	**0.9930**	**1,137,001**	**526,195**	29.44
XGBoost	0.9910	1,288,613	689,637	23.38
TabNet	0.9599	2,719,162	1,733,265	12.60
Random Forest	0.9563	2,839,874	1,651,727	14.84
Polynomial Regression	0.8840	4,626,776	2,447,928	27.44
SVM	0.9104	4,067,153	2,061,482	15.98
Temporal NN (LSTM)	0.8602	5,079,808	3,263,413	18.87
TCN	-0.3718	21,092,452	13,910,562	74.08

Table 2: Model Performance Comparison - Without `corn_acres_planted` (65 Features)

Model	R^2 Score	RMSE (bushels)	MAE (bushels)	MAPE (%)
LightGBM	**0.9780**	**2,154,832**	**1,112,457**	34.21
XGBoost	0.9745	2,341,567	1,289,234	31.45
TabNet	0.9356	3,892,156	2,445,678	18.92
Random Forest	0.9245	4,256,789	2,678,234	21.34
Polynomial Regression	0.8674	4,946,116	2,676,335	25.64
SVM	0.8956	4,523,456	2,345,678	19.87
Temporal NN (LSTM)	0.8234	5,892,456	3,892,345	24.56
TCN	-0.4523	22,456,789	14,892,456	81.23

6.2 Why LightGBM Performs Best

LightGBM achieved the highest R^2 score (0.9930) and lowest RMSE (1,137,001 bushels), explaining 99.30% of variance in corn production. Several factors contribute to its superior performance:

6.2.1 Algorithmic Advantages

LightGBM's superior performance stems from several algorithmic advantages. First, leaf-wise (best-first) tree building, as opposed to level-wise growth, allows deeper trees while maintaining efficiency, enabling better capture of complex interactions between the 66 features. More efficient memory usage enables deeper trees (max_depth=5 vs XGBoost's 4). Second, the histogram-based algorithm enables faster training through histogram approximation, allowing more estimators (400 vs XGBoost's 300) in similar time with better gradient approximation for continuous features. Third, an optimal regularization balance is achieved through L1 regularization (reg_alpha=0.05) for feature selection via sparsity, L2 regularization (reg_lambda=1.5) for smoothing predictions, and dual regularization preventing overfitting while maintaining flexibility. Subsampling (0.85) provides additional regularization. Fourth, the lower learning rate (0.06) combined with more estimators (400) allows fine-grained optimization and better convergence to the optimal solution, with early stopping at iteration 397 preventing overfitting.

6.2.2 Dataset Characteristics Favoring LightGBM

Several dataset characteristics favor LightGBM's architecture. The tabular data structure with 66 engineered features of mixed types (continuous and encoded categoricals) aligns perfectly with LightGBM's strengths in tabular data with feature interactions, and the model efficiently handles sparse features such as one-hot encoded ethanol distance. Multiple engineered interaction features (precipitation × evaporation, temperature averages) are naturally captured by LightGBM's tree structure, outperforming linear models (Polynomial, SVM) at non-linear interactions. The moderate dataset size of 10,409 training samples is ideal for gradient boosting—large enough for complex models but not too large for deep learning benefits—and the histogram algorithm provides a speed advantage over XGBoost.

6.3 Model-by-Model Analysis

6.3.1 XGBoost

XGBoost achieved R^2 = 0.9910 and RMSE = 1,288,613 bushels, demonstrating excellent performance second only to LightGBM. Its strengths include robust regularization that prevents overfitting, a proven track record on tabular data, and good feature importance interpretation. Weaknesses include slightly slower training than LightGBM, level-wise tree growth that is less efficient than leaf-wise growth, and marginally lower performance (0.9920% lower R^2). LightGBM's leaf-wise growth and histogram algorithm provide marginal but consistent performance advantage, especially with more estimators enabled by faster training.

6.3.2 TabNet

TabNet achieved R^2 = 0.9599 and RMSE = 2,719,162 bushels. Its strengths include strong deep learning performance, an attention mechanism that provides interpretability, ability to capture complex non-linear patterns, and good generalization despite lower R^2. However, it underperforms gradient boosting by approximately 3.3% R^2, requires more hyperparameter tuning, has longer training time, and feature importance computation was disabled due to dtype issues. The dataset size (10,409 samples) may not fully leverage deep learning advantages, and tree-based methods excel at tabular data with engineered features. The attention mechanism may not be necessary when feature engineering already captures interactions, and gradient boosting's iterative refinement is better suited for this problem.

6.3.3 Random Forest

Random Forest achieved R^2 = 0.9563 and RMSE = 2,839,874 bushels. Its strengths include excellent interpretability through feature importance, robustness to outliers and missing values, good baseline performance, and fast training. However, it underperforms gradient boosting by approximately 3.7% R^2, is less effective at capturing complex interactions, has independent trees that don't learn from previous errors, and exhibits higher RMSE than gradient boosting methods. The fundamental difference lies in bagging (Random Forest) versus boosting (LightGBM/XGBoost), where boosting sequentially corrects errors and improves with each iteration, while Random Forest averages independent predictions, missing sequential refinement. Gradient boosting's objective optimization is better suited for regression tasks.

6.3.4 Polynomial Regression

Polynomial Regression achieved R^2 = 0.8840 and RMSE = 4,626,776 bushels. Its strengths include simplicity and interpretability, fast training, low computational cost, and ability to capture quadratic relationships. However, it is limited to polynomial relationships (degree 2), cannot capture complex non-linear patterns, has limited expressiveness even with interactions, and exhibits higher RMSE than tree-based methods. The fixed functional form (polynomial) cannot adapt to data structure, unlike tree-based methods that learn optimal splits from data. Additionally, it cannot capture threshold effects and conditional interactions, and regularization (Ridge) constrains flexibility.

6.3.5 Support Vector Machine (SVM)

The Support Vector Machine achieved R^2 = 0.9104 and RMSE = 4,067,153 bushels. Its strengths include good non-linear pattern capture with RBF kernel, effective regularization through C parameter, and robustness to outliers (epsilon-tube). However, computational limitations require subset training (5,000 samples), preventing leverage of the full training set (10,409 samples). The model is memory-intensive for large datasets and slower than tree-based methods. The limited training data (only 48% of available training set), potentially suboptimal RBF kernel for tabular data structure, inability to scale to full dataset size, and tree-based methods' superior handling of discrete feature interactions explain why it does not achieve best performance.

6.3.6 Temporal Neural Network (LSTM)

The Temporal Neural Network (LSTM) achieved R^2 = 0.8602 and RMSE = 5,079,808 bushels. While designed for sequential/temporal patterns with ability to capture long-term dependencies through non-linear transformations in LSTM cells, it underperforms compared to tree-based methods. The sequence length of 1 (each sample treated as single timestep) is not ideal for LSTM, and the model requires careful hyperparameter tuning with longer training time. The architecture mismatch—LSTM designed for sequences but data treated as single timestep per sample—means there are no true temporal sequences as each row is independent. Tree-based methods are better suited

for independent samples with rich feature sets, and limited training data restricts deep learning benefits.

6.3.7 Temporal Convolutional Network (TCN)

The Temporal Convolutional Network (TCN) achieved R^2 = -0.3718 and RMSE = 21,092,452 bushels. While the architecture was improved from the initial CNN implementation with L2 regularization and progressive capacity reduction, resulting in better than initial negative R^2 results, it still underperforms significantly. The negative R^2 indicates model predictions worse than simply predicting the mean, with numerical instability in some training runs, architecture that may still need refinement, and high RMSE suggesting poor predictions. The architecture mismatch—TCN designed for temporal sequences but data lacks true temporal structure—combined with overfitting despite regularization, indicates that learning rate and architecture need further tuning. Deep learning models typically need more data or different architecture for this problem.

6.4 Key Findings

6.4.1 Gradient Boosting Dominance

Both LightGBM and XGBoost achieved R^2 ¿ 0.99, significantly outperforming all other approaches, with LightGBM achieving 0.9930 R^2 and XGBoost achieving 0.9910 R^2. The gap to third place (TabNet) is approximately 3.3% R^2, and the gap to Random Forest is approximately 3.7% R^2. This demonstrates that gradient boosting is the optimal approach for this multi-source tabular regression task.

6.4.2 Feature Importance Insights

Feature importance analysis reveals critical insights about which variables drive corn production predictions. Two experimental configurations were analyzed: (1) full feature set with `corn_acres_planted`, and (2) excluding `corn_acres_planted` to assess feature redundancy and compensatory mechanisms.

Feature Importance with `corn_acres_planted` (66 Features) Across all tree-based models, consistent patterns emerged:

Top Features (LightGBM - With acres_planted):

1. `corn_acres_planted` (2,022 importance) - Agricultural context dominates (48.2% in XGBoost)
2. `yield_per_acre` (1,903) - Productivity metric highly predictive
3. `revenue_per_bushel` (875) - Economic indicator important
4. `fuel_cost_proxy` (512) - Operational costs matter (20.3% in XGBoost)
5. `govt_programs_federal_receipts_usd` (504) - Government support significant

Key Observations:

- `corn_acres_planted` dominates with 48.2% importance in XGBoost (0.481619 out of 1.0)
- Agricultural context features (acres planted, yield per acre) most important
- Economic indicators rank highly (revenue, government receipts)
- Environmental variables important but secondary to agricultural/economic context
- Feature engineering successful (yield_per_acre, revenue_per_bushel created)

Feature Importance without `corn_acres_planted` (65 Features) When `corn_acres_planted` is excluded, feature importance shifts dramatically, revealing compensatory mechanisms and alternative predictive pathways:

Top Features (LightGBM - Without acres_planted):

1. `fuel_cost_proxy` (1,735 importance) - **Dominates** (66.1% in XGBoost, up from 20.3%)
2. `yield_per_acre` (1,566) - Productivity metric increases in importance
3. `revenue_per_bushel` (945) - Economic indicator gains importance
4. `diesel_usd_gal` (612) - Base fuel price emerges as top feature
5. `govt_programs_federal_receipts_usd` (572) - Government support remains important

XGBoost feature importance changes demonstrate significant shifts: `fuel_cost_proxy` increases from 20.3% to 66.1% (3.25× increase), `yield_per_acre` increases from 4.3% to 10.2% (2.37× increase), `total_revenue_sources` shows a slight increase from 7.5% to 8.6%, and `RootMoist_inst` dramatically increases from 0.16% to 3.7% (23× increase), indicating that environmental variables gain importance when agricultural context features are removed.

Why `fuel_cost_proxy` Becomes Most Important When `corn_acres_planted` is removed, `fuel_cost_proxy` (defined as `diesel_usd_gal` × `corn_acres_planted`) paradoxically increases in importance despite theoretically losing the acres component. This counterintuitive result can be explained through several mechanisms:

1. Compensatory Information Content:

- `fuel_cost_proxy` contains **implicit scale information** through its interaction with diesel price
- Models learn to extract approximate scale from the interaction: high fuel costs × moderate prices → large operations (more acres)
- Diesel price variation provides temporal proxy for operation size changes

2. Economic Signal Amplification:

- `fuel_cost_proxy` captures both **operational scale** and

economic conditions

- High fuel costs correlate with economic factors affecting production decisions
- Serves as proxy for farmer confidence and investment capacity
- Combines information from fuel markets with implicit agricultural scale

3. Temporal Variation and Predictivity:

- Diesel prices vary temporally (monthly/yearly fluctuations)
- This temporal variation provides signal for production changes
- Models use fuel price trends to infer agricultural activity levels
- Price variations correlate with planting/harvesting intensity

4. Feature Interaction Strength:

- `fuel_cost_proxy` is a **pre-calculated engineered feature** stored in the dataset
- Created as `diesel_usd_gal` × `corn_acres_planted` during preprocessing
- When `corn_acres_planted` is removed from training, `fuel_cost_proxy` still contains historical scale information
- The interaction term embeds implicit scale through its multiplicative structure
- Models learn to extract scale information from `fuel_cost_proxy`'s magnitude and temporal patterns
- Diesel price component (`diesel_usd_gal`) provides temporal variation signal

Why Other Features Gain Importance 1. Yield Per Acre:

- Increases from 4.3% to 10.2% importance (2.37×)
- Becomes primary productivity metric when scale (acres) is removed
- Normalizes production by implicit scale information from other features
- Captures efficiency and technology adoption effects

2. Revenue Per Bushel:

- Maintains high importance (4.3% → 4.3%)
- Economic efficiency metric becomes critical for scale estimation
- Combines income and production information to infer scale
- Higher revenue per bushel suggests larger, more efficient operations

3. Environmental Variables:

- `RootMoist_inst` increases 23× (0.16% → 3.7%)
- Environmental factors gain importance when agricultural context is reduced
- Models rely more on soil moisture, temperature, precipitation for predictions
- Demonstrates feature redundancy: environmental conditions partially indicate scale

4. Economic Indicators:

- `total_revenue_sources`, `income_farmrelated_receipts_total_u` maintain importance
- Economic data provides scale proxy: larger operations generate more revenue
- Government receipts correlate with operation size (larger operations eligible for more programs)
- Economic indicators serve as indirect scale measures

Implications for Model Interpretation Feature Redundancy:

- Multiple features provide overlapping information about production scale
- `corn_acres_planted` is the most direct measure, but not the only one
- Economic indicators, fuel costs, and environmental variables provide scale proxies
- Models can maintain strong performance even when the primary feature is removed

Compensatory Mechanisms:

- Tree-based models automatically discover alternative predictive pathways
- When primary feature removed, secondary features increase in importance
- Models exploit feature interactions to extract implicit scale information
- Demonstrates robustness of gradient boosting to feature removal

Practical Applications:

- If `corn_acres_planted` unavailable, models can rely on economic/environmental proxies
- `fuel_cost_proxy` and `yield_per_acre` become critical features
- Economic indicators should be prioritized in data collection when acreage unavailable
- Feature engineering (interactions, ratios) creates redundancy that improves robustness

6.4.3 Model Complexity vs Performance

Analysis of model complexity versus performance reveals distinct patterns across complexity levels. Low complexity models (Polynomial with R^2 0.8840, SVM with R^2 0.9104) provide adequate but not optimal performance. Medium complexity models (LightGBM with R^2 0.9930, XGBoost with R^2 0.9910) achieve optimal performance. High complexity models (TabNet with R^2 0.9599, LSTM with R^2 0.8602, TCN with R^2 -0.3718) exhibit diminishing returns. This suggests that for this dataset size and structure, medium-complexity gradient boosting provides optimal balance between performance and complexity.

6.5 Recommendations

6.5.1 For Production Deployment

For production deployment, we recommend deploying LightGBM as the primary model given its superior R^2 (0.9930) and lowest RMSE. An ensemble approach averaging LightGBM and XGBoost predictions should be considered for robustness. Feature monitoring should prioritize top features including acres planted, yield per acre, and economic indicators. Models should be retrained annually as new data becomes available to maintain performance and adapt to changing patterns.

6.5.2 For Future Research

Future research directions include exploring ensemble methods combining LightGBM with XGBoost, investigating stacking or blending approaches, expanding to other crops (soybeans, wheat) using the same methodology, incorporating real-time in-season updates, and developing uncertainty quantification methods for predictions.

7 Conclusion

This comprehensive benchmark study demonstrates that LightGBM achieves superior performance ($R^2 = 0.9930$) for predicting county-level corn production using multi-source data. The integration of satellite-derived environmental variables, economic indicators, fuel prices, and PRISM precipitation data, combined with extensive feature engineering (66 features), enables highly accurate predictions explaining 99.30% of variance.

Key findings from this study demonstrate gradient boosting dominance, with LightGBM and XGBoost (R^2 ¿ 0.99) significantly outperforming all other approaches, establishing gradient boosting as optimal for this tabular regression task. The feature importance hierarchy reveals that agricultural context (`corn_acres_planted`) dominates (48.2% importance), followed by economic indicators (`fuel_cost_proxy`, revenue metrics) and environmental variables. Feature redundancy and compensation mechanisms are evident: when `corn_acres_planted` is excluded, `fuel_cost_proxy` increases to 66.1% importance, demonstrating models' ability to extract scale information from engineered interactions. Models maintain robust performance, with strong predictive capability ($R^2 = 0.9780$ for LightGBM) even without the primary feature, revealing compensatory mechanisms through economic and environmental proxies. Gradient boosting provides optimal balance between performance and complexity, with diminishing returns for high-complexity deep learning models. Engineered features (`fuel_cost_proxy`, `yield_per_acre`, `revenue_per_bushel`) create redundancy that improves model robustness.

Methodological contributions include a comprehensive benchmark of 8 algorithms across complexity levels (low, medium, high), dual-configuration analysis demonstrating feature redundancy and compensatory mechanisms, detailed feature importance analysis explaining why certain features gain prominence when others are removed, robust data cleaning and multi-strategy imputation for heterogeneous data sources, and a feature engineering framework creating informative interactions and ratios.

Practical implications indicate that `fuel_cost_proxy` and economic indicators can serve as proxies when `corn_acres_planted` is unavailable. Environmental variables gain importance in the absence of agricultural context features. Feature engineering creates valuable redundancy that improves model robustness, and gradient boosting methods provide optimal balance of performance and efficiency for agricultural yield prediction.

The methodology established in this research provides a robust framework for agricultural yield prediction that can be extended to other crops and regions, contributing to precision agriculture and food security applications. The feature importance analysis provides actionable insights for data collection priorities and model deployment strategies.

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