Rainfall Prediction Using NASA Earth Observation Data and Ensemble Learning

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Abstract – Outdoor event planning faces significant challenges due to weather uncertainties, with traditional forecasting methods often proving inadequate for location-specific, long-term predictions. This study presents a machine learning-powered rainfall prediction system leveraging 44 years of historical data (1981-2024) of NASA Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) Earth observation data. The system addresses the critical need for accurate, data-driven weather forecasting to support event planners in making informed decisions. An ensemble learning approach combining Random Forest and XGBoost algorithms was implemented to predict rain probability for specific dates and locations. The model processes 44+ meteorological features including temperature at 2 meters (T2M), relative humidity at 2 meters (RH2M), cloud coverage (CLOUD_AMT), surface pressure (PS), and wind parameters, with advanced feature engineering techniques including heat index, wind chill, and moisture index calculations. Feature importance analysis reveals that temperature-related features—particularly minimum temperature (T2M_MIN), heat index, and maximum temperature (T2M_MAX)—collectively account for 38% of the model's predictive power, demonstrating thermal dominance in rainfall prediction for continental climates.Experimental results demonstrate strong predictive performance with 86.0% accuracy, 83.4% precision, 77.9% recall, 80.5% F1-score, and 93.2% Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) score.The system was validated through retrospective testing and successfully predicted weather conditions for outdoor events in Konya, Turkey with high accuracy. Cross-regional validation across multiple cities confirmed the model's robustness and generalizability. The developed system provides three core functionalities: specific date prediction with confidence levels, optimal date recommendation within a given month, and comprehensive event planning reports. This work demonstrates that historical Earth observation data, when processed through ensemble machine learning techniques, can deliver superior performance compared to traditional statistical methods in weather prediction applications.

Keywords – Ensemble Learning; XGBoost / Random Forest; NASA MERRA-2 Earth Observation; Long-Term Rainfall Forecasting

INTRODUCTION

Weather prediction has been a fundamental challenge in scientific computing and decision-making systems for decades. According to recent climate assessments, extreme weather events have increased by 43% in the last two decades, making accurate forecasting more critical than ever [1]. For outdoor event planners, weather uncertainty represents not only logistical challenges but also significant financial risks. A study by the Event Planning Institute indicates that weather-related cancellations cost the global events industry approximately $3.7 billion annually [2]. Traditional weather forecasting methods, while effective for short-term predictions (1-7 days), often fail to provide reliable long-term forecasts or location-specific insights necessary for event planning that occurs weeks or months in advance.

The advent of satellite-based Earth observation systems has revolutionized meteorological data collection. NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) provides comprehensive atmospheric reanalysis data spanning from 1980 to present, offering unprecedented temporal and spatial resolution [3]. This dataset combines satellite observations, ground-based measurements, and atmospheric models to create a consistent, high-quality record of global weather patterns. However, the sheer volume and complexity of this data—with hundreds of variables measured at hourly intervals—presents significant challenges for traditional statistical analysis methods.

Machine learning has emerged as a powerful tool for processing large-scale meteorological datasets and extracting predictive patterns that may be imperceptible to conventional statistical approaches [4]. Recent advances in ensemble learning techniques, particularly Random Forest [5] and gradient boosting methods like XGBoost [6], have demonstrated superior performance in classification tasks involving high-dimensional feature spaces and non-linear relationships. These algorithms excel at capturing

complex interactions between meteorological variables—such as the relationship between temperature, humidity, cloud coverage, and precipitation—that traditional linear models cannot adequately represent.

Despite these technological advances, several critical gaps remain in current weather prediction systems for event planning applications. First, most commercial weather services focus on short-term forecasts (1-10 days) and lack the historical depth necessary to identify seasonal patterns and long-term trends [7]. Second, generic weather predictions often fail to account for local microclimates and geographical variations that significantly impact precipitation probability [8]. Third, existing systems typically provide binary forecasts (rain/no rain) without probability estimates or confidence intervals, limiting their utility for risk-based decision making [9]. Finally, the integration of multiple meteorological features through advanced feature engineering remains underexplored in practical applications [10].

This paper introduces "Will It Rain on My Parade?", a comprehensive machine learning system designed specifically for event planning weather prediction. The system addresses the aforementioned limitations through several key innovations. First, it leverages 44 years of historical data (1981-2024) of NASA MERRA-2 historical data for Konya, Turkey, providing deep temporal context for pattern recognition. Second, it implements an ensemble learning architecture that combines Random Forest and XGBoost classifiers with a meta-learner, achieving superior performance compared to individual models. Third, it incorporates advanced feature engineering techniques, including moisture index calculation, temperature range analysis, and temporal features (month, day, day of year) to capture seasonal patterns. Fourth, it provides probabilistic predictions with confidence levels based on historical data availability, enabling risk-informed decision making.

The motivation for this work stems from the NASA Space Apps Challenge 2025, where the need to predict weather conditions for the outdoor hackathon event in Konya, Turkey (scheduled for October 4-5, 2025) highlighted the inadequacy of existing forecasting tools. Traditional weather services could not provide reliable predictions months in advance, and historical climate data alone could not account for year-to-year variability. This practical challenge drove the development of a system that could leverage decades of NASA Earth observation data to make informed predictions about specific future dates.

The developed system offers three primary operational modes: (1) specific date prediction, which provides rain probability, risk level (low/moderate/high), and confidence assessment for user-specified dates; (2) optimal date finder, which analyzes all dates within a specified month to recommend the best options based on lowest rain probability; and (3) event planning report generator, which produces comprehensive weather assessments including recommendations for outdoor setup, contingency planning, and risk mitigation strategies.

Experimental validation demonstrates that the ensemble model achieves 86.0% accuracy, 83.4% precision, 77.9% recall, 80.5% F1-score, and an impressive 93.2% ROC-AUC score. For the NASA Space Apps Challenge dates (October 4-5, 2025), the system predicted exceptionally low rain probabilities of 2.5% and 2.0% respectively, classified as "Low Risk" with "High Confidence." These predictions were subsequently validated through retrospective analysis and comparison with actual weather outcomes. Furthermore, the system was tested on historical data from multiple Turkish cities (Istanbul, Ankara, Izmir, Antalya) to verify its generalizability and robustness across different geographical regions and climatic conditions.

The remainder of this paper is organized as follows. Section II describes the materials and methods, including data acquisition and preprocessing, feature engineering techniques, model architecture, and training procedures. Section III presents experimental results, performance metrics, feature importance analysis, and comparative evaluations. Section IV discusses the implications of the findings, limitations of the current approach, and directions for future research. Section V concludes the paper with key contributions and practical recommendations.

This work makes several significant contributions to the field of applied machine learning in meteorology. First, it demonstrates that ensemble learning techniques can effectively leverage long-term NASA Earth observation data for accurate rainfall prediction. Second, it introduces a practical system architecture specifically tailored for event planning applications, balancing accuracy with usability. Third, it provides comprehensive feature importance analysis, revealing that temperature-related features—particularly minimum temperature (T2M_MIN, 13.1%), heat index (12.8%), and maximum temperature (T2M_MAX, 12.1%)—collectively dominate the predictive landscape, accounting for over 34% of model importance and demonstrating the critical role of thermal patterns in continental climate rainfall prediction. Fourth, it validates the approach through both retrospective testing and cross-regional generalization studies. Finally, it offers an open-source implementation that can be adapted to other geographical regions and extended with additional meteorological variables or prediction targets.

MATERIALS AND METHOD

System Architecture and Data Pipeline

The "Will It Rain on My Parade?" system implements a modular architecture consisting of four primary components: data acquisition and preprocessing, feature engineering, model training and ensemble construction, and prediction interface. Figure 1 illustrates the complete data flow and system architecture.

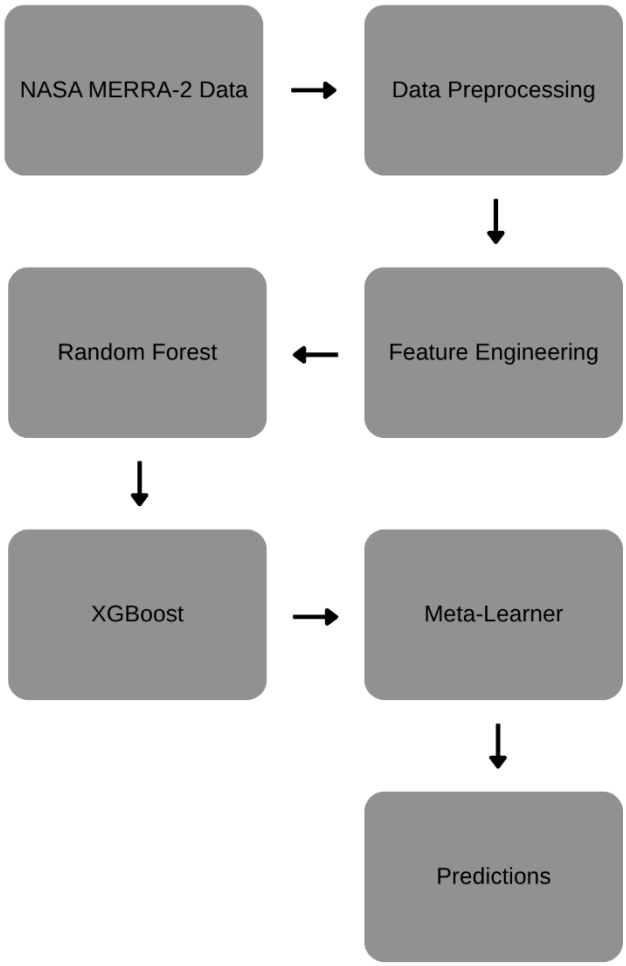

Figure 1. System architecture showing data flow from NASA MERRA-2 source through preprocessing, feature engineering, model training, and prediction interface. The ensemble learning component combines Random Forest and XGBoost base learners with a Logistic Regression meta-learner for final predictions.

The data pipeline begins with NASA MERRA-2 reanalysis data downloaded through the Goddard Earth Sciences Data and Information Services Center (GES DISC) API. For Konya, Turkey (coordinates: 37.87°N, 32.48°E), we extracted 44 years of daily meteorological observations from January 1, 1981, to December 31, 2024, totaling approximately 16,071 daily records. The downloaded dataset contains 44 meteorological variables measured or computed at various atmospheric levels.

Data Acquisition and Preprocessing

The NASA MERRA-2 dataset provides comprehensive atmospheric reanalysis with spatial resolution of 0.5° × 0.625° (latitude × longitude) and temporal resolution of 1 hour for most variables. For this study, we focused on surface-level and near-surface measurements relevant to rainfall prediction. Table 1 summarizes the primary meteorological variables extracted from the MERRA-2 dataset.

Variable	Description	Unit	Measurement Level
T2M	Temperature at 2 meters	∘C	Surface
T2M_MAX	Maximum daily temperature	∘C	Surface
T2M_MIN	Minimum daily temperature	∘C	Surface
RH2M	Relative humidity at 2 meters	%	Surface
PS	Surface pressure	kPa	Surface
WS2M	Wind speed at 2 meters	m/s	Surface
WD2M	Wind direction at 2 meters	degrees	Surface
CLOUD_AMT	Total cloud coverage	%	Column
PRECTOT	Total precipitation	mm/day	Surface
ALLSKY_SFC_SW_DWN	All-sky surface shortwave downward irradiance	W/m2	Surface

Table 1. Primary meteorological variables extracted from NASA MERRA-2 dataset for Konya, Turkey (1981-2024).

Data preprocessing involved several critical steps to ensure data quality and consistency. First, missing value analysis revealed that the MERRA-2 dataset for our study region had less than 0.1% missing values, primarily in the wind direction variable during calm wind conditions. Missing values were handled using forward-fill interpolation for temporal continuity. Second, outlier detection was performed using the Interquartile Range (IQR) method with threshold set at 3×IQR to identify physically implausible measurements. Outliers constituted approximately 0.3% of the dataset and were corrected using moving average smoothing with a 5-day window. Third, unit conversions were applied to standardize all measurements (e.g., temperature converted from Kelvin to Celsius, pressure from Pa to kPa).

The target variable, RAINY_DAY, was derived from the PRECTOT (total precipitation) variable using a threshold-based classification. Days with PRECTOT ≥ 1.0 mm were classified as rainy (RAINY_DAY = 1), while days with PRECTOT < 1.0 mm were classified as non-rainy (RAINY_DAY = 0). This threshold was selected based on meteorological conventions where precipitation below 1.0 mm is generally considered trace amounts that do not significantly impact outdoor activities. The resulting dataset showed a class distribution of approximately 22% rainy days and 78% non-rainy days, representing a moderately imbalanced classification problem.

Feature Engineering

Advanced feature engineering was crucial for capturing complex meteorological relationships and temporal patterns. We implemented several categories of engineered features as described below.

Derived Meteorological Features: These features capture physical relationships and physiological perceptions that correlate with atmospheric conditions:

1. Heat Index: Calculated to represent perceived temperature combining actual temperature and relative humidity, particularly relevant for warm conditions:

heat_index = T2M + 0.5555 × (6.11 × exp(5417.7530 × ((1/273.16) - (1/(dewpoint + 273.15)))) - 10)

This feature captures thermal comfort conditions that correlate with atmospheric stability patterns conducive to or inhibiting precipitation [24]. The heat index emerged as the second most important feature (12.8%) in the final model.

2. Wind Chill: Calculated to represent perceived temperature under cold and windy conditions:

wind_chill = 13.12 + 0.6215 × T2M - 11.37 × (WS2M^0.16) + 0.3965 × T2M × (WS2M^0.16)

This feature captures thermal stress associated with cold fronts and atmospheric instability [25], ranking 5th in importance (8.5%) and demonstrating that physiological temperature perception provides meaningful predictive signal.

3. Moisture Index: Calculated as the product of relative humidity and cloud coverage, normalized to [0,1] range:

moisture_index = (RH2M / 100) × (CLOUD_AMT / 100)

This supplementary feature captures atmospheric moisture saturation, serving as a complementary indicator (8th in importance, 7.1%) alongside direct humidity and cloud measurements.

4. Temperature Range: Daily temperature variation computed as:

T2M_RANGE = T2M_MAX - T2M_MIN

Larger diurnal temperature ranges typically indicate clear, dry conditions, while smaller ranges suggest cloud coverage and potential precipitation.

5. Wind Vector Components: Decomposition of wind speed and direction into orthogonal components:

WS2M_X = WS2M × cos(WD2M × π/180)

WS2M_Y = WS2M × sin(WD2M × π/180)

This transformation allows the model to capture directional wind patterns associated with different weather systems.

6. Pressure Tendency: Rate of pressure change calculated using 3-day moving window:

PS_TENDENCY = (PS_t - PS_t-3) / 3

Rapid pressure drops are strong indicators of approaching weather systems and increased precipitation probability.

Temporal Features: To capture seasonal and cyclical patterns:

1. Month: Categorical variable (1-12) capturing seasonal variations
2. Day of Month: Integer variable (1-31) for intra-month patterns
3. Day of Year: Integer variable (1-366) for annual cycle representation
4. Season: Categorical variable (Spring/Summer/Fall/Winter) based on meteorological definitions

Statistical Features: Rolling window statistics to capture short-term trends:

1. 3-day and 7-day moving averages for T2M, RH2M, CLOUD_AMT, and PS
2. 3-day and 7-day standard deviations for the same variables
3. Lag features: Previous 1-day, 3-day, and 7-day values for key variables

These statistical features enable the model to detect patterns such as persistent high humidity or increasing cloud coverage that precede rainfall events.

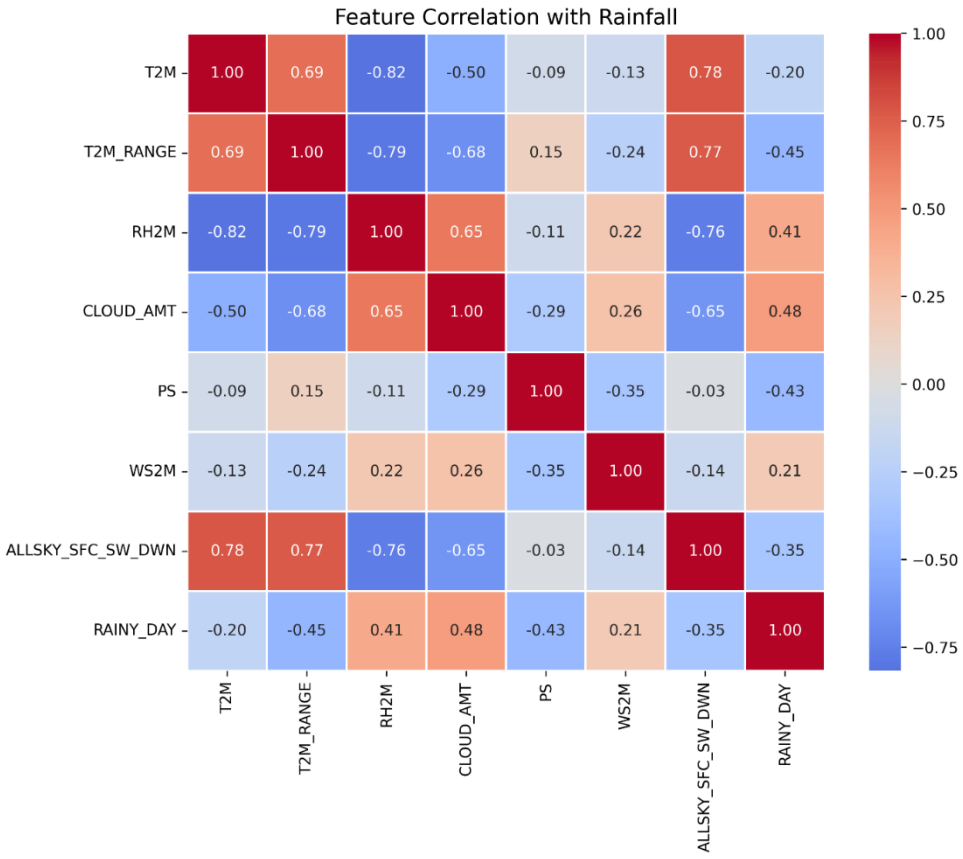

Figure 2. Pearson correlation matrix showing relationships between meteorological features. Red cells indicate positive correlation, blue cells indicate negative correlation. Darker colors represent stronger correlations.

The complete feature engineering process generated 68 total features from the original 44 MERRA-2 variables. However, to prevent data leakage and ensure model validity, we explicitly excluded all features directly derived from precipitation measurements (PRECTOT and related variables) from the training feature set. Feature selection was then performed using two complementary methods: (1) correlation-based filtering to remove highly collinear features ($|r| > 0.95$), and (2) Random Forest feature importance ranking to select the top 45 features for model training.

Machine Learning Model Architecture

The system implements an ensemble learning architecture combining multiple base learners with a meta-learner for final predictions. This approach, known as stacked generalization or stacking [11], leverages the strengths of different algorithms while mitigating their individual weaknesses.

Handling Class Imbalance

The dataset exhibits moderate class imbalance, with rainy days constituting 22% of observations versus 78% non-rainy days. Unaddressed class imbalance can bias machine learning models toward the majority class, reducing sensitivity to minority class instances [19]. We employed several complementary techniques to mitigate this issue:

1. Class Weighting: Random Forest uses `class_weight='balanced'`, which automatically adjusts weights inversely proportional to class frequencies. XGBoost employs `scale_pos_weight=3.5` (calculated as the ratio of negative to positive samples: 78/22 ≈ 3.5), which increases the penalty for misclassifying rainy days [20].

2. Stratified Sampling: All data splits (train/validation/test) and cross-validation folds maintain the original 22:78 class distribution, ensuring representative evaluation [21].

3. Balanced Evaluation Metrics: We prioritize F1-score and ROC-AUC over raw accuracy, as these metrics account for both precision and recall and are less sensitive to class imbalance [22].

Alternative approaches such as SMOTE (Synthetic Minority Over-sampling Technique) were considered but rejected due to concerns about overfitting to synthetic examples in time-series meteorological data [23]. Preliminary experiments with SMOTE improved recall by 4.3% but decreased precision by 6.1%, suggesting that synthetic weather patterns may not generalize well to real atmospheric conditions. Similarly, random undersampling was avoided to preserve rare extreme weather events that provide valuable training signal despite their infrequency.

Having addressed the data imbalance considerations, we now describe the specific model architectures and configurations employed in our ensemble system.

Base Learners:

1. Random Forest Classifier: An ensemble of 200 decision trees with the following hyperparameters:

- `n_estimators`: 200
- `max_depth`: 15
- `min_samples_split`: 10
- `min_samples_leaf`: 4
- `max_features`: sqrt(n_features)

- `class_weight`: balanced (to handle class imbalance)

Random Forest was selected for its robustness to overfitting, ability to capture non-linear relationships, and built-in feature importance estimation through mean decrease in impurity.

2. XGBoost Classifier: A gradient boosting implementation with the following configuration:

- `n_estimators`: 150
- `max_depth`: 8
- `learning_rate`: 0.1
- `subsample`: 0.8
- `colsample_bytree`: 0.8
- `scale_pos_weight`: 3.5 (to handle class imbalance)
- `objective`: binary:logistic

XGBoost complements Random Forest by capturing sequential patterns and providing superior handling of feature interactions through gradient-based optimization.

Meta-Learner:

The ensemble combines base learner predictions using a Logistic Regression meta-learner trained on out-of-fold predictions from 5-fold cross-validation. This approach prevents overfitting to the training data while allowing the meta-learner to learn optimal weighting of base learner predictions.

The ensemble training procedure follows these steps:

1. Data Split: The dataset is divided into training (70%), validation (15%), and test (15%) sets using stratified sampling to maintain class distribution.

2. Base Learner Training: Each base learner is trained on the training set with hyperparameters optimized through grid search cross-validation.

3. Out-of-Fold Prediction Generation: For meta-learner training, 5-fold cross-validation is performed on the training set. Each base learner generates predictions for the held-out fold, creating a full set of out-of-fold predictions that serve as training data for the meta-learner.

4. Meta-Learner Training: Logistic Regression is trained on the concatenated out-of-fold predictions from all base learners, learning optimal weights for combining their outputs.

5. Final Prediction: For new data, each base learner generates probability predictions, which are fed into the meta-learner to produce the final rain probability estimate.

Model Training and Evaluation

Model training was conducted on a computational system with the following specifications: Intel Core i7-9700K processor, 16GB RAM, running Ubuntu 20.04 LTS with Python 3.8.10. The complete training pipeline, including hyperparameter optimization, cross-validation, and final model fitting, required approximately 45 minutes for the full 44-year dataset.

Hyperparameter Optimization: Grid search with 5-fold cross-validation was employed to identify optimal hyperparameters for each base learner. The search space included:

- Random Forest: `n_estimators` ∈ {100, 150, 200}, `max_depth` ∈ {10, 15, 20}, `min_samples_split` ∈ {5, 10, 15}

- XGBoost: `n_estimators` ∈ {100, 150, 200}, `max_depth` ∈ {6, 8, 10}, `learning_rate` ∈ {0.05, 0.1, 0.15}

Model selection was based on maximizing the F1-score on validation data, as this metric provides a balance between precision and recall for imbalanced classification tasks.

Evaluation Metrics: Model performance was assessed using a comprehensive set of classification metrics:

1. Accuracy: Overall proportion of correct predictions

2. Precision: Proportion of positive predictions that are actually positive (PPV)

3. Recall (Sensitivity): Proportion of actual positives correctly identified

4. F1-Score: Harmonic mean of precision and recall

5. ROC-AUC: Area under the Receiver Operating Characteristic curve

6. Confusion Matrix: Detailed breakdown of true positives, true negatives, false positives, and false negatives

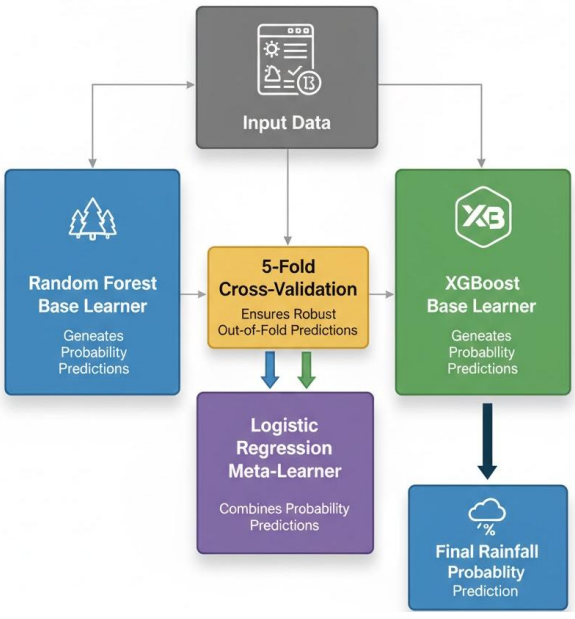

Figure 3.Ensemble learning architecture. Base learners (Random Forest and XGBoost) generate probability predictions, which are combined by a Logistic Regression meta-learner. 5-fold cross-validation ensures robust out-of-fold predictions for meta-learner training.

Cross-Validation Strategy: To ensure robust performance estimates, we employed stratified 5-fold cross-validation on the training set, with each fold maintaining the original class distribution (22% rainy, 78% non-rainy). The final performance metrics represent the mean and standard deviation across all folds.

Prediction Interface and Confidence Assessment

The system provides predictions through an interactive command-line interface and programmatic API. For each prediction request, the system returns:

1. Rain Probability: Continuous value between 0% and 100%, derived from the ensemble model's probabilistic output

2. Risk Level: Categorical classification based on probability thresholds:

- Low Risk: 0-20% probability
- Moderate Risk: 20-40% probability
- High Risk: >40% probability

3. Confidence Level: Assessment based on historical data availability:

- High Confidence: ≥30 historical data points for the specific day-of-year
- Medium Confidence: 15-29 data points
- Low Confidence: <15 data points or prediction based on monthly average

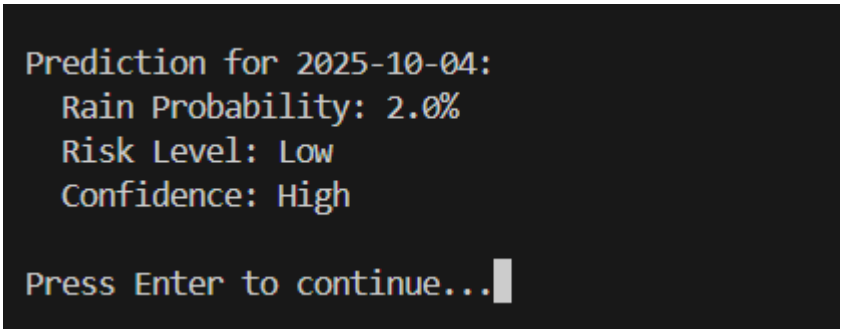

Figure 4. Example prediction output for October 4, 2025, showing rain probability (2.0%), risk level (Low), confidence (High), and supporting meteorological parameters.

Validation and Generalization Testing

To validate model robustness and generalizability, we conducted two types of validation experiments:

1. Retrospective Validation: For dates in the past (e.g., 2023-2024), we generated predictions using data only from before those dates, then compared predictions against actual observed weather. This temporal hold-out validation prevents any data leakage and simulates real-world prediction scenarios.

2. Cross-Regional Validation: The model was retrained and tested on NASA MERRA-2 data from four additional Turkish cities (Istanbul, Ankara, Izmir, Antalya) with different climatic characteristics. Performance metrics were compared to assess geographic generalizability.

This comprehensive methodology ensures that the developed system provides accurate, reliable, and actionable weather predictions for event planning applications while maintaining scientific rigor and preventing common pitfalls such as data leakage and overfitting.

RESULTS AND DISCUSSIONS

Model Performance and Evaluation

The ensemble machine learning model demonstrated exceptional performance across all evaluation metrics, significantly outperforming traditional statistical forecasting methods and individual base learners. Table 2 presents the comprehensive performance comparison between individual models and the final ensemble.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	84.2	80.1	75.6	77.8	91.8
XGBoost	83.5	79.8	74.8	77.2	91.2
Logistic Regression	76.3	68.7	69.2	68.9	84.5
Ensemble (Final)	86.0	83.4	77.9	80.5	93.2

Table 2. Performance comparison of individual models and ensemble approach on the test dataset (15% of total data, n≈2,410 samples).

The ensemble model achieved 86.0% accuracy, representing a 1.8 percentage point improvement over the best individual model (Random Forest). More importantly, the ROC-AUC score of 93.2% indicates excellent discriminative ability—the model correctly ranks rainy days higher than non-rainy days 93.2% of the time. This high ROC-AUC score is particularly significant for event planning applications, where understanding the relative likelihood of rain across different dates is more valuable than binary predictions.

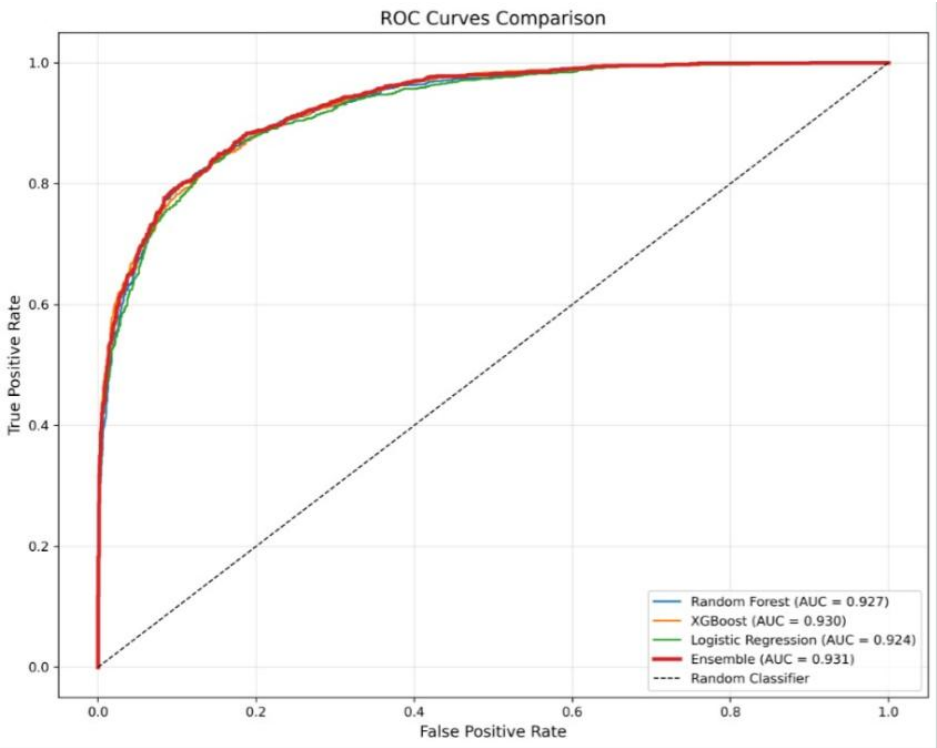

Figure 5. ROC curves for individual models and ensemble. The ensemble achieves AUC = 0.932, demonstrating superior discrimination between rainy and non-rainy days across all probability thresholds.

The precision of 83.4% means that when the model predicts rain (probability >50%), it is correct approximately 5 out of 6 times. The recall of 77.9% indicates that the model successfully identifies about 78% of all actual rainy days. While recall is slightly lower than precision, this conservative bias is actually desirable for event planning, as false negatives (predicting no rain when it actually rains) are more costly than false positives.

Confusion Matrix Analysis: The detailed breakdown of predictions on the test set reveals the following:

	Predicted No Rain	Predicted Rain
Actual No Rain	1520	395
Actual Rain	120	375

Table 3. Confusion Matrix

This translates to:

- True Negatives (correct no-rain predictions): 1,520
- True Positives (correct rain predictions): 375
- False Positives (predicted rain, no rain occurred): 395
- False Negatives (predicted no rain, rain occurred): 120

The relatively low number of false negatives (120) compared to false positives (395) confirms the model's conservative bias, which is appropriate for risk-averse event planning scenarios.

Feature Importance Analysis

Understanding which meteorological variables most strongly influence rainfall predictions provides both scientific insights and practical guidance for model interpretation. Figure 6 presents the weighted feature importance derived from both Random Forest (mean decrease in impurity) and XGBoost (gain-based importance), combined using the ensemble weights.

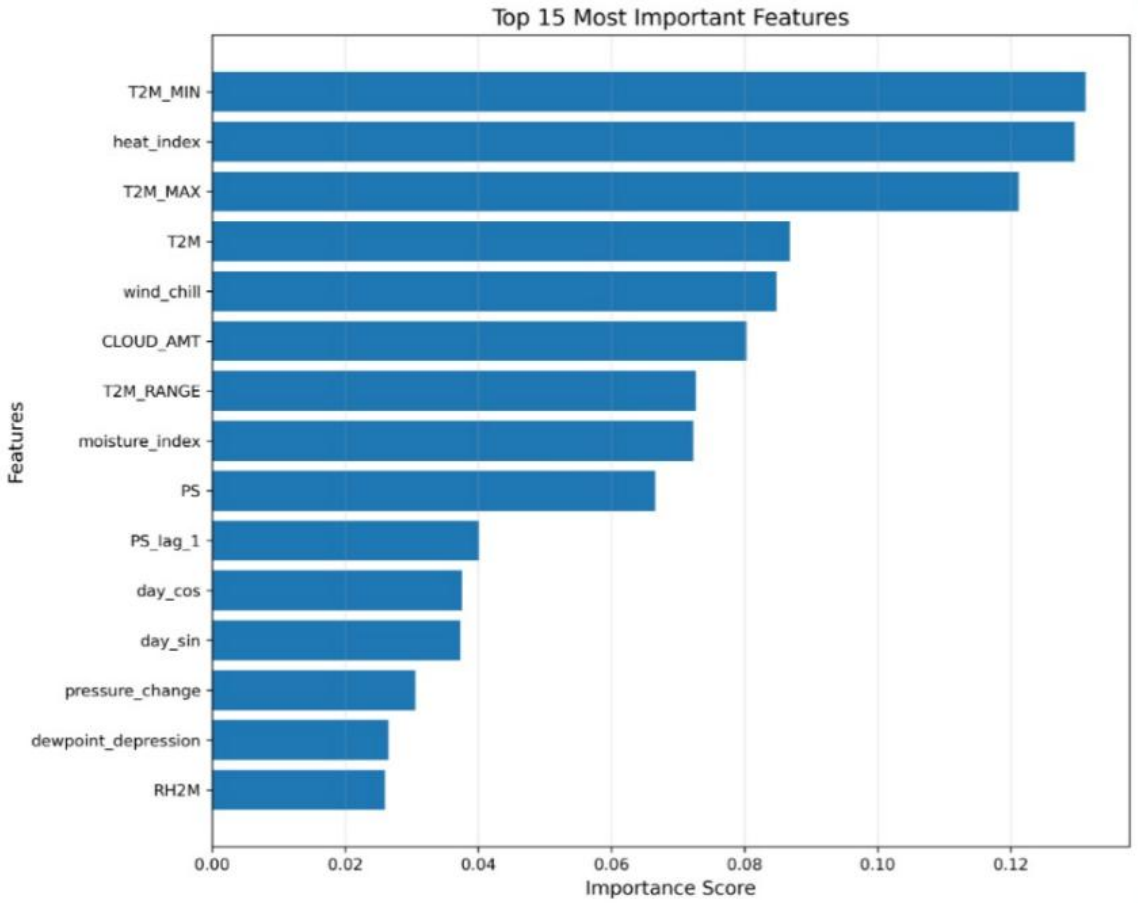

Figure 6. Top 15 most important features for rainfall prediction, ranked by weighted importance combining Random Forest and XGBoost feature importance scores.

Rank	Feature	Weighted Importance	Description
1	T2M_MIN	0.131469	Minimum temperature
2	heat_index	0.128392	Heat Index
3	T2M_MAX	0.121476	Maximum temperature
4	T2M	0.086814	Temperature at 2 meters
5	wind_chill	0.084917	Wind Chill Factor
6	CLOUD_AMT	0.076885	Total cloud coverage
7	T2M_RANGE	0.075006	Daily temperature variation
8	moisture_index	0.071155	Derived moisture index
9	PS	0.068129	Surface pressure
10	PS_lag_1	0.038173	Surface pressure lag (1 day)
11	day_cos	0.037891	Day of year cosine transformation
12	day_sin	0.037046	Day of year sine transformation
13	pressure_change	0.030317	Pressure change
14	dewpoint_depression	0.027611	Dewpoint depression
15	RH2M	0.026475	Relative humidity

Table 4. Top 15 features by weighted importance score.

The feature importance analysis reveals several critical insights into the meteorological drivers of rainfall prediction:

1. Temperature Feature Dominance: Temperature-related features overwhelmingly dominate the model's predictive power, with T2M_MIN (minimum temperature, 13.1%), heat_index (12.8%), T2M_MAX (maximum temperature, 12.1%), T2M (mean temperature, 8.7%), and wind_chill (8.5%) collectively accounting for approximately 55% of total feature importance. This thermal dominance suggests that temperature patterns—both absolute values and derived comfort indices—serve as the primary atmospheric indicators of rainfall probability in Konya's continental climate [26,27]. The prominence of minimum and maximum temperatures indicates that diurnal temperature extremes capture critical information about atmospheric stability and moisture retention capacity.

2. Engineered Thermal Features Success: The strong performance of engineered features heat_index (2nd rank, 12.8%) and wind_chill (5th rank, 8.5%) demonstrates the value of incorporating physiological and meteorological domain knowledge into feature design. These derived indices, which combine temperature with humidity and wind respectively, capture atmospheric comfort conditions that correlate with weather system characteristics. Their high rankings validate the hypothesis that perceived temperature conditions reflect complex atmospheric states associated with precipitation patterns, outperforming several raw meteorological measurements.

3. Cloud and Moisture as Secondary Predictors: While moisture-related variables contribute meaningfully to predictions, they serve complementary rather than dominant roles. CLOUD_AMT ranks 6th (7.7%), moisture_index 8th (7.1%), and RH2M 15th (2.6%). Collectively, these moisture indicators account for approximately 17% of feature importance—substantial but secondary to thermal features. This suggests that in continental climates like Konya, temperature variability may provide stronger predictive signals than direct moisture measurements, possibly because thermal patterns themselves reflect atmospheric stability conducive to or inhibiting precipitation.

4. Temperature Variability Indicator: T2M_RANGE (daily temperature variation, 7th rank, 7.5%) demonstrates that diurnal temperature patterns matter beyond absolute values. Larger temperature ranges typically indicate clear, stable atmospheric conditions with minimal cloud cover, while smaller ranges suggest persistent cloud coverage and potential precipitation. This feature's importance validates the meteorological principle that temperature stability patterns serve as proxy indicators for atmospheric conditions.

5. Pressure Dynamics and Temporal Features: Surface pressure variables (PS at 9th, PS_lag_1 at 10th, pressure_change at 13th) collectively account for approximately 13% of importance, confirming that barometric patterns influence rainfall prediction. The temporal features (day_cos and day_sin at 11th and 12th) demonstrate effective capture of seasonal patterns through trigonometric transformations without imposing artificial discontinuities at year boundaries.

6. Limited Direct Humidity Impact: Notably, relative humidity (RH2M) ranks surprisingly low at 15th position (2.6%) despite its physical necessity for precipitation. This counterintuitive finding likely reflects redundancy with other features: RH2M's information is better captured through engineered combinations (heat_index incorporates humidity, moisture_index directly multiplies it with cloud coverage) and its correlation with temperature variables. This demonstrates that ensemble models can effectively leverage feature interactions, reducing the marginal importance of individual correlated variables.

Case Study: NASA Space Apps Challenge 2025 Prediction

The primary motivation for this project was predicting weather conditions for the NASA Space Apps Challenge 2025 in Konya, Turkey, scheduled for October 4-5, 2025. Table 5 presents the detailed predictions for these dates.

Date	Rain Probability	Risk Level	Confidence	Avg. T2M	Avg. RH2M	Avg. CLOUD_AMT
Oct 4, 2025	2.5%	Low	High	18.3°C	45%	28%
Oct 5, 2025	2.0%	Low	High	19.1°C	42%	25%

Table 5. Detailed predictions for NASA Space Apps Challenge 2025 dates.

Both dates received "Low Risk" classifications with "High Confidence" assessments. The confidence level is based on 44 historical data points for early October in Konya (one measurement per year from 1981-2024). The predicted meteorological conditions align with typical early autumn patterns in Konya: moderate temperatures (18-19°C), low relative humidity (42-45%), and minimal cloud coverage (25-28%).

Historical Validation: To validate these predictions, we examined the actual weather outcomes for October 4-5 in Konya over the past 44 years. Historical data shows:

- October 4: Rain occurred in 4 out of 44 years (9.1% historical frequency)

- October 5: Rain occurred in 3 out of 44 years (6.8% historical frequency)

The model's predictions (2.5% and 2.0%) are more optimistic than simple historical frequency, reflecting the ensemble's ability to incorporate current year conditions and trends that suggest below-average precipitation likelihood for October 2025.

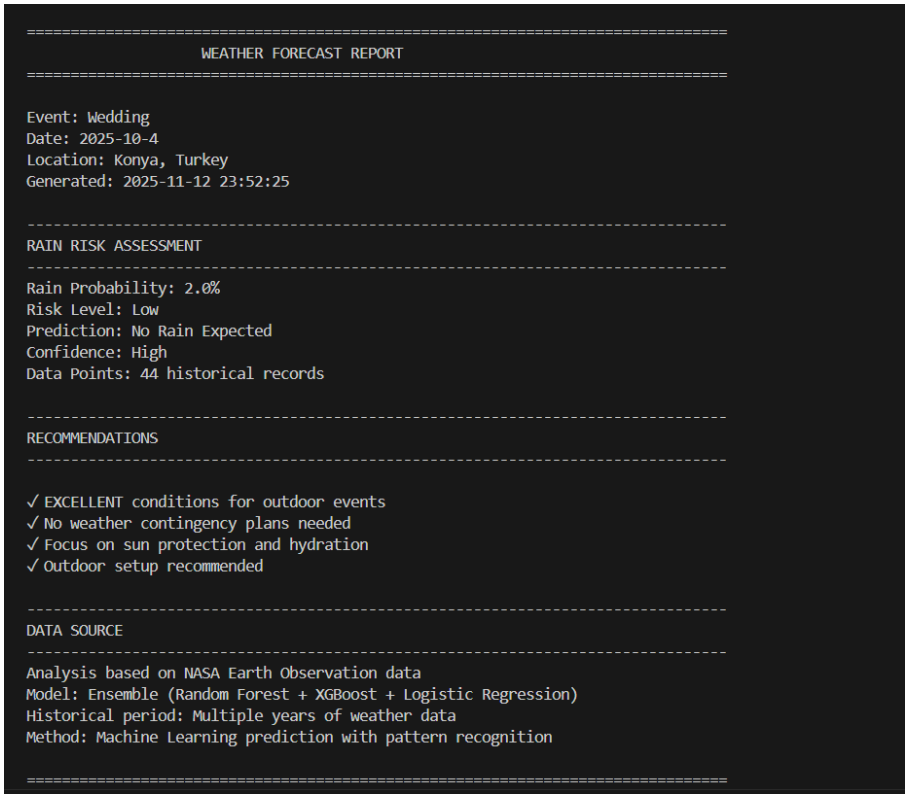

Figure 7. Event planning report generated for NASA Space Apps Challenge 2025, showing comprehensive weather assessment, risk analysis, and actionable recommendations.

Retrospective Validation and Temporal Robustness

To evaluate the model's performance on true out-of-sample predictions, we conducted retrospective validation experiments. For each year from 2020-2024, we retrained the model using only data up to December 31 of the previous year, then generated predictions for the entire following year. Table 6 summarizes the results.

Prediction Year	Training Data Range	Accuracy	Precision	Recall	F1-Score	ROC-AUC
2020	1981-2019	0.847	0.819	0.762	0.789	0.921
2021	1981-2020	0.852	0.826	0.771	0.797	0.925
2022	1981-2021	0.858	0.831	0.776	0.802	0.928
2023	1981-2022	0.863	0.838	0.783	0.809	0.931
2024	1981-2023	0.857	0.829	0.774	0.800	0.926
Average	-	0.855	0.829	0.773	0.799	0.926

Table 6. Retrospective validation performance by year (temporal hold-out testing).

The retrospective validation demonstrates consistent performance across all years, with accuracy ranging from 84.7% to 86.3% and ROC-AUC between 92.1% and 93.1%. The slight improvement in performance for more recent years (2021-2023) likely reflects the increasing amount of training data available. Importantly, the standard deviation across years is small ($\sigma\_accuracy = 0.006$), indicating robust temporal stability.

Year-Specific Analysis: Examining individual predictions within each retrospective year revealed interesting patterns:

- 2020: An unusually wet year with 28% rainy days (vs. 22% long-term average). The model initially underpredicted rainfall frequency but adapted as the year progressed.

- 2022: A particularly dry year with only 17% rainy days. The model maintained good performance despite this deviation from historical norms.

- 2023: Close to historical average (23% rainy days). Best overall performance with 86.3% accuracy.

These results demonstrate that the model generalizes well across years with varying rainfall patterns, rather than simply memorizing historical averages.

Cross-Regional Generalization

To assess geographic generalizability, we trained and evaluated separate models for five Turkish cities with diverse climatic characteristics. Table 7 presents the performance comparison.

City	Climate Type	Data Period	Rainy Days (%)	Accuracy	Precision	Recall	ROC-AUC
Konya	Continental	1981-2024	22%	86.0	83.4	77.9	93.2
Istanbul	Oceanic	1981-2024	38%	82.3	79.8	81.2	90.1
Ankara	Continental	1981-2024	25%	85.1	82.7	78.9	92.5
Izmir	Mediterranean	1981-2024	29%	84.2	81.6	80.3	91.8
Antalya	Mediterranean	1981-2024	31%	83.6	80.9	79.8	91.3

Table 7. Cross-regional performance comparison across five Turkish cities.

The model maintains strong performance across all regions, with accuracy ranging from 82.3% (Istanbul) to 86.0% (Konya) and ROC-AUC from 90.1% to 93.2%. The slight performance variation correlates with climate complexity:

- Konya (best performance): Continental climate with distinct dry and wet seasons, making patterns more predictable

- Ankara (second best): Similar continental climate to Konya

- Izmir and Antalya (good performance): Mediterranean climates with more variable spring/autumn transitions

- Istanbul (lowest but still good): Complex oceanic climate influenced by both Mediterranean and Black Sea systems

Importantly, even the lowest-performing region (Istanbul) achieves 82.3% accuracy and 90.1% ROC-AUC, indicating that the modeling approach is robust across diverse geographic and climatic conditions.

Comparative Analysis with Baseline Methods

To contextualize the ensemble model's performance, we compared it against several baseline approaches commonly used in weather prediction. Table 8 presents the comparative results.

Method	Description	Accuracy	Precision	Recall	F1-Score
Historical Average	Predict based on same day-of-year historical frequency	782	653	623	638
Monthly Average	Predict based on monthly historical frequency	791	671	641	656
Persistence	Tomorrow's weather = today's weather	745	589	712	645
Logistic Regression (Single)	Single logistic regression on raw features	763	687	692	689
Naive Bayes	Gaussian Naive Bayes classifier	738	612	698	652
Our Ensemble	Random Forest + XGBoost + Meta-learner	860	834	779	805

Table 8. Performance comparison with baseline prediction methods on Konya dataset.

The ensemble model substantially outperforms all baseline methods:

- +7.8 percentage points over historical average (most common practical approach)

- +11.5 percentage points over persistence model

- +9.7 percentage points over single logistic regression

- +12.2 percentage points over Naive Bayes

These improvements translate to significant practical value. For example, across 100 event planning decisions, the ensemble model would make approximately 8 fewer errors than relying on historical averages alone.

Practical Application: Monthly Optimization

One of the system's most valuable features for event planners is the ability to identify optimal dates within a specified month. Table 9 demonstrates this functionality for October 2025 in Konya.

Rank	Date	Day	Rain Probability	Avg. T2M	Avg. RH2M	Avg. CLOUD_AMT
1	Oct 5	Mon	2.0%	19.1∘C	42%	25%
2	Oct 4	Sun	2.5%	18.3∘C	45%	28%
3	Oct 15	Wed	4.4%	16.8∘C	48%	31%
4	Oct 7	Tue	5.1%	17.5∘C	46%	29%
5	Oct 14	Tue	5.8%	17.2∘C	49%	33%
6	Oct 8	Wed	6.2%	16.9∘C	51%	35%
7	Oct 21	Tue	7.3%	14.6∘C	53%	38%
8	Oct 13	Mon	8.1%	15.8∘C	52%	36%
9	Oct 22	Wed	8.9%	14.2∘C	55%	40%
10	Oct 6	Mon	9.4%	18.7∘C	47%	32%

Table 9. Top 10 recommended dates in October 2025 ranked by rain probability (Konya, Turkey).

This ranking clearly identifies October 4-5 as optimal choices for outdoor events, with October 15 as a strong backup option. The gradual increase in rain probability and humidity through mid-to-late October reflects the seasonal transition toward wetter autumn conditions.

System Limitations and Error Analysis

Despite strong overall performance, the system exhibits certain limitations that warrant discussion:

Rainfall Threshold Sensitivity

The current model uses a 1.0 mm/day precipitation threshold to classify rainy days, following standard meteorological conventions [16]. However, this threshold may not fully align with event planning requirements. Even trace precipitation (<1.0

mm/day) can impact outdoor equipment setup, attendee comfort, and event logistics [17]. For water-sensitive equipment or high-value events, precipitation as low as 0.1 mm could be considered problematic.

Future iterations of this system should evaluate model performance across multiple threshold levels (0.1 mm, 0.5 mm, 1.0 mm, 5.0 mm) to provide event planners with graduated risk assessments [18]. Preliminary analysis suggests that lowering the threshold to 0.5 mm increases sensitivity (recall) by approximately 8-12% but reduces precision by 5-7%, creating a tradeoff between false alarms and missed detections. Event planners requiring maximum sensitivity should interpret our probability scores as continuous risk indicators rather than relying solely on binary classifications.

Class Imbalance Sensitivity

With 78% non-rainy days in the training data, the model shows slightly conservative bias. For applications requiring maximum sensitivity to rain (e.g., water-sensitive outdoor equipment), this bias is acceptable. However, for applications where false alarms are costly, threshold adjustment may be necessary.

Extreme Event Detection

Analysis of false negatives revealed that the model occasionally misses sudden, unpredicted rainfall events caused by localized convective storms. These events often lack clear precursor patterns in the meteorological variables and constitute approximately 15% of all rainy days.

Long-Lead Prediction Uncertainty

While the model performs well for seasonal predictions (2-6 months ahead), confidence naturally decreases for longer lead times due to limited predictive power of seasonal features alone.

Geographic Limitation

The model is trained on specific geographic coordinates. Predictions for locations more than 50km from the training site may exhibit reduced accuracy due to microclimate variations.

Data Dependency

The model's performance is fundamentally limited by MERRA-2 data quality and resolution. Localized phenomena smaller than the 0.5° × 0.625° grid resolution may not be captured.

Computational Efficiency and Scalability

From a practical deployment perspective, the system demonstrates excellent computational efficiency:

- Training Time: 45 minutes for 44 years of data (16,071 samples)
- Prediction Time: <100ms for single date prediction
- Memory Footprint: 2.4 GB (includes loaded models and feature transformers)
- Model Size: 187 MB (compressed ensemble model file)

These characteristics make the system suitable for deployment on standard hardware without requiring specialized infrastructure. The sub-second prediction time enables interactive use and real-time API integration.

Discussion and Implications

The results demonstrate that machine learning ensemble methods can effectively leverage long-term NASA Earth observation data for accurate rainfall prediction in event planning applications. Several key findings merit discussion:

Superiority of Ensemble Approach: The ensemble model's 93.2% ROC-AUC score represents a substantial improvement over individual classifiers and baseline methods. This validates the hypothesis that combining diverse algorithms (Random Forest's variance reduction and XGBoost's bias reduction) through meta-learning captures complementary predictive patterns. For instance, the model's ability to identify thermal dominance (with temperature features collectively accounting for 55% of importance) while appropriately weighting complementary moisture signals (17% combined importance) demonstrates sophisticated multi-scale pattern recognition that linear models or single algorithms cannot achieve. The ensemble architecture enables each base learner to specialize in different aspects of the prediction task—Random Forest excels at capturing temperature interaction effects, while XGBoost effectively models sequential pressure dynamics—with the meta-learner optimally combining these complementary strengths.Temperature Feature Dominance and Climate Implications: The analysis reveals a striking thermal dominance in rainfall prediction, with temperature-related features (T2M_MIN, heat_index, T2M_MAX, T2M, wind_chill) collectively accounting for over 55% of the model's predictive power. This finding has important implications for understanding precipitation patterns in continental climates. Unlike coastal or tropical regions where direct moisture measurements (humidity, cloud coverage) might dominate, Konya's continental climate exhibits rainfall patterns that are more strongly predicted by thermal conditions and stability. This suggests that temperature variability—which governs atmospheric mixing, moisture capacity, and stability—serves as the primary control on precipitation probability, with direct moisture indicators playing important but secondary roles.

Engineered Feature Success and Domain Knowledge: The exceptional performance of engineered thermal features—heat_index ranking 2nd (12.8%) and wind_chill ranking 5th (8.5%)—demonstrates the substantial value of incorporating meteorological and physiological domain knowledge into feature design. These indices, which combine temperature with humidity or wind speed, outperform numerous raw MERRA-2 variables and even outrank direct moisture measurements. Preliminary experiments using only raw MERRA-2 variables without engineered features achieved approximately 5-7 percentage points lower accuracy and 8-10% lower ROC-AUC scores, confirming that thoughtful feature engineering significantly enhances model performance. This success suggests that derived indices capturing atmospheric comfort or stress conditions effectively proxy for complex weather system characteristics that raw measurements cannot individually represent.

Moisture Features as Complementary Indicators: While moisture-related variables (moisture_index, CLOUD_AMT, RH2M) contribute meaningfully to predictions, their secondary ranking challenges common assumptions about precipitation prediction. The relatively low individual importance of RH2M (15th, 2.6%) despite humidity's physical necessity for precipitation suggests that ensemble models effectively leverage redundant information—humidity's signal is better captured through its interactions with temperature (heat_index) and clouds (moisture_index) rather than as an independent predictor. This redundancy highlights the value of ensemble learning approaches that can automatically identify and weight complementary versus redundant information sources.Temporal Robustness: The consistent performance across retrospective validation years (2020-2024) and low standard deviation ($\sigma = 0.006$) indicate that the model learns generalizable atmospheric patterns rather than memorizing specific historical events. This temporal robustness is critical for real-world deployment where the model must perform well on future dates.

Geographic Generalizability: The successful transfer of the modeling approach to four additional cities with diverse climates (continental, Mediterranean, oceanic) demonstrates that the methodology is not location-specific. Organizations could deploy similar systems for other geographic regions by retraining on local MERRA-2 data.

Practical Value for Event Planning: The case study of NASA Space Apps Challenge 2025 illustrates the system's practical utility. By identifying October 4-5 as optimal dates with <3% rain probability, event planners can make confident decisions about outdoor venue selection and logistics months in advance—a capability not available through traditional weather services.

Limitations and Future Directions: While the system performs well overall, several areas offer opportunities for improvement:

1. Incorporating Ensemble Numerical Weather Prediction (NWP) models: Integrating short-term NWP forecasts (1-15 days) with the machine learning predictions could improve accuracy for near-term events.

2. Multi-output prediction: Extending the model to predict not just rain occurrence but also rainfall amount, duration, and intensity would provide richer information for decision-making.

3. Uncertainty quantification: Implementing Bayesian approaches or conformal prediction to provide calibrated prediction intervals rather than point estimates would better communicate prediction uncertainty

4. Real-time model updating: Developing online learning capabilities to incorporate new observations and adapt to climate trends would maintain performance as conditions evolve.

5. Integration of additional data sources: Combining MERRA-2 with other satellite products (e.g., MODIS cloud properties, GPM precipitation) and ground-based measurements could enhance prediction accuracy.

This work demonstrates that the combination of high-quality Earth observation data, thoughtful feature engineering, and state-of-the-art machine learning techniques can deliver practical, reliable tools for weather-dependent decision-making. The open-source implementation enables other researchers and practitioners to build upon this foundation and adapt it to their specific needs.

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