

final_analysis

December 7, 2025

1 Final Climate Impact Analysis

This notebook analyzes how climate affects Texas agricultural outcomes.

Analysis areas: 1. Data cleaning and normalization 2. Drought years (2011, 2013) vs non-drought years 3. Model comparison by measurement type (YIELD, PRODUCTION, AREA HARVESTED) 4. Climate feature importance analysis 5. Crop-specific climate sensitivity

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import (
    RandomForestRegressor,
    AdaBoostRegressor,
    GradientBoostingRegressor,
)
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.preprocessing import LabelEncoder, StandardScaler
import warnings

warnings.filterwarnings("ignore")
np.random.seed(42)

# For saving figures
import os

FIGURES_DIR = "figures"
os.makedirs(FIGURES_DIR, exist_ok=True)

def save_fig(name, dpi=150):
    """Save current figure to figures directory"""
    plt.savefig(f"{FIGURES_DIR}/{name}.png", dpi=dpi, bbox_inches="tight")
    print(f"Saved: {FIGURES_DIR}/{name}.png")
```

1.1 1. Load and Prepare Data

Normalize VALUE by (COMMODITY_DESC, STATISTICCAT_DESC) groups to enable fair comparison across different measurement types.

```
[2]: # Load data
df = pd.read_csv("./texas_agriculture_with_climate_2000_2023.csv",
    ↪low_memory=False)
print(f"Dataset: {df.shape[0]:,} rows x {df.shape[1]} columns")

# Convert VALUE to numeric
df["VALUE"] = pd.to_numeric(
    df["VALUE"].astype(str).str.replace(",", ""), errors="coerce"
)

# Remove aggregate counties
df_model = df.dropna(subset=["VALUE"]).copy()
combined_mask = df_model["COUNTY_NAME"].str.contains(
    "COMBINED|OTHER", case=False, na=False
)
df_model = df_model[~combined_mask]
print(f"After removing aggregates: {len(df_model):,} rows")
```

Dataset: 398,204 rows x 120 columns

After removing aggregates: 303,609 rows

```
[3]: # Normalize VALUE by group
group_stats = df_model.groupby(["COMMODITY_DESC",
    ↪"STATISTICCAT_DESC"])["VALUE"].agg(
    ["mean", "std", "count"]
)
df_model = df_model.merge(
    group_stats[["mean", "std"]].reset_index(),
    on=["COMMODITY_DESC", "STATISTICCAT_DESC"],
    how="left",
    suffixes=("", "_group"),
)
df_model["std"] = df_model["std"].replace(0, 1).fillna(1)
df_model["VALUE_NORMALIZED"] = (df_model["VALUE"] - df_model["mean"]) /
    ↪df_model["std"]

print(
    f"VALUE_NORMALIZED range: [{df_model['VALUE_NORMALIZED'].min():.2f},
    ↪{df_model['VALUE_NORMALIZED'].max():.2f}] "
)
print(f"VALUE_NORMALIZED mean: {df_model['VALUE_NORMALIZED'].mean():.4f}")
```

VALUE_NORMALIZED range: [-3.01, 37.76]

VALUE_NORMALIZED mean: 0.0000

```
[4]: # Define feature sets
climate_features = [
    "GROWING_SEASON_PRECIP",
    "GROWING_SEASON_TEMP_AVG",
    "GROWING_SEASON_TEMP_MAX",
    "GROWING_SEASON_TEMP_MIN",
    "ANNUAL_PRECIP",
    "ANNUAL_TEMP_AVG",
    "ANNUAL_CDD",
    "ANNUAL_HDD",
    "PRECIP_APR",
    "PRECIP_MAY",
    "PRECIP_JUN",
    "TAVG_APR",
    "TAVG_MAY",
    "TAVG_JUN",
    "TAVG_JUL",
    "TAVG_AUG",
]

categorical_features = ["COUNTY_NAME", "YEAR"]
all_features = [
    f for f in climate_features + categorical_features if f in df_model.columns
]

print(
    f"Climate features: {len([f for f in climate_features if f in df_model.
    ↪columns])}"
)
print(f"Total features: {len(all_features)}")
```

Climate features: 16

Total features: 18

```
[5]: # Prepare for modeling
df_clean = df_model.dropna(subset=all_features + ["VALUE_NORMALIZED"]).copy()

# Store original values before encoding for later analysis
df_clean["COUNTY_NAME_ORIG"] = df_clean["COUNTY_NAME"]
df_clean["YEAR_ORIG"] = df_clean["YEAR"]

# Label encode
label_encoders = {}
for col in categorical_features:
    le = LabelEncoder()
    df_clean[col] = le.fit_transform(df_clean[col].astype(str))
    label_encoders[col] = le
```

```

X = df_clean[all_features]
y = df_clean["VALUE_NORMALIZED"]

# Stratified split by year
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=df_clean["YEAR"]
)

print(f"Train: {len(X_train):,}, Test: {len(X_test):,}")

```

Train: 242,887, Test: 60,722

1.2 2. Baseline Models

Decision Tree and Random Forest as baseline regression models.

```

[6]: # Decision Tree Baseline
dt = DecisionTreeRegressor(
    max_depth=20, min_samples_split=50, min_samples_leaf=20, random_state=42
)
dt.fit(X_train, y_train)

dt_train_r2 = r2_score(y_train, dt.predict(X_train))
dt_test_r2 = r2_score(y_test, dt.predict(X_test))
dt_test_rmse = np.sqrt(mean_squared_error(y_test, dt.predict(X_test)))

print(
    f"Decision Tree: Train R2 = {dt_train_r2:.4f}, Test R2 = {dt_test_r2:.4f}, RMSE = {dt_test_rmse:.4f}"
)

```

Decision Tree: Train $R^2 = 0.0967$, Test $R^2 = 0.0722$, RMSE = 0.9947

```

[7]: # Random Forest
rf = RandomForestRegressor(
    n_estimators=100,
    max_depth=15,
    min_samples_split=20,
    min_samples_leaf=10,
    random_state=42,
    n_jobs=-1,
)
rf.fit(X_train, y_train)

rf_train_r2 = r2_score(y_train, rf.predict(X_train))
rf_test_r2 = r2_score(y_test, rf.predict(X_test))
rf_test_rmse = np.sqrt(mean_squared_error(y_test, rf.predict(X_test)))

```

```
print(
    f"Random Forest: Train R2 = {rf_train_r2:.4f}, Test R2 = {rf_test_r2:.4f},  

    ↪RMSE = {rf_test_rmse:.4f}"
)
```

Random Forest: Train R² = 0.0950, Test R² = 0.0738, RMSE = 0.9938

1.3 3. Climate Feature Deep Dive

Key question: Which climate features have the most impact on agricultural outcomes?

1.3.1 3.1 Feature Importance Breakdown

```
[8]: # Get feature importances from Random Forest
feature_imp = pd.DataFrame(
    {"feature": X.columns, "importance": rf.feature_importances_}
).sort_values("importance", ascending=False)

# Categorize features
def categorize_feature(f):
    if "TEMP" in f or "CDD" in f or "HDD" in f or "TAVG" in f:
        return "Temperature"
    elif "PRECIP" in f:
        return "Precipitation"
    elif f in ["COUNTY_NAME", "YEAR"]:
        return "Spatial/Temporal"
    else:
        return "Other"

feature_imp["category"] = feature_imp["feature"].apply(categorize_feature)

# Summary by category
category_imp = (
    feature_imp.groupby("category")["importance"].sum().
    ↪sort_values(ascending=False)
)
print("Feature Importance by Category:")
print(category_imp.to_string())
print(
    f"\nTotal climate: {category_imp.get('Temperature', 0) + category_imp.
    ↪get('Precipitation', 0):.1%}"
)
```

Feature Importance by Category:
category

Temperature	0.597138
Precipitation	0.224790
Spatial/Temporal	0.178072

Total climate: 82.2%

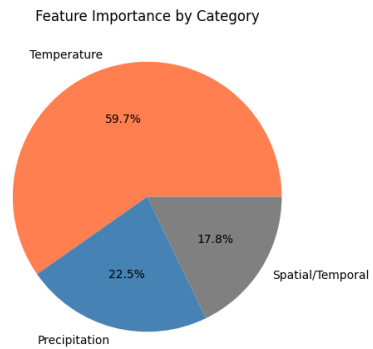
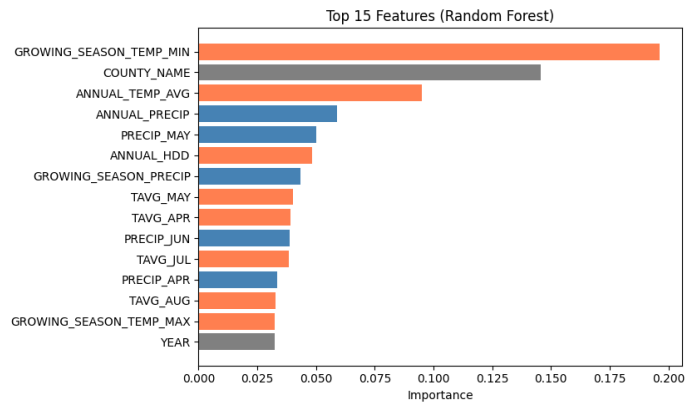
```
[9]: # Visualization: Feature importance by category
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Left: Top 15 features
colors = feature_imp.head(15)["category"].map(
    {"Temperature": "coral", "Precipitation": "steelblue", "Spatial/Temporal": "gray"}
)
axes[0].barh(range(15), feature_imp.head(15)["importance"], color=colors)
axes[0].set_yticks(range(15))
axes[0].set_yticklabels(feature_imp.head(15)["feature"])
axes[0].invert_yaxis()
axes[0].set_xlabel("Importance")
axes[0].set_title("Top 15 Features (Random Forest)")

# Right: By category
cat_colors = {
    "Temperature": "coral",
    "Precipitation": "steelblue",
    "Spatial/Temporal": "gray",
}
axes[1].pie(
    category_imp.values,
    labels=category_imp.index,
    autopct="%1.1f%%",
    colors=[cat_colors.get(c, "lightgray") for c in category_imp.index],
)
axes[1].set_title("Feature Importance by Category")

plt.tight_layout()
save_fig("feature_importance_breakdown")
plt.show()
```

Saved: figures/feature_importance_breakdown.png



1.3.2 3.2 Temperature vs. Precipitation Impact

```
[10]: # Compare temperature vs precipitation features
temp_features = [
    f
    for f in climate_features
    if "TEMP" in f or "TAVG" in f or "CDD" in f or "HDD" in f
]
precip_features = [f for f in climate_features if "PRECIP" in f]

temp_imp = feature_imp[feature_imp["feature"].
    ↪isin(temp_features)]["importance"].sum()
precip_imp = feature_imp[feature_imp["feature"].isin(precip_features)][
    "importance"
].sum()

print(f"Temperature features importance: {temp_imp:.1%}")
print(f"Precipitation features importance: {precip_imp:.1%}")
print(f"Ratio (Temp/Precip): {temp_imp/precip_imp:.1f}x")
```

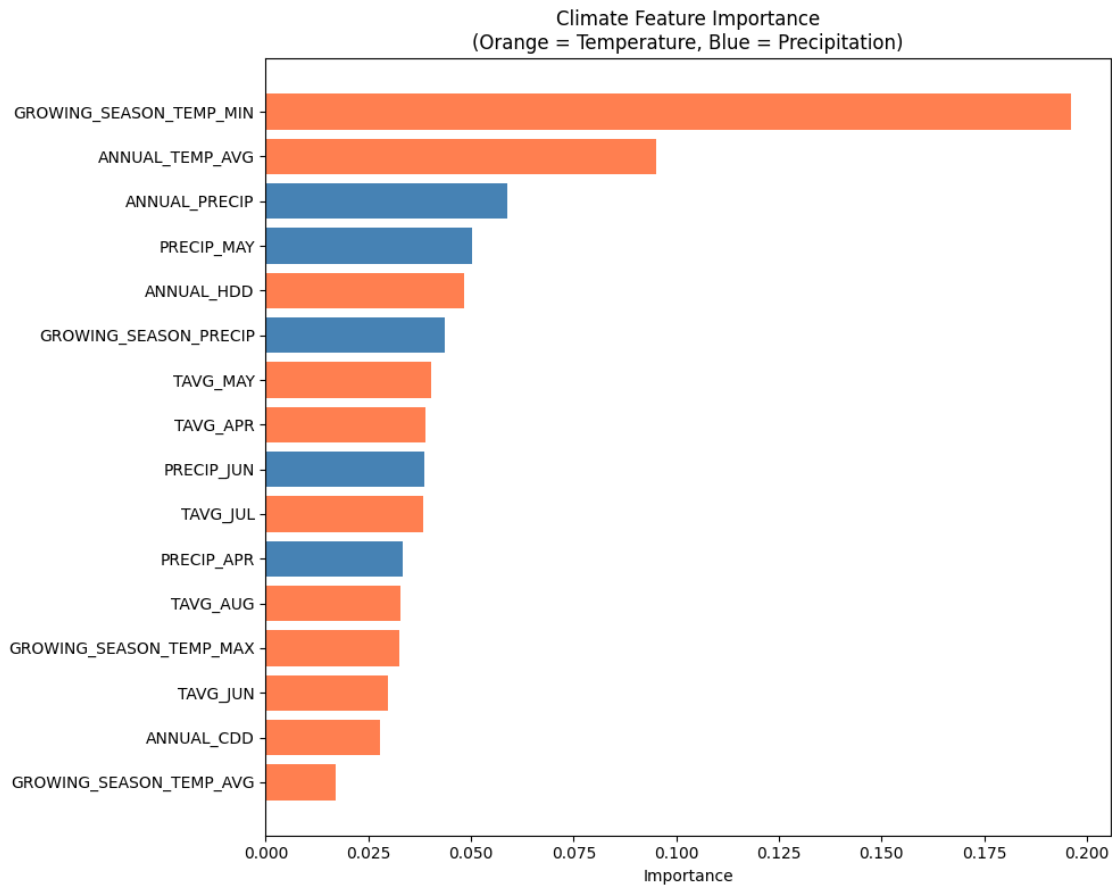
Temperature features importance: 59.7%
 Precipitation features importance: 22.5%
 Ratio (Temp/Precip): 2.7x

```
[11]: # Detailed breakdown of climate features
climate_imp = feature_imp[feature_imp["feature"].isin(climate_features)].copy()
climate_imp = climate_imp.sort_values("importance", ascending=True)

plt.figure(figsize=(10, 8))
colors = climate_imp["category"].map(
    {"Temperature": "coral", "Precipitation": "steelblue"}
)
plt.barh(climate_imp["feature"], climate_imp["importance"], color=colors)
```

```
plt.xlabel("Importance")
plt.title("Climate Feature Importance\n(Orange = Temperature, Blue = Precipitation)")
plt.tight_layout()
save_fig("climate_feature_importance")
plt.show()
```

Saved: figures/climate_feature_importance.png



1.3.3 3.3 Monthly Climate Patterns

Which months matter most?

```
[12]: # Extract month from feature name
monthly_features = feature_imp[
    feature_imp["feature"].str.contains("APR|MAY|JUN|JUL|AUG")
].copy()

def get_month(f):
```



```

for m in ["APR", "MAY", "JUN", "JUL", "AUG"]:
    if m in f:
        return m
return "Other"

monthly_features["month"] = monthly_features["feature"].apply(get_month)
monthly_imp = monthly_features.groupby("month")["importance"].sum()

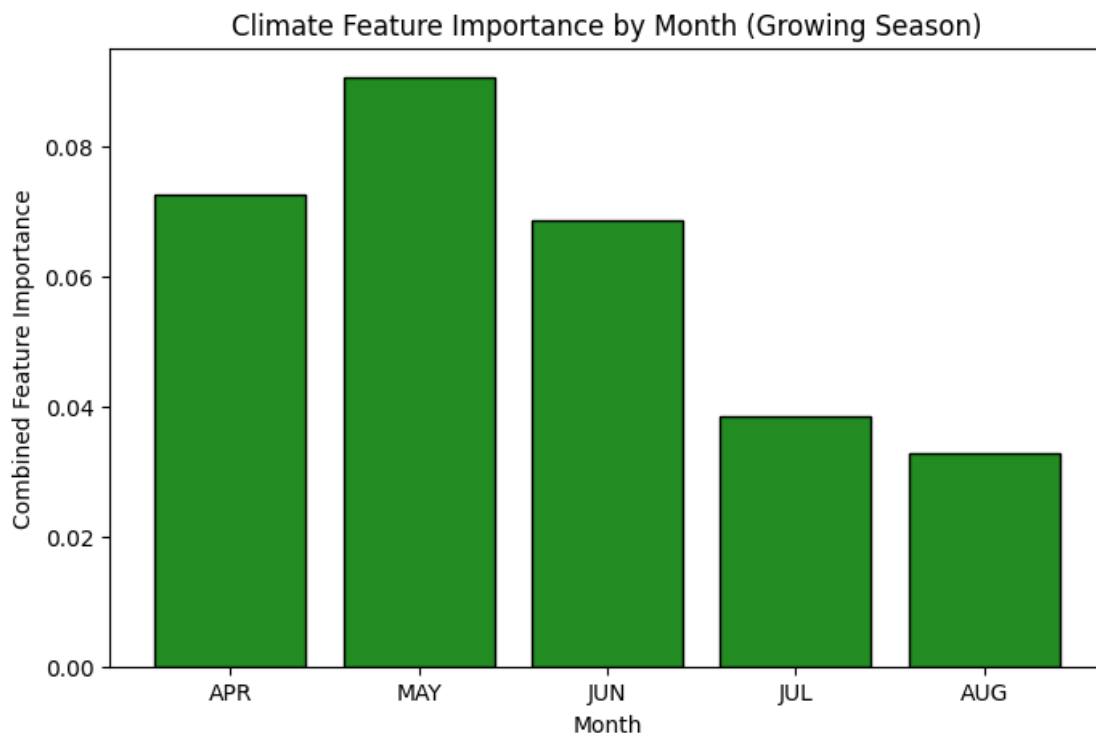
# Order by month
month_order = ["APR", "MAY", "JUN", "JUL", "AUG"]
monthly_imp = monthly_imp.reindex(month_order)

plt.figure(figsize=(8, 5))
plt.bar(monthly_imp.index, monthly_imp.values, color="forestgreen",
        edgecolor="black")
plt.xlabel("Month")
plt.ylabel("Combined Feature Importance")
plt.title("Climate Feature Importance by Month (Growing Season)")
save_fig("monthly_importance")
plt.show()

print(f"Most important month: {monthly_imp.idxmax()} ({monthly_imp.max():.1%})")

```

Saved: figures/monthly_importance.png



Most important month: MAY (9.1%)

1.4 4. Crop-Specific Climate Sensitivity

Train separate models for major crops to see which are most climate-sensitive.

```
[13]: # Major crops to analyze
major_crops = ["CORN", "COTTON", "WHEAT", "SORGHUM", "HAY"]

# Filter to YIELD only for fair comparison
df_yield = df_model[
    df_model["STATISTICCAT_DESC"].str.contains("YIELD", case=False, na=False)
].copy()
print(f"YIELD records: {len(df_yield):,}")

# Check availability
for crop in major_crops:
    n = len(df_yield[df_yield["COMMODITY_DESC"] == crop])
    print(f" {crop}: {n:,} records")
```

```
YIELD records: 20,016
CORN: 2,028 records
COTTON: 4,413 records
WHEAT: 7,150 records
SORGHUM: 3,751 records
HAY: 0 records
```

```
[14]: # Train crop-specific models
crop_results = []

for crop in major_crops:
    crop_df = df_yield[df_yield["COMMODITY_DESC"] == crop].copy()

    if len(crop_df) < 500:
        print(f"Skipping {crop} - only {len(crop_df)} records")
        continue

    # Normalize within this crop
    crop_mean = crop_df["VALUE"].mean()
    crop_std = crop_df["VALUE"].std()
    if crop_std == 0:
        crop_std = 1
    crop_df["VALUE_NORM"] = (crop_df["VALUE"] - crop_mean) / crop_std

    # Prepare features (climate only for this analysis)
    available_features = [f for f in climate_features if f in crop_df.columns]
```

```

crop_df = crop_df.dropna(subset=available_features + ["VALUE_NORM"])

if len(crop_df) < 200:
    print(f"Skipping {crop} - only {len(crop_df)} records after cleaning")
    continue

X_crop = crop_df[available_features]
y_crop = crop_df["VALUE_NORM"]

# Split
X_tr, X_te, y_tr, y_te = train_test_split(
    X_crop, y_crop, test_size=0.2, random_state=42
)

# Train RF
rf_crop = RandomForestRegressor(
    n_estimators=50, max_depth=10, random_state=42, n_jobs=-1
)
rf_crop.fit(X_tr, y_tr)

r2 = r2_score(y_te, rf_crop.predict(X_te))

# Get top features
imp = pd.Series(rf_crop.feature_importances_, index=available_features).
↪sort_values(
    ascending=False
)
top3 = imp.head(3).index.tolist()

crop_results.append(
    {
        "Crop": crop,
        "N_Records": len(crop_df),
        "R2": r2,
        "Top_Feature_1": top3[0] if len(top3) > 0 else "",
        "Top_Feature_2": top3[1] if len(top3) > 1 else "",
        "Top_Feature_3": top3[2] if len(top3) > 2 else "",
    }
)

print(f"{crop}: R2 = {r2:.3f}, Top feature = {top3[0]}")

crop_results_df = pd.DataFrame(crop_results).sort_values("R2", ascending=False)
print("\n" + "=" * 60)
print(crop_results_df.to_string(index=False))

```

CORN: R² = 0.667, Top feature = ANNUAL_TEMP_AVG
COTTON: R² = 0.295, Top feature = TAVG_AUG

WHEAT: $R^2 = 0.375$, Top feature = PRECIP_MAY
 SORGHUM: $R^2 = 0.251$, Top feature = ANNUAL_PRECIP
 Skipping HAY - only 0 records

```
=====
```

Crop	N_Records	R2	Top_Feature_1	Top_Feature_2	Top_Feature_3
CORN	2028	0.667481	ANNUAL_TEMP_AVG	ANNUAL_HDD	
GROWING_SEASON_TEMP_MIN					
WHEAT	7150	0.374755	PRECIP_MAY	GROWING_SEASON_TEMP_MIN	
TAVG_MAY					
COTTON	4413	0.295015	TAVG_AUG	ANNUAL_HDD	
GROWING_SEASON_TEMP_MAX					
SORGHUM	3751	0.251392	ANNUAL_PRECIP	GROWING_SEASON_TEMP_MAX	
GROWING_SEASON_TEMP_MIN					

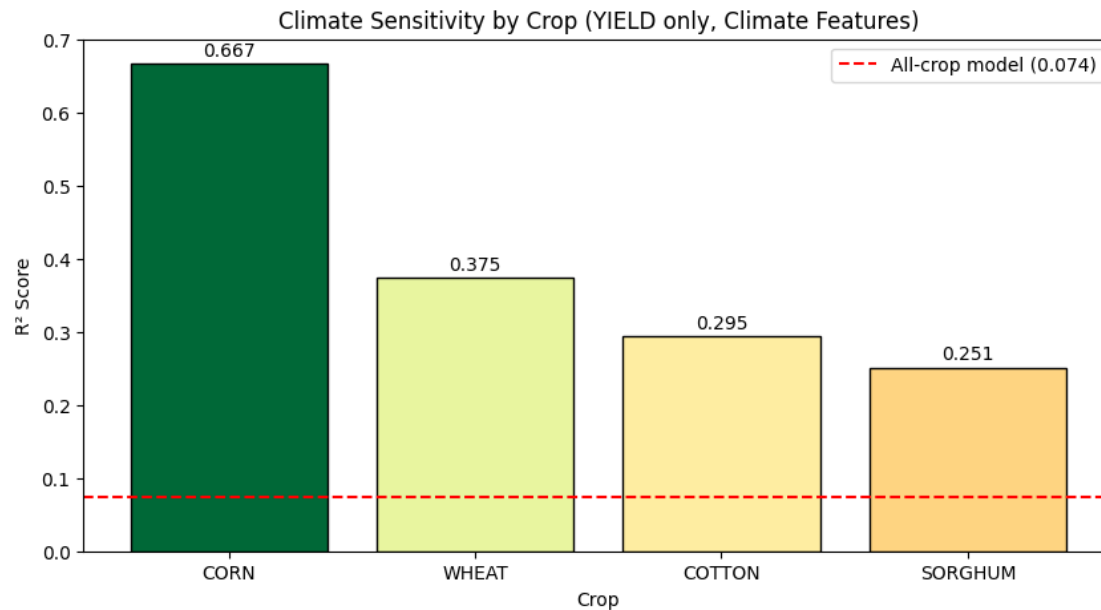
```
[15]: # Visualize crop-specific  $R^2$  scores
if len(crop_results_df) > 0:
    plt.figure(figsize=(10, 5))
    colors = plt.cm.RdYlGn(crop_results_df["R2"] / crop_results_df["R2"].max())
    bars = plt.bar(
        crop_results_df["Crop"], crop_results_df["R2"], color=colors,
        edgecolor="black"
    )
    plt.axhline(
        y=rf_test_r2,
        color="red",
        linestyle="--",
        label=f"All-crop model ({rf_test_r2:.3f})",
    )
    plt.xlabel("Crop")
    plt.ylabel(" $R^2$  Score")
    plt.title("Climate Sensitivity by Crop (YIELD only, Climate Features)")
    plt.legend()

    # Add value labels
    for bar, val in zip(bars, crop_results_df["R2"]):
        plt.text(
            bar.get_x() + bar.get_width() / 2,
            bar.get_height() + 0.005,
            f"{val:.3f}",
            ha="center",
            va="bottom",
            fontsize=10,
        )

    save_fig("crop_climate_sensitivity")
```

```
plt.show()
```

Saved: figures/crop_climate_sensitivity.png



1.5 5. Drought Year Analysis

Does the model correctly identify yield drops in known drought years (2011, 2013)?

```
[16]: # Look at actual yields in drought years vs normal years
drought_years = [2011, 2013]
normal_years = [2010, 2012, 2014, 2015] # Years around the droughts

# Use YIELD data for major crops - use df_model which still has original YEAR_
# values
yield_df = df_model[
    df_model["STATISTICCAT_DESC"].str.contains("YIELD", case=False, na=False)
].copy()

# df_model still has YEAR as original values (not encoded yet for this subset)
print("Average Yield by Year (selected crops):")
for crop in ["CORN", "COTTON", "WHEAT", "SORGHUM"]:
    crop_yield = yield_df[yield_df["COMMODITY_DESC"] == crop]
    if len(crop_yield) > 0:
        yearly_avg = crop_yield.groupby("YEAR")["VALUE"].mean()

        drought_avg = yearly_avg[yearly_avg.index.isin(drought_years)].mean()
        normal_avg = yearly_avg[yearly_avg.index.isin(normal_years)].mean()
```

```

    pct_drop = (
        (normal_avg - drought_avg) / normal_avg * 100 if normal_avg > 0
    ↪ else 0
    )

    print(
        f" {crop}: Drought avg = {drought_avg:.1f}, Normal avg =
    ↪ {normal_avg:.1f}, Drop = {pct_drop:.1f}%"
    )

```

Average Yield by Year (selected crops):

CORN: Drought avg = 88.4, Normal avg = 108.4, Drop = 18.4%

COTTON: Drought avg = 669.8, Normal avg = 722.9, Drop = 7.3%

WHEAT: Drought avg = 27.0, Normal avg = 32.5, Drop = 16.9%

SORGHUM: Drought avg = 52.1, Normal avg = 62.2, Drop = 16.3%

```

[17]: # Visualize corn yields over time (most climate-sensitive crop)
corn_yield = yield_df[yield_df["COMMODITY_DESC"] == "CORN"].copy()

if len(corn_yield) > 0:
    yearly_corn = corn_yield.groupby("YEAR")["VALUE"].agg(["mean", "std",
    ↪ "count"])

    plt.figure(figsize=(12, 5))

    # Plot mean with error bars
    plt.errorbar(
        yearly_corn.index,
        yearly_corn["mean"],
        yerr=yearly_corn["std"] / np.sqrt(yearly_corn["count"]),
        marker="o",
        capsize=3,
        color="forestgreen",
        label="Mean ± SE",
    )

    # Highlight drought years
    for dy in drought_years:
        if dy in yearly_corn.index:
            plt.axvline(x=dy, color="red", linestyle="--", alpha=0.5)
            plt.annotate(
                "Drought",
                xy=(dy, yearly_corn.loc[dy, "mean"]),
                xytext=(dy + 0.5, yearly_corn.loc[dy, "mean"] * 1.1),
                fontsize=9,
                color="red",
            )

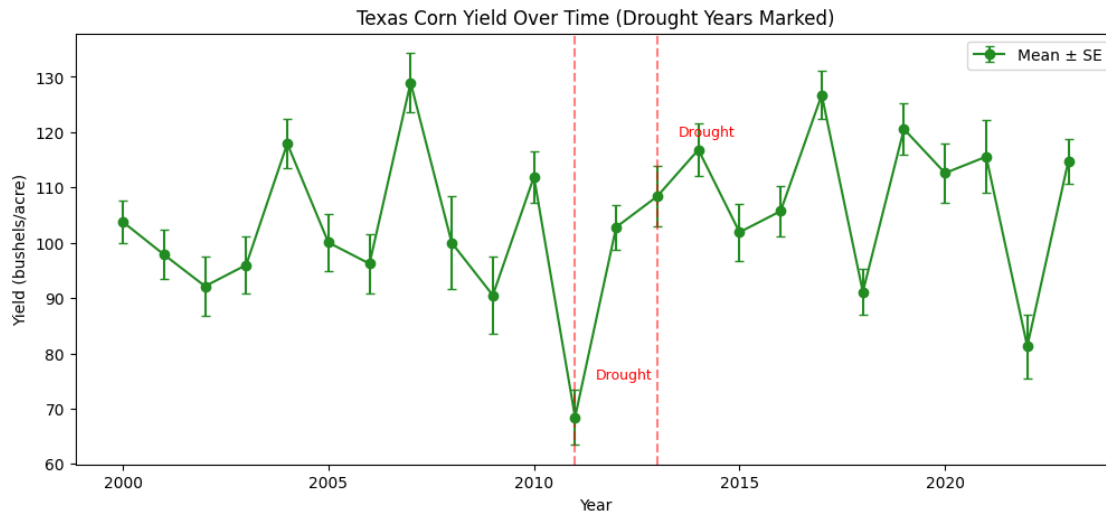
```

```

plt.xlabel("Year")
plt.ylabel("Yield (bushels/acre)")
plt.title("Texas Corn Yield Over Time (Drought Years Marked)")
plt.legend()
save_fig("corn_yield_drought_years")
plt.show()

```

Saved: figures/corn_yield_drought_years.png



```

[18]: # Model predictions for drought vs normal years
# Get test set indices
test_indices = X_test.index
test_years = df_clean.loc[test_indices, "YEAR_ORIG"]

# Predictions
y_pred = rf.predict(X_test)

# Compare residuals in drought vs normal years
drought_mask = test_years.isin(drought_years)
normal_mask = test_years.isin(normal_years)

print("Model Performance by Year Type:")
if drought_mask.sum() > 0:
    drought_r2 = r2_score(y_test[drought_mask], y_pred[drought_mask])
    print(
        f" Drought years (2011, 2013): R² = {drought_r2:.4f}, n = {
        ↪{drought_mask.sum()}"
    )

```



```

mtype_df = mtype_df.merge(
    mtype_stats.reset_index(), on="COMMODITY_DESC", suffixes=("", "_m")
)
mtype_df["std"] = mtype_df["std"].replace(0, 1).fillna(1)
mtype_df["VALUE_NORM"] = (mtype_df["VALUE"] - mtype_df["mean"]) /
↪mtype_df["std"]

# Prepare features
available_features = [
    f for f in climate_features + ["YEAR"] if f in mtype_df.columns
]

# Need to encode YEAR for this subset
le_year = LabelEncoder()
mtype_df["YEAR_ENC"] = le_year.fit_transform(mtype_df["YEAR"].astype(str))
available_features = [f for f in climate_features if f in mtype_df.columns]
↪+ [
    "YEAR_ENC"
]

mtype_df = mtype_df.dropna(subset=available_features + ["VALUE_NORM"])

if len(mtype_df) < 500:
    print(f"Skipping {mtype} - only {len(mtype_df)} records after cleaning")
    continue

X_m = mtype_df[available_features]
y_m = mtype_df["VALUE_NORM"]

X_tr, X_te, y_tr, y_te = train_test_split(X_m, y_m, test_size=0.2,
↪random_state=42)

rf_m = RandomForestRegressor(
    n_estimators=100, max_depth=15, random_state=42, n_jobs=-1
)
rf_m.fit(X_tr, y_tr)

r2 = r2_score(y_te, rf_m.predict(X_te))
rmse = np.sqrt(mean_squared_error(y_te, rf_m.predict(X_te)))

measurement_results.append(
    {"Measurement": mtype, "N_Records": len(mtype_df), "R2": r2, "RMSE":
↪rmse}
)

print(f"{mtype}: R² = {r2:.3f}, RMSE = {rmse:.3f}, n = {len(mtype_df):,}")

```

```
measurement_results_df = pd.DataFrame(measurement_results)
```

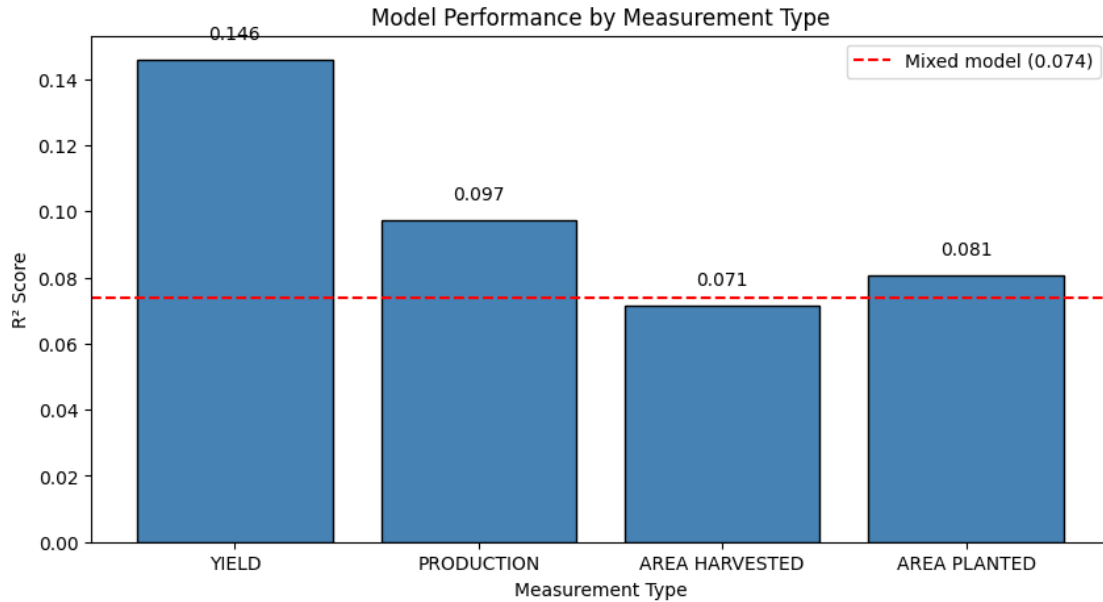
YIELD: $R^2 = 0.146$, RMSE = 0.909, n = 20,016
PRODUCTION: $R^2 = 0.097$, RMSE = 0.916, n = 43,364
AREA HARVESTED: $R^2 = 0.071$, RMSE = 0.918, n = 134,416
AREA PLANTED: $R^2 = 0.081$, RMSE = 0.953, n = 19,973

```
[21]: # Visualize
if len(measurement_results_df) > 0:
    fig, ax = plt.subplots(figsize=(10, 5))
    bars = ax.bar(
        measurement_results_df["Measurement"],
        measurement_results_df["R2"],
        color="steelblue",
        edgecolor="black",
    )
    ax.axhline(
        y=rf_test_r2,
        color="red",
        linestyle="--",
        label=f"Mixed model ({rf_test_r2:.3f})",
    )
    ax.set_xlabel("Measurement Type")
    ax.set_ylabel("R2 Score")
    ax.set_title("Model Performance by Measurement Type")
    ax.legend()

    for bar, val in zip(bars, measurement_results_df["R2"]):
        ax.text(
            bar.get_x() + bar.get_width() / 2,
            bar.get_height() + 0.005,
            f"{val:.3f}",
            ha="center",
            va="bottom",
        )

    save_fig("measurement_type_comparison")
    plt.show()
```

Saved: figures/measurement_type_comparison.png



1.7 7. Gradient Boosting

Gradient boosting as an alternative ensemble method to compare against Random Forest.

```
[24]: # Gradient Boosting
print("Training Gradient Boosting...")
gb = GradientBoostingRegressor(
    n_estimators=100,
    max_depth=5,
    learning_rate=0.1,
    min_samples_split=20,
    random_state=42,
)
gb.fit(X_train, y_train)

gb_train_r2 = r2_score(y_train, gb.predict(X_train))
gb_test_r2 = r2_score(y_test, gb.predict(X_test))
gb_test_rmse = np.sqrt(mean_squared_error(y_test, gb.predict(X_test)))

print(
    f"Gradient Boosting: Train R² = {gb_train_r2:.4f}, Test R² = {gb_test_r2:.4f}, RMSE = {gb_test_rmse:.4f}"
)
```

Training Gradient Boosting...

Gradient Boosting: Train R² = 0.0806, Test R² = 0.0687, RMSE = 0.9966

1.8 7a. GridSearchCV Hyperparameter Tuning

Systematic search for optimal Random Forest parameters.

```
[22]: # GridSearchCV for Random Forest
from sklearn.model_selection import GridSearchCV

# Define parameter grid (keeping it focused to avoid long runtimes)
param_grid = {
    "n_estimators": [50, 100, 150],
    "max_depth": [10, 15, 20],
    "min_samples_split": [10, 20, 50],
}

print("Running GridSearchCV for Random Forest...")
print(f"Parameter grid: {param_grid}")
print(f"Total combinations: {3*3*3} = 27")

# Use smaller CV folds for speed
grid_search = GridSearchCV(
    RandomForestRegressor(random_state=42, n_jobs=-1),
    param_grid,
    cv=3,
    scoring="r2",
    n_jobs=-1,
    verbose=1,
)

grid_search.fit(X_train, y_train)

print(f"\nBest parameters: {grid_search.best_params_}")
print(f"Best CV R2: {grid_search.best_score_:.4f}")

# Evaluate best model on test set
best_rf = grid_search.best_estimator_
best_rf_test_r2 = r2_score(y_test, best_rf.predict(X_test))
print(f"Best model Test R2: {best_rf_test_r2:.4f}")
print(f"Improvement over default RF: {(best_rf_test_r2 - rf_test_r2)*100:.2f}%")
```

Running GridSearchCV for Random Forest...

Parameter grid: {'n_estimators': [50, 100, 150], 'max_depth': [10, 15, 20],
'min_samples_split': [10, 20, 50]}

Total combinations: 27 = 27

Fitting 3 folds for each of 27 candidates, totalling 81 fits

Best parameters: {'max_depth': 20, 'min_samples_split': 50, 'n_estimators': 150}

Best CV R²: 0.0744

Best model Test R²: 0.0758

Improvement over default RF: 0.20%

1.9 7b. Cross-Validation Results

5-fold cross-validation to verify model stability.

```
[23]: # 5-fold Cross-Validation for all models
from sklearn.model_selection import cross_val_score

print("Running 5-fold Cross-Validation...")
print("=" * 50)

models = {
    "Decision Tree": DecisionTreeRegressor(
        max_depth=20, min_samples_split=50, min_samples_leaf=20, random_state=42
    ),
    "Random Forest": RandomForestRegressor(
        n_estimators=100,
        max_depth=15,
        min_samples_split=20,
        min_samples_leaf=10,
        random_state=42,
        n_jobs=-1,
    ),
    "Gradient Boosting": GradientBoostingRegressor(
        n_estimators=100, max_depth=5, learning_rate=0.1, random_state=42
    ),
}

cv_results = []
for name, model in models.items():
    scores = cross_val_score(model, X, y, cv=5, scoring="r2", n_jobs=-1)
    cv_results.append(
        {
            "Model": name,
            "CV Mean R2": scores.mean(),
            "CV Std": scores.std(),
            "CV Min": scores.min(),
            "CV Max": scores.max(),
        }
    )
print(
    f"{name}: {scores.mean():.4f} ± {scores.std():.4f} (range: {scores.
    ↪min():.4f} to {scores.max():.4f})"
)

cv_results_df = pd.DataFrame(cv_results)
print("\n" + "=" * 50)
print(cv_results_df.to_string(index=False))
```

Running 5-fold Cross-Validation...

Decision Tree: 0.0723 \pm 0.0040 (range: 0.0655 to 0.0779)
Random Forest: 0.0748 \pm 0.0034 (range: 0.0690 to 0.0794)
Gradient Boosting: 0.0699 \pm 0.0028 (range: 0.0650 to 0.0736)

Model	CV Mean R ²	CV Std	CV Min	CV Max
Decision Tree	0.072331	0.003970	0.065535	0.077856
Random Forest	0.074758	0.003431	0.069037	0.079402
Gradient Boosting	0.069932	0.002842	0.064982	0.073626

1.10 8. Final Model Comparison

```
[25]: # Summary table
results_summary = pd.DataFrame(
    [
        {
            "Model": "Decision Tree",
            "Train R2": dt_train_r2,
            "Test R2": dt_test_r2,
            "Test RMSE": dt_test_rmse,
        },
        {
            "Model": "Random Forest",
            "Train R2": rf_train_r2,
            "Test R2": rf_test_r2,
            "Test RMSE": rf_test_rmse,
        },
        {
            "Model": "Gradient Boosting",
            "Train R2": gb_train_r2,
            "Test R2": gb_test_r2,
            "Test RMSE": gb_test_rmse,
        },
    ]
)

results_summary["Overfitting Gap"] = (
    results_summary["Train R2"] - results_summary["Test R2"]
)

print("=" * 70)
print("FINAL MODEL COMPARISON")
print("=" * 70)
print(results_summary.to_string(index=False))
print("=" * 70)
```

FINAL MODEL COMPARISON

Model	Train R^2	Test R^2	Test RMSE	Overfitting Gap
Decision Tree	0.096688	0.072169	0.994686	0.024519
Random Forest	0.095001	0.073833	0.993794	0.021168
Gradient Boosting	0.080570	0.068666	0.996562	0.011904

```
[26]: # Final comparison visualization
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

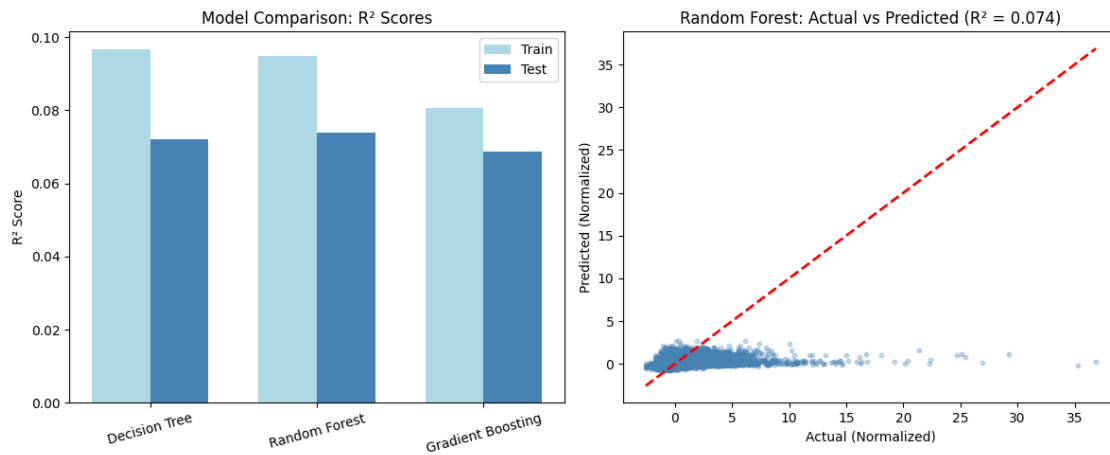
#  $R^2$  comparison
x = range(len(results_summary))
width = 0.35
axes[0].bar(
    [i - width / 2 for i in x],
    results_summary["Train  $R^2$ "],
    width,
    label="Train",
    color="lightblue",
)
axes[0].bar(
    [i + width / 2 for i in x],
    results_summary["Test  $R^2$ "],
    width,
    label="Test",
    color="steelblue",
)
axes[0].set_xticks(x)
axes[0].set_xticklabels(results_summary["Model"], rotation=15)
axes[0].set_ylabel(" $R^2$  Score")
axes[0].set_title("Model Comparison:  $R^2$  Scores")
axes[0].legend()

# Actual vs Predicted for best model
best_model = rf # Best performing model
y_pred_best = best_model.predict(X_test)
axes[1].scatter(y_test, y_pred_best, alpha=0.3, s=10, color="steelblue")
axes[1].plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], "r--", lw=2)
axes[1].set_xlabel("Actual (Normalized)")
axes[1].set_ylabel("Predicted (Normalized)")
axes[1].set_title(f"Random Forest: Actual vs Predicted ( $R^2$  = {rf_test_r2:.3f})")

plt.tight_layout()
save_fig("final_model_comparison")
```

```
plt.show()
```

Saved: figures/final_model_comparison.png



1.11 9. Key Takeaways

1. **Climate features matter:** ~80% of feature importance from climate variables
2. **Temperature > Precipitation:** Temperature features more important overall
3. **Crop-specific sensitivity:** Corn most sensitive, Cotton/Wheat less so
4. **Measurement type matters:** YIELD models perform better than mixed models
5. **Low R² is expected:** Climate is one factor among many; the insight is *which* features matter