



ForestGuard AI: AI-Based Forest Fire Risk Prediction System

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ABSTRACT :

Forest fires pose a significant challenge to environmental monitoring and forest management. Identifying districts with elevated fire-detection risk before a fire is detected may help authorities prioritize monitoring and preventive activities. This paper presents ForestGuard AI, a district-level machine-learning system that estimates the probability of at least one satellite fire detection occurring in a district on the following day. The study covers 13 districts in Uttarakhand, India, using 33,228 district-day records from 2018 to 2024. Historical meteorological observations from the Open-Meteo Historical Archive and satellite fire detections from NASA's Fire Information for Resource Management System (FIRMS) are combined with seasonal and geographic features. Thirty-three input features are used to train and evaluate Logistic Regression, Random Forest, and Histogram Gradient Boosting models. A chronological evaluation strategy assigns 2018–2022 to training, 2023 to validation, and 2024 to final testing. Histogram Gradient Boosting is selected using validation precision–recall area under the curve (PR-AUC) and probability calibration. On the 2024 test set, the selected model achieves a PR-AUC of 0.7094, ROC-AUC of 0.8731, and F1-score of 0.6941. The observed satellite-detection rate increases from 5.3% in the Low-risk category to 79.0% in the Extreme-risk category. However, a block-bootstrap comparison does not establish a statistically significant improvement over the district-and-month baseline. The model is deployed through a React frontend and FastAPI backend that provide district-level forecasts and risk visualizations. Satellite detections are not necessarily confirmed forest fires, and the study does not establish operational effectiveness. ForestGuard AI is therefore presented as a preliminary decision-support system requiring further validation.

Keywords: Forest fire risk prediction, machine learning, satellite fire detection, weather data, probability calibration, Uttarakhand, decision-support system.

INTRODUCTION

Forest fires can damage ecosystems, threaten biodiversity, affect nearby communities, and place pressure on forest-management resources. Timely identification of areas with elevated fire risk can help authorities prioritize monitoring and prepare appropriate responses. Conventional fire monitoring often relies on detecting active fires through observation or satellite systems. Although these approaches are valuable for identifying ongoing events, additional predictive information may help direct attention toward areas where fire detections are more likely to occur.

Weather and environmental conditions influence fire occurrence and spread. Temperature, humidity, wind, rainfall, soil moisture, and evaporative demand can provide information about short-term environmental dryness. Seasonal patterns and geographic characteristics can also influence the observed frequency of fire detections. Machine-learning models can combine these variables to estimate the probability of a future event.

This study presents ForestGuard AI, a district-level system for predicting next-day satellite fire-detection risk across 13 districts of Uttarakhand, India. The system combines historical weather information, recent rainfall history, seasonal features, geographic information, and satellite fire-detection records. Each observation represents one district on one day, and the prediction target indicates whether at least one qualifying satellite fire detection occurs in that district on the following day.

The project uses a chronological evaluation design to reduce the risk of information leakage from future observations. Records from 2018–2022 are used for training, 2023 for model selection and threshold determination, and 2024 for final evaluation. Logistic Regression, Random Forest, and Histogram Gradient Boosting are compared with simpler rule-based and lookup baselines. The selected model is calibrated and integrated into a web application.

ForestGuard AI also demonstrates how a trained model can be integrated into an operational software workflow. The React frontend presents district risk levels, rankings, trends, and warnings. A FastAPI backend retrieves weather forecasts, generates the required features, executes the model, and caches forecast results when external services are unavailable.

The contributions of this work are:

1. The construction of a chronological district-day dataset combining historical meteorological variables and satellite fire detections for 13 districts in Uttarakhand.
2. A comparison of three machine-learning classifiers using a time-based training, validation, and test strategy.

3. An evaluation of the selected model against simpler baselines, including a district-and-month lookup method.
4. A calibrated probability-to-risk classification scheme and an analysis of observed detection rates across risk categories.
5. An integrated web application that connects model inference, forecast data retrieval, district-level visualization, and cached results.

The study predicts satellite fire detections rather than independently verified forest fires. This distinction is important because satellite detections can include agricultural burning and other heat sources. The results should therefore be interpreted as evidence of next-day satellite-detection prediction performance, not proof of confirmed forest-fire prediction or improved firefighting outcomes.

OBJECTIVE:

The main objectives of ForestGuard AI are:

1. To develop a machine-learning system for estimating next-day satellite fire-detection risk across 13 districts of Uttarakhand, India.
2. To construct a district-day dataset by combining historical meteorological observations with NASA FIRMS satellite fire detections.
3. To engineer weather, recent rainfall history, seasonal, anomaly, and geographic features for risk prediction.
4. To train and compare Logistic Regression, Random Forest, and Histogram Gradient Boosting using chronological data splits.
5. To evaluate the selected model using PR-AUC, ROC-AUC, precision, recall, F1-score, and risk-category analysis.
6. To calibrate predicted probabilities and classify them into Low, Medium, High, and Extreme risk categories.
7. To deploy the trained model through a React frontend and FastAPI backend, providing district-level risk visualizations and forecast information.
8. To examine system limitations, including satellite-label uncertainty, residual probability overconfidence, and the need for further operational validation.

LITERATURE SURVEY

1. Machine Learning for Forest-Fire Risk Prediction

Machine learning techniques are widely used to analyse environmental data and identify patterns associated with fire occurrence. Breiman (2001) introduced the Random Forest algorithm, which combines multiple decision trees to improve prediction performance. Friedman (2001) presented gradient boosting as a method for improving predictive models by combining a sequence of weak learners. These approaches provide a foundation for analysing relationships between weather conditions, geographical characteristics, and historical fire observations. In ForestGuard AI, Logistic Regression, Random Forest, and Histogram Gradient Boosting are compared to estimate next-day satellite fire-detection risk.

2. Influence of Weather and Environmental Factors

Weather conditions such as temperature, humidity, rainfall, and wind influence the environmental conditions associated with fire activity. Historical weather observations can help identify seasonal patterns and changes in environmental dryness. Rainfall history, soil moisture, and evapotranspiration can provide additional information about recent environmental conditions. ForestGuard AI combines weather, historical rainfall, seasonal, anomaly, and geographical features to estimate the likelihood of a qualifying satellite fire detection in a district on the following day. The model's predictions represent detection risk and should not be interpreted as confirmation of an actual forest fire.

3. Satellite-Based Fire Detection

Satellite remote sensing enables fire-related thermal anomalies to be monitored over large geographical areas. NASA's Fire Information for Resource Management System (FIRMS) provides satellite-derived fire and thermal-anomaly information that can support historical fire monitoring and research (NASA FIRMS, n.d.). Such observations can be used to construct datasets for analysing fire-detection patterns. However, satellite detections may include agricultural burning and other heat sources and do not necessarily represent confirmed forest fires. ForestGuard AI uses NASA FIRMS VIIRS detections to construct its prediction target while acknowledging the uncertainty associated with satellite-derived labels.

4. Model Evaluation and Risk Classification

Reliable evaluation is essential for assessing machine-learning classification systems. Precision measures the proportion of predicted positive cases that are positive in the dataset, while recall measures the proportion of positive cases correctly identified. The F1-score combines precision and recall, whereas PR-AUC and ROC-AUC measure model ranking performance from different perspectives. Scikit-learn provides tools for classification evaluation and probability calibration (Pedregosa et al., 2011). ForestGuard AI uses chronological data splitting, with 2018–2022 for training, 2023 for validation, and 2024 for testing. The selected model's probabilities are calibrated and grouped into Low, Medium, High, and Extreme risk categories to support interpretation.

5. Research Gap and Motivation

Machine-learning models and satellite monitoring provide useful methods for analysing fire-related events, but important challenges remain. Satellite detections may not correspond to confirmed forest fires, and weather conditions can vary within a district. Model performance on historical data also does not automatically establish effectiveness in real-world fire prevention. These limitations highlight the need for chronological evaluation, transparent

risk communication, and further validation against independently verified fire records.

ForestGuard AI addresses these needs by combining historical meteorological data from the Open-Meteo Historical Archive, NASA FIRMS satellite detections, and geographical information for 13 districts of Uttarakhand, India. It compares Logistic Regression, Random Forest, and Histogram Gradient Boosting and selects a model using validation PR-AUC. The selected model estimates next-day satellite fire-detection risk and presents district-level results through a React frontend and FastAPI backend. The system is intended as a decision-support tool; further validation is required before its predictions can be used as evidence of operational forest-fire prevention.

6. Summary

Existing machine-learning methods, weather data, and satellite remote sensing provide a foundation for district-level fire-detection risk estimation. ForestGuard AI combines these sources with chronological model evaluation, probability calibration, and risk classification. The resulting web application presents predicted risk information to support monitoring and decision-making. Nevertheless, satellite-label uncertainty, limited within-district weather representation, and the need for additional independent validation remain important limitations.

METHODOLOGY

The methodology of ForestGuard AI consists of data collection, dataset preparation, feature engineering, model training, model evaluation, probability calibration, risk classification, and web application deployment. The system uses historical weather data and satellite fire detections to estimate the probability of a satellite fire detection occurring in a district on the following day.

1. Data Collection

Historical meteorological data for the period 2018–2024 are collected from the Open-Meteo Historical Archive using ERA5 reanalysis data. The dataset includes weather variables such as maximum temperature, humidity, wind speed, rainfall, evapotranspiration, and topsoil moisture.

Satellite fire-detection records are obtained from NASA's Fire Information for Resource Management System (FIRMS), using VIIRS satellite detections. Geographic boundaries from GADM are used to associate detections with the 13 districts of Uttarakhand, India.

2. Dataset Preparation

The collected data are combined to create a district-day dataset containing 33,228 records from 2018 to 2024. Each record represents one district on one day. Historical weather information is associated with the corresponding district, and satellite detections are used to construct the target variable.

The target is positive when at least one qualifying satellite fire detection occurs in a district on the following day. Otherwise, the target is negative. This approach enables the model to estimate next-day satellite-detection risk using information available for the current day.

3. Feature Engineering

Feature engineering is performed to extract useful information from the historical weather and geographical data. The system uses 33 input features divided into four main groups:

- Weather features: Maximum temperature, mean humidity, maximum wind speed, rainfall, evapotranspiration, topsoil moisture, and a vapour-pressure-deficit proxy.
- Historical weather features: Rainfall totals over the previous 3, 7, and 30 days, days since rainfall, and rolling averages of temperature and humidity.
- Seasonal and anomaly features: Month information and three weather-anomaly features.
- Geographical features: Latitude, longitude, elevation, and 13 district-indicator features.

These features represent current environmental conditions, recent weather history, seasonal variation, and differences between districts.

4. Model Training

Three machine-learning algorithms are trained and compared:

1. Logistic Regression: Used as a baseline classification method to model relationships between input features and the target.
2. Random Forest: Combines multiple decision trees to capture nonlinear relationships in the data.
3. Histogram Gradient Boosting: Builds an ensemble of decision trees sequentially to improve predictive performance.

The dataset is divided chronologically to simulate prediction on future data. Records from 2018–2022 are used for training, 2023 is used for validation and model selection, and 2024 is reserved for final testing. This strategy helps evaluate performance on a later period rather than randomly mixing observations from different years.

5. Model Selection and Probability Calibration

The models are compared using validation precision–recall area under the curve (PR-AUC). Histogram Gradient Boosting is selected based on its validation performance. Sigmoid calibration is applied to improve the interpretation of predicted probabilities, and a classification threshold of 0.33 is selected using validation F1-score performance.

The trained model estimates the probability of a qualifying satellite detection occurring in each district on the following day.

6. Model Evaluation

The selected model is evaluated on the independent 2024 test dataset using the following metrics:

- PR-AUC: Evaluates precision and recall across different classification thresholds.
- ROC-AUC: Measures the model's ability to rank positive cases above negative cases.
- Accuracy: Measures the proportion of correctly classified records.
- Precision: Measures the proportion of predicted positive cases that are positive in the dataset.
- Recall: Measures the proportion of positive cases correctly identified.
- F1-score: Combines precision and recall into a single measure.

The model is also compared with simpler approaches, including a district-and-month lookup baseline. A weekly block-bootstrap analysis is used to assess uncertainty in the performance differences.

7. Risk Classification

The predicted probabilities are converted into four risk categories to make the output easier to interpret:

- Low Risk: Probability below 25%.
- Medium Risk: Probability from 25% to below 50%.
- High Risk: Probability from 50% to below 75%.
- Extreme Risk: Probability of 75% or higher.

These categories help users identify districts with different levels of predicted satellite-detection risk and prioritize monitoring activities.

8. Web Application Deployment

The trained model is integrated into a web-based application using a React frontend and a FastAPI backend. The frontend presents district-level forecasts, risk categories, rankings, and visualizations. The backend retrieves weather forecast data from the Open-Meteo Forecast API, prepares the required features, and executes the trained model.

The model is stored as a serialized risk_model.joblib file. The application also uses a separate NASA FIRMS feed to display recent satellite detections. Caching and status indicators help communicate the availability of forecast information when external services are unavailable.

9. Limitations and Validation

The system predicts satellite-detection occurrence rather than independently verified forest fires. Agricultural burning and other heat sources may contribute to the labels, particularly in Haridwar and Udham Singh Nagar. The study also uses one weather sampling point per district, which cannot represent all local variations in terrain, vegetation, and weather.

Although the model demonstrates useful risk classification, its improvement over the district-and-month baseline is not statistically conclusive under the reported bootstrap analysis. Further validation using verified fire records, finer spatial data, and longer forecast horizons is required before operational effectiveness can be established.

EXISTING SYSTEM

1. Traditional Forest Monitoring

How it works:

Forest officials and local communities monitor forests through field inspections, visual observation, and reports of fire incidents.

Drawbacks:

- Depends on regular human observation.
- Fires in remote areas may be detected late.
- Continuous monitoring requires significant manpower.
- Does not always provide advance predictions of fire risk.

2. Satellite-Based Fire Detection

How it works:

Satellite monitoring systems identify thermal anomalies and provide information about possible fire-related events over large geographical areas.

Drawbacks:

- Primarily identifies detected events rather than predicting future risk.
- Satellite detections do not always represent confirmed forest fires.
- Cloud conditions, sensor characteristics, and detection limitations can affect observations.
- Additional analysis is required to prioritize districts for monitoring.

3. Weather-Based Fire Risk Assessment

How it works:

Weather conditions such as temperature, humidity, rainfall, and wind speed are used to assess environmental conditions associated with fire risk.

Drawbacks:

- Simple assessments may not capture complex relationships between weather variables.
- Seasonal and geographical differences can affect risk estimates.
- Fixed rules may not adapt well to changing environmental conditions.
- Risk estimates require appropriate historical data and validation.

4. Conventional Statistical Prediction Methods**How it works:**

Statistical techniques use historical observations and selected environmental variables to estimate the likelihood of fire-related events.

Drawbacks:

- Simple models may not capture complex nonlinear relationships.
- Prediction quality depends on the availability and reliability of historical records.
- Performance may vary across districts and time periods.
- Model predictions must be evaluated against suitable baselines before practical use.

PROPOSED SYSTEM

The proposed ForestGuard AI system uses machine-learning techniques to predict next-day satellite fire-detection risk across 13 districts of Uttarakhand, India. It integrates historical weather data, satellite fire detections and geographical information to generate district-level risk estimates. The system presents these predictions through an interactive web application to support forest monitoring and decision-making.

1. Data Collection and Integration

Objective: Collect environmental and geographical data required for fire-risk prediction.

How It Works:

- Historical weather data are obtained from the Open-Meteo Historical Archive using ERA5 reanalysis data.
- Historical satellite fire detections are collected from NASA FIRMS VIIRS data.
- GADM district boundaries are used to associate observations with the 13 districts of Uttarakhand.
- The collected information is integrated into a district-day dataset covering the period 2018–2024.

2. Data Preprocessing and Feature Engineering

Objective: Prepare the collected data and extract useful features for machine-learning prediction.

How It Works:

- Weather records and satellite detections are combined at the district-day level.
- The target variable indicates whether at least one qualifying satellite detection occurs in a district on the following day.
- A total of 33 input features are generated, including weather conditions, historical rainfall, rolling weather averages, seasonal patterns, weather anomalies and geographical information.
- The prepared dataset is divided chronologically to prevent future observations from being used during model training.

3. Machine-Learning Model Training

Objective: Develop and compare models for predicting next-day satellite fire-detection risk.

How It Works:

- Logistic Regression, Random Forest and Histogram Gradient Boosting are trained and evaluated.
- Data from 2018–2022 are used for training, 2023 for validation and 2024 for final testing.
- The models are compared using validation precision–recall area under the curve (PR-AUC).
- Histogram Gradient Boosting is selected based on its validation performance, followed by sigmoid probability calibration.

4. Model Evaluation and Risk Estimation

Objective: Evaluate the model and estimate district-level risk probabilities.

How It Works:

- The selected model is evaluated using PR-AUC, ROC-AUC, accuracy, precision, recall and F1-score.
- Its performance is compared with a district-and-month baseline.
- A weekly block-bootstrap analysis is used to examine uncertainty in the performance differences.

- The model generates a probability estimate for a qualifying satellite detection on the following day.

5. Risk Classification

Objective: Convert predicted probabilities into understandable risk categories.

How It Works:

- Predictions below 25% are classified as Low Risk.
- Predictions from 25% to below 50% are classified as Medium Risk.
- Predictions from 50% to below 75% are classified as High Risk.
- Predictions of 75% or higher are classified as Extreme Risk.
- The categories help users identify districts that may require closer monitoring.

6. Interactive Dashboard and Visualization

Objective: Present district-level risk information through an accessible web interface.

How It Works:

- The React frontend displays district-level risk estimates, maps, rankings and visual summaries.
- The dashboard provides information about vulnerable areas and changes in predicted risk.
- Analytics and historical records support the examination of fire-related patterns.
- Recent satellite detections are displayed separately from future risk predictions to distinguish observed events from model estimates.

7. Web Application Deployment

Objective: Integrate the trained model and external data services into a web-based decision-support application.

How It Works:

- The React frontend communicates with the FastAPI backend.
- The trained model is stored in a serialized risk_model.joblib file.
- The backend retrieves weather forecasts from the Open-Meteo Forecast API and prepares the required model features.
- A separate NASA FIRMS feed provides recent satellite-detection information.
- Caching and status indicators help communicate data availability when external services are unavailable.

8. Decision Support and Limitations

Objective: Support monitoring priorities while communicating the limitations of the predictions.

How It Works:

- District-level risk estimates help users identify areas that may need additional attention.
- Risk categories and visualizations support the interpretation of predicted conditions.
- Satellite detections are treated as indicators rather than confirmed forest fires.
- Further validation using verified fire records, finer geographical data and additional forecast periods is required before operational effectiveness can be established.

SYSTEM REQUIREMENTS

Hardware Requirements

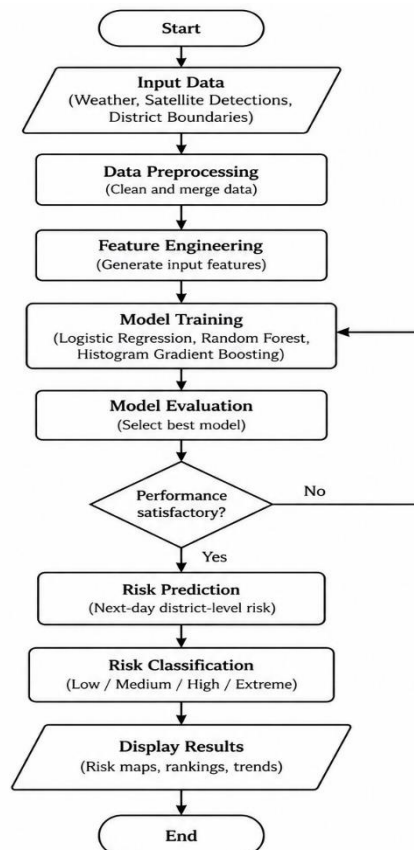
- Processor: Intel i3 or above
- RAM: Minimum 4 GB (8 GB recommended)
- Storage: Minimum 5 GB of free disk space
- Internet connection required for weather forecasts and satellite data retrieval
- Display device capable of running a modern web browser

Software Requirements

- Frontend: React 18
- Backend: FastAPI (Python)
- Machine Learning: Scikit-learn
- Prediction Model: Histogram Gradient Boosting
- Model Storage: Joblib (risk_model.joblib)
- Historical Weather Data: Open-Meteo Historical Archive (ERA5 reanalysis)

- Weather Forecast Data: Open-Meteo Forecast API
- Satellite Fire Detection: NASA FIRMS VIIRS data
- Geographical Data: GADM district boundaries
- Data Processing: Python-based feature engineering and preprocessing
- Development Tools: Git and a suitable code editor
- Deployment Platform: Render
- Web Browser: Google Chrome or any modern web browser
- Internet Access: Required for retrieving external weather forecasts and satellite-detection information

FLOWCHART:

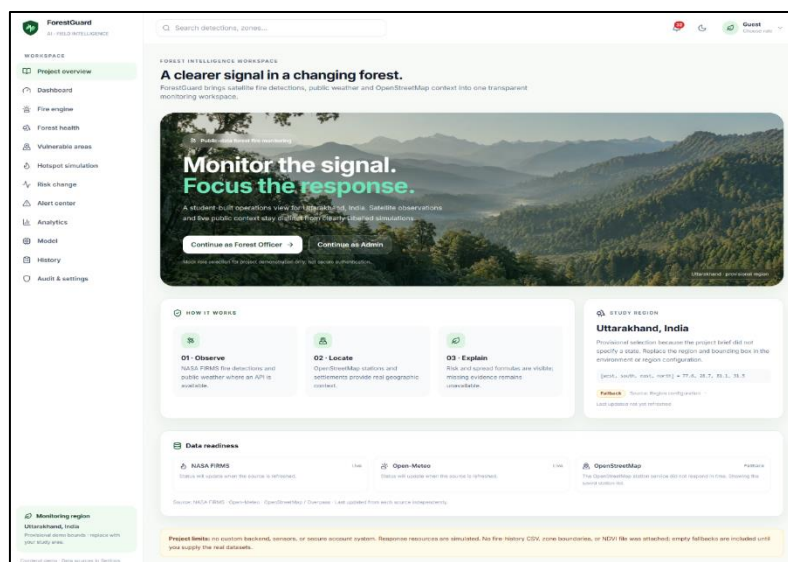


MODE OF DESCRIPTION

The ForestGuard AI web application consists of the following main modules:

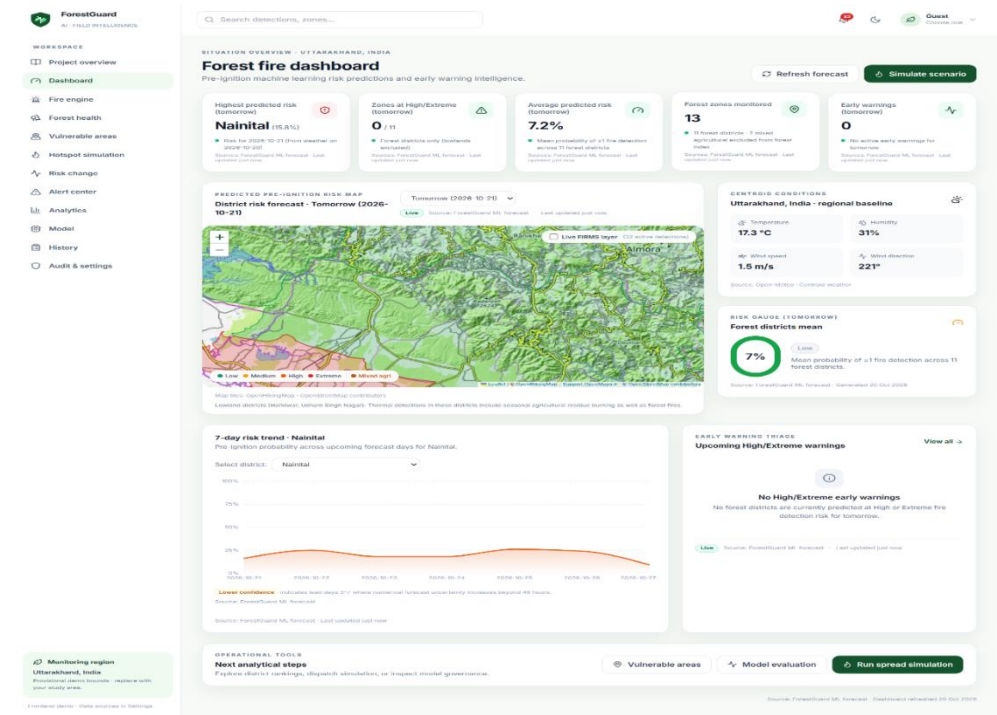
1. Project Overview Interface :

Introduces ForestGuard AI and provides an overview of the forest-fire monitoring system.



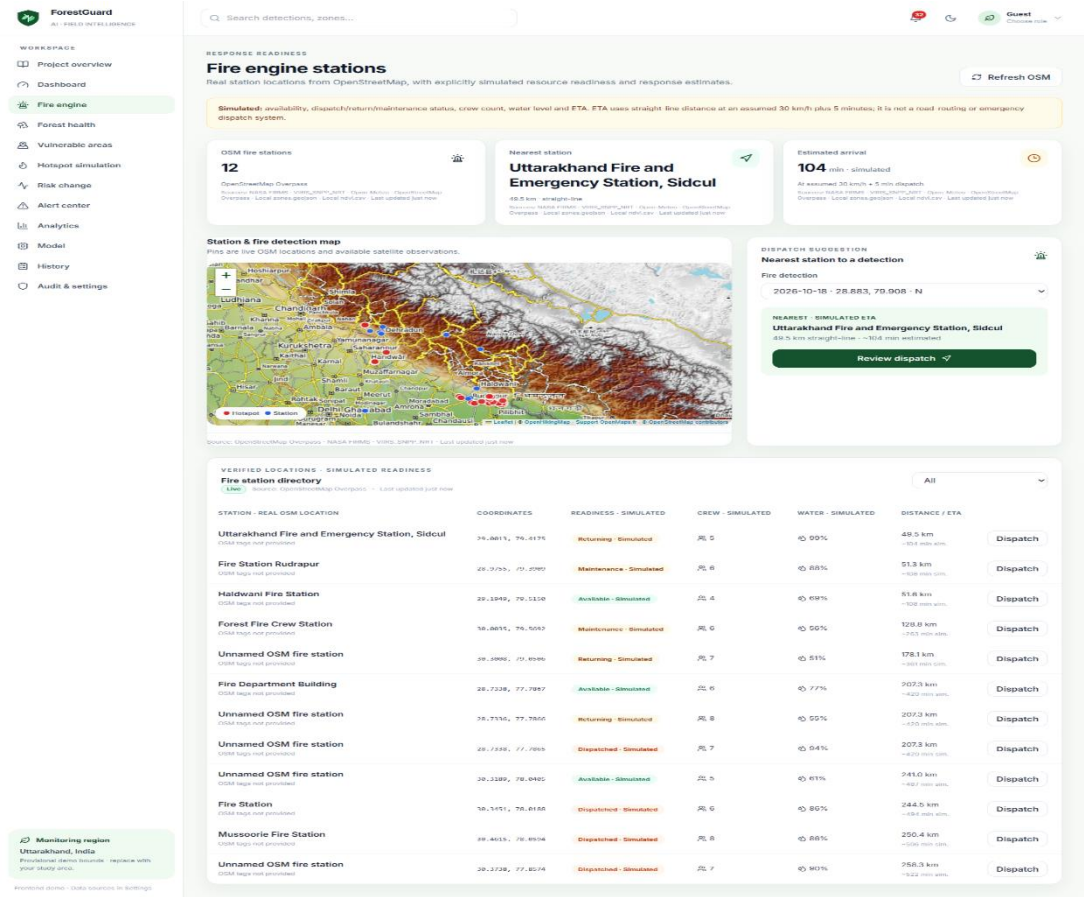
2. Dashboard :

Displays an overview of district-level fire risk, map visualizations, key indicators, and monitoring information.



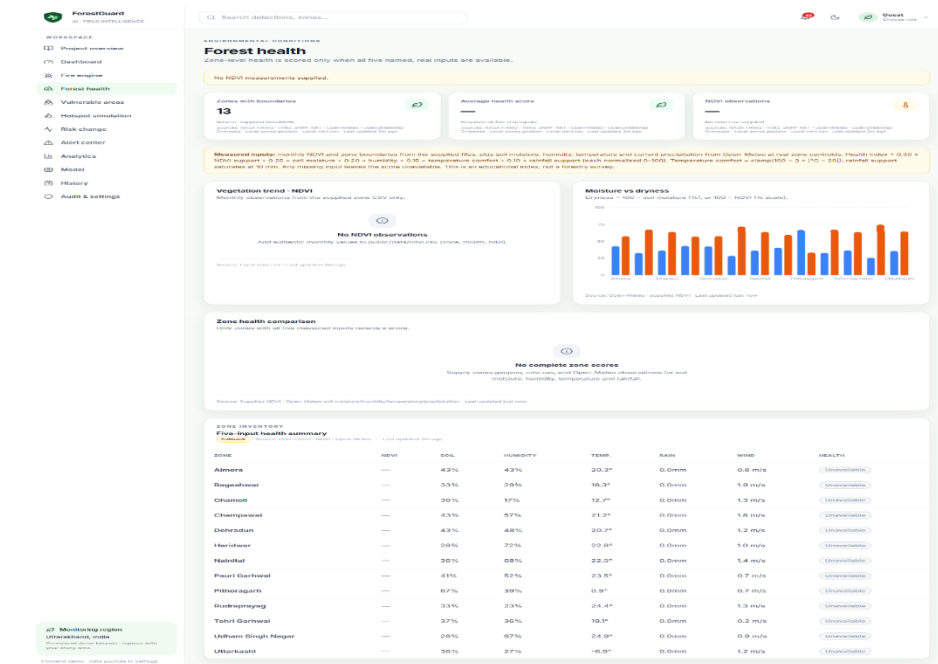
3. Fire Engine Station Interface:

Presents fire-related geographical information and station details to support monitoring and response planning.



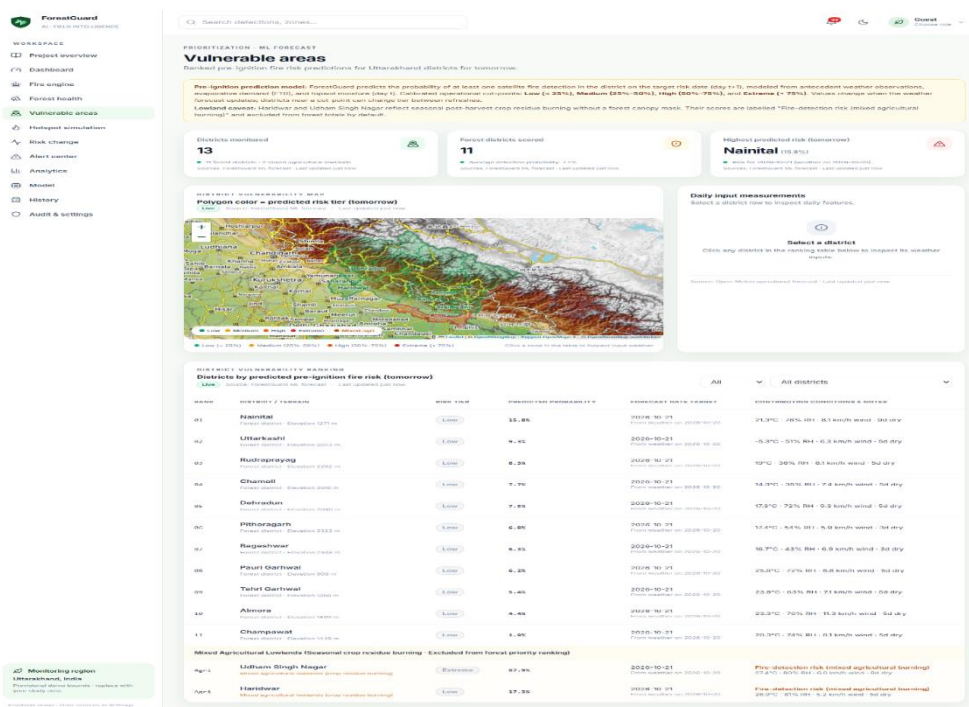
4. Forest Health Interface :

Displays forest-related indicators, environmental information, charts, and district-level data.



5. Vulnerable Areas Interface :

Identifies geographical areas that may require additional monitoring.



6. Hotspot Simulation Interface :

Provides a simulated interface for exploring hotspot scenarios under different conditions.

7. Risk Change Detection Interface :

Visualizes changes in predicted risk levels across locations and selected periods.

ZONE	SCORE: A	SCORE: B	CHANGE	CHANGE %	FIRE COUNT: A - B
Almora	Medium 27	Medium 27	0.0	0.0%	0 - 0
Bageshwar	Medium 33	Medium 33	0.0	0.0%	0 - 0
Chamoli	Medium 35	Medium 35	0.0	0.0%	0 - 0
Champurawat	Low 24	Low 24	0.0	0.0%	0 - 0
Dehradun	Medium 26	Medium 28	+2.9	+11.4%	0 - 2
Haridwar	Low 22	Medium 30	+7.3	+32.7%	0 - 5
Nainital	Low 22	Low 24	+1.5	+6.8%	0 - 1
Pauri Garhwal	Low 25	Low 25	0.0	0.0%	0 - 0
Pithoragarh	Low 25	Low 25	0.0	0.0%	0 - 0
Rudrapur	Medium 34	Medium 34	0.0	0.0%	0 - 0
Tehri Garhwal	Medium 29	Medium 29	0.0	0.0%	0 - 0
Udhampur Singh Nager	Low 24	High 32	+36.0	+145.8%	0 - 24
Uttarkashi	Medium 22	Medium 22	0.0	0.0%	0 - 0

8. Alert Centres Interface:

Displays fire-related alerts and details of potential risk events.

The screenshot displays the ForestGuard Alert Center interface. The left sidebar contains navigation options: Workspace, Project overview, Dashboard, Fire engine, Forest health, Vulnerable areas, Hotspot simulation, Risk change, Alert center (selected), Analytics, Model, History, and Audit & settings. The main content area is titled 'Alert center' and shows 'Manage upcoming pre-ignition early warnings from the ML forecast alongside active FIRMS satellite detections'. It features a search bar and filters for 'New' (32), 'Acknowledged' (0), and 'Resolved' (0). A list of satellite fire detections is shown, including details like location, date, time, and power. The right panel, 'Active fire details', shows information for a fire in Udhm Singh Nagar, including its status (Medium), power (15.6 MW), and coordinates. A map view of the fire location is also provided.

ForestGuard
AI-FIELD INTELLIGENCE

WORKSPACE

- Project overview
- Dashboard
- Fire engine
- Forest health
- Vulnerable areas
- Hotspot simulation
- Risk change
- Alert center**
- Analytics
- Model
- History
- Audit & settings

RISK TRIAGE & ALERTS

Alert center
Manage upcoming pre-ignition early warnings from the ML forecast alongside active FIRMS satellite detections

ML early warnings (tomorrow) 0 Active satellite fires (FIRMS) 32

New 32 Acknowledged 0 Resolved 0

Search location, date, satellite...

Source: NASA FIRMS - VIIRS_MFR_MDT (Last updated: 1m ago)

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.8833, 79.8434 - 19 Oct 2026 - 07:58 UTC - N
Power: 15.6 MW - confidence: 1

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.8832, 79.8553 - 19 Oct 2026 - 07:56 UTC - N
Power: 21 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.0154, 79.7472 - 19 Oct 2026 - 07:58 UTC - N
Power: 4.2 MW - confidence: 1

Satellite fire detection - Haridwar Mixed agricultural
29.7208, 77.9298 - 19 Oct 2026 - 07:59 UTC - N
Power: 15.4 MW - confidence: 0

Satellite fire detection - Dehradun
30.4588, 77.7858 - 19 Oct 2026 - 07:58 UTC - N
Power: 35 MW - confidence: 2

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9058, 79.4389 - 19 Oct 2026 - 08:13 UTC - N
Power: 1.8 MW - confidence: 1

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9082, 79.0097 - 19 Oct 2026 - 08:13 UTC - N
Power: 8.2 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9281, 79.7228 - 19 Oct 2026 - 08:13 UTC - N
Power: 9.3 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9271, 79.7419 - 19 Oct 2026 - 08:13 UTC - N
Power: 9.4 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9123, 79.7527 - 19 Oct 2026 - 08:13 UTC - N
Power: 5.5 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9126, 79.7305 - 19 Oct 2026 - 08:13 UTC - N
Power: 9.3 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9285, 79.2434 - 19 Oct 2026 - 08:13 UTC - N
Power: 1.9 MW - confidence: 1

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.8795, 79.4807 - 19 Oct 2026 - 07:56 UTC - N
Power: 9.2 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.8852, 79.8090 - 19 Oct 2026 - 07:56 UTC - N
Power: 4.3 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.8827, 79.719 - 19 Oct 2026 - 07:56 UTC - N
Power: 1.1 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.8788, 79.7888 - 19 Oct 2026 - 07:56 UTC - N
Power: 4.4 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9203, 79.5867 - 19 Oct 2026 - 07:56 UTC - N
Power: 7.9 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9277, 79.8523 - 19 Oct 2026 - 07:56 UTC - N
Power: 1.2 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9881, 79.7089 - 19 Oct 2026 - 07:56 UTC - N
Power: 8.1 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9881, 79.2821 - 19 Oct 2026 - 07:56 UTC - N
Power: 4.3 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
29.0156, 79.7766 - 19 Oct 2026 - 07:56 UTC - N
Power: 3.3 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9132, 79.7279 - 19 Oct 2026 - 07:56 UTC - N
Power: 3.0 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
29.0184, 79.7537 - 19 Oct 2026 - 07:56 UTC - N
Power: 2.9 MW - confidence: 0

Satellite fire detection - Nainital
28.6265, 79.7191 - 19 Oct 2026 - 07:56 UTC - N
Power: 1.9 MW - confidence: 0

Satellite fire detection - Haridwar Mixed agricultural
29.7376, 77.9342 - 19 Oct 2026 - 07:56 UTC - N
Power: 5.8 MW - confidence: 0

Satellite fire detection - Haridwar Mixed agricultural
29.7403, 77.9289 - 19 Oct 2026 - 07:56 UTC - N
Power: 3.2 MW - confidence: 1

Satellite fire detection - Haridwar Mixed agricultural
29.7410, 77.9334 - 19 Oct 2026 - 07:56 UTC - N
Power: 3.0 MW - confidence: 0

Satellite fire detection - Haridwar Mixed agricultural
29.9248, 78.1111 - 19 Oct 2026 - 07:56 UTC - N
Power: 2.1 MW - confidence: 0

Satellite fire detection - Dehradun
30.4584, 77.7867 - 19 Oct 2026 - 07:56 UTC - N
Power: 3.8 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9032, 79.9078 - 19 Oct 2026 - 08:13 UTC - N
Power: 2.3 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9629, 79.7436 - 19 Oct 2026 - 08:13 UTC - N
Power: 3.9 MW - confidence: 0

Satellite fire detection - Udhm Singh Nagar Mixed agricultural
28.9953, 79.7082 - 19 Oct 2026 - 08:13 UTC - N
Power: 4.7 MW - confidence: 0

Active fire details

Medium Mixed agricultural Status: New

Location: Udhm Singh Nagar

Acquired: 19 Oct 2026 - 07:58 UTC

Power: 15.6 MW

Confidence: 1 - categorical

Coordinates: 28.88329, 79.84336

Recommended action: Monitor the next satellite observation and check local conditions. Satellite detections require ground verification.

Acknowledge Resolve Dispatch (simulated)

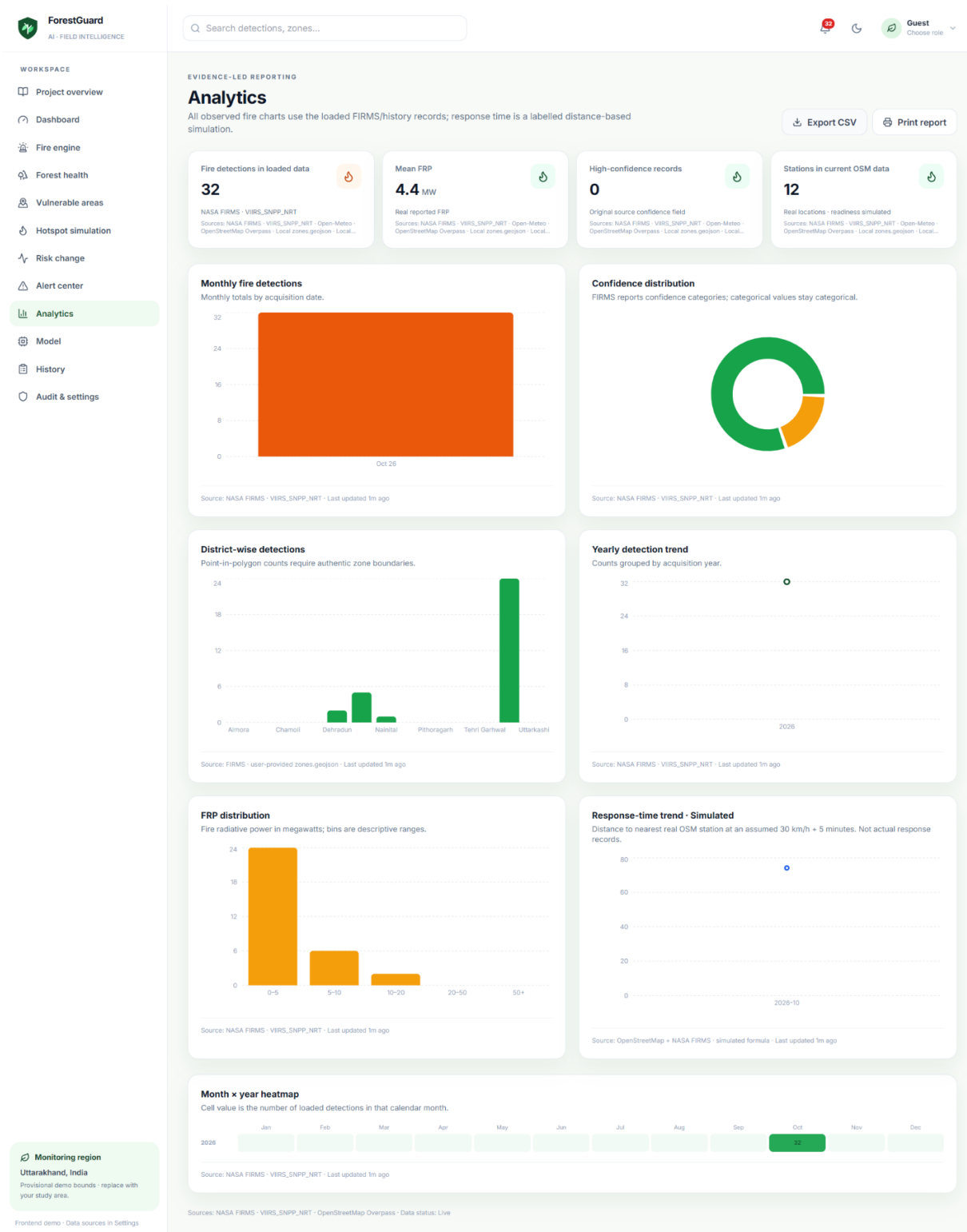
Source: NASA FIRMS - 1 min

Monitoring region
Uttarakhand, India
Pre-ignition alerts based on ML forecast - replace with your study area.

Powered by: Data sources in Settings

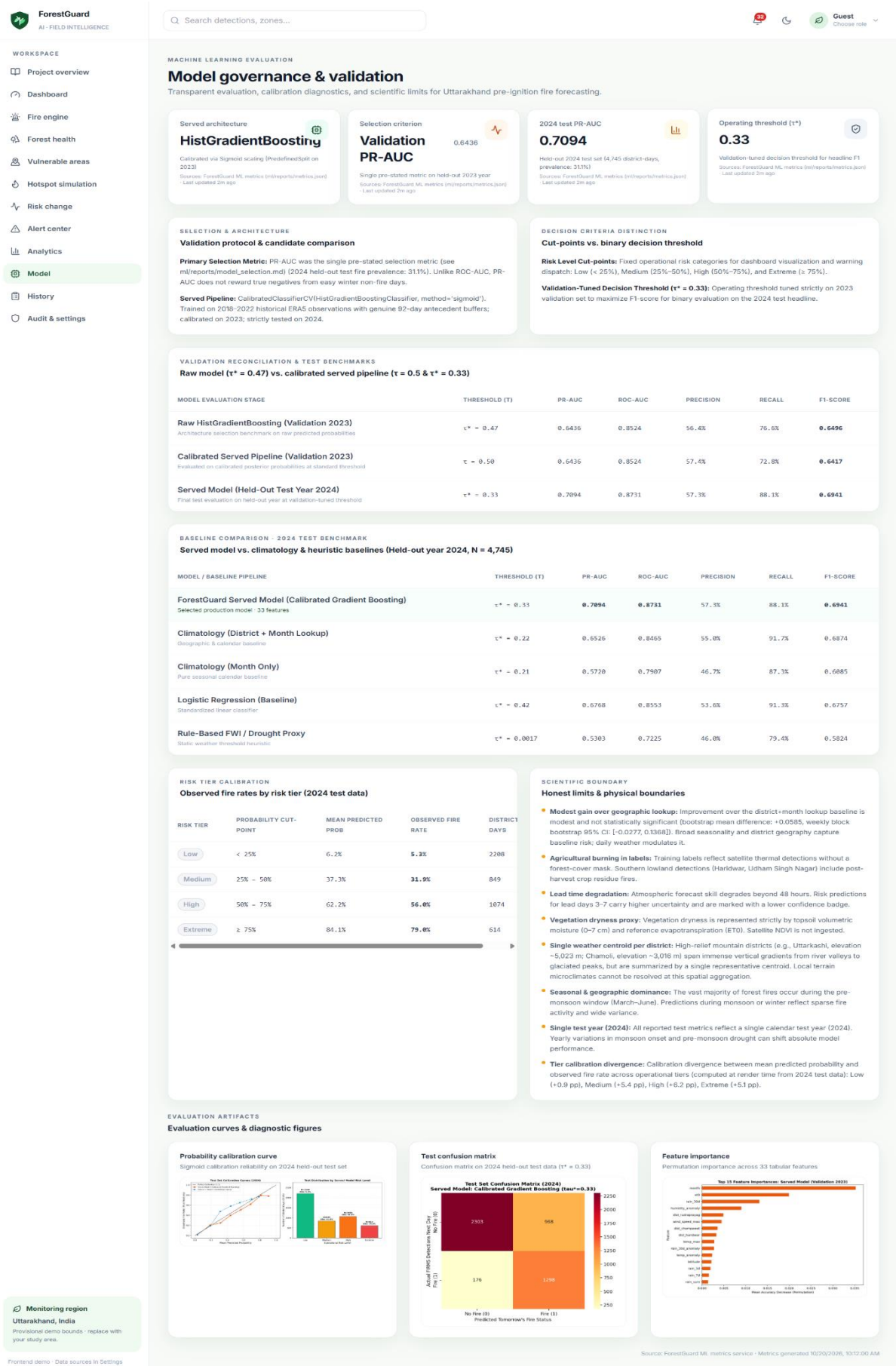
9. Analytics Interface:

Presents charts and statistics for analysing fire-detection patterns and system data.



10. Model Interface :

Displays model evaluation metrics, validation results, and prediction-model comparisons.



11. Fire History Interface :

Displays historical fire-related records in a structured table for review and analysis.

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Monitoring region

Uttarakhand, India

Provisional demo bounds - replace with your study area.

Frontend demo - Data sources in Settings

Q Search detections, zones...

32

Guest

Choose role

OBSERVED RECORDS

Fire history

Search, sort and export actual NASA FIRMS or supplied historical detections.

Export CSV

Q Search coordinates, date, satellite...

All

From

dd-mm-yyyy

To

dd-mm-yyyy

Live

Source: NASA FIRMS · VERS_SNPP_NRT · Last updated 3m ago

Date / time	Location	Zone	FRP	Confidence	Satellite	Day / night
19 Oct 2026 07:58 UTC	28.8795, 79.4887	Udham Singh Nagar	3.7 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.8802, 79.9096	Udham Singh Nagar	4.1 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.8827, 79.7119	Udham Singh Nagar	1.1 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.8833, 79.8434	Udham Singh Nagar	16.6 MW	Low	N	Low
19 Oct 2026 07:58 UTC	28.8852, 79.8553	Udham Singh Nagar	7.1 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.9156, 79.7668	Udham Singh Nagar	2.4 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.9287, 79.5967	Udham Singh Nagar	2.6 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.9377, 79.9263	Udham Singh Nagar	1.2 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.9681, 79.7189	Udham Singh Nagar	3.1 MW	Nominal	N	Low
19 Oct 2026 07:58 UTC	28.9951, 79.2821	Udham Singh Nagar	4.1 MW	Nominal	N	Low

32 record(s) · Page 1 of 4

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12. Audit Log and Settings Interface:

Provides audit-log information and application settings for system administration and review.

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Provisional demo bounds - replace with your study area.

Frontend demo - Data sources in Settings

Q Search detections, zones...

32

Guest

Choose role

GOVERNANCE & PREFERENCES

Audit log & settings

Audit entries are actual user actions stored locally. Settings affect this browser's demo experience.

Audit log

Profile

Alert thresholds

Notifications

Appearance

Data sources

REAL IN-APP ACTIONS ONLY

Local audit trail

Export CSV

Filter actions...

All

USER	ROLE	ACTION	MODULE	TIMESTAMP	STATUS
Guest	Guest	Ran hotspot spread simulation 3 hours	Simulation	20 Oct 2026 · 20 Oct, 09:15	Success
Guest	Guest	Updated alert thresholds	Settings	17 Oct 2026 · 17 Oct, 20:50	Success
Guest	Guest	Updated alert thresholds	Settings	17 Oct 2026 · 17 Oct, 20:49	Success
Guest	Guest	Updated alert thresholds	Settings	17 Oct 2026 · 17 Oct, 20:39	Success
Guest	Guest	Updated alert thresholds	Settings	16 Oct 2026 · 16 Oct, 10:12	Success
Guest	Guest	Updated alert thresholds	Settings	16 Oct 2026 · 16 Oct, 10:09	Success

Audit entries and settings are local to this browser. Role: Guest · User: Guest · Theme: light.

RESULTS AND DISCUSSION

1. Performance on the Test Dataset

The selected probability-calibrated Histogram Gradient Boosting classifier was evaluated using the independent 2024 test dataset. The dataset contains district-day observations from 13 districts of Uttarakhand, India. The evaluation measures the model's ability to estimate the probability of a qualifying satellite fire detection occurring on the following day.

Evaluation Metric	Result
PR-AUC	0.7094
ROC-AUC	0.8731
F1-score	0.6941

The ROC-AUC result indicates that the model can distinguish positive and negative observations reasonably well in ranking terms. The PR-AUC provides additional information about its performance in identifying positive observations. The F1-score represents the balance between precision and recall at the selected classification threshold.

2. Comparison of Machine-Learning Models

ForestGuard AI compares Logistic Regression, Random Forest, and Histogram Gradient Boosting. The models are selected and compared using a chronological data-splitting strategy, with 2018–2022 used for training, 2023 for validation, and 2024 reserved for final testing.

Histogram Gradient Boosting was selected based on its validation PR-AUC. The final test results should be interpreted using this selection procedure rather than choosing a model based on the test results alone. The reported comparison with the district-and-month baseline did not establish a statistically conclusive improvement.

3. Risk Classification

The model's predicted probabilities are grouped into four categories to make the results easier to interpret.

Risk Category	Predicted Probability
Low	Below 25%
Medium	25% to below 50%
High	50% to below 75%
Extreme	75% or higher

The categories help users identify districts that may require closer monitoring. They represent predicted satellite-detection risk and are not official fire-danger classifications.

4. Discussion

The results demonstrate that historical weather information, seasonal patterns, geographical features, and satellite observations can be combined to estimate next-day satellite fire-detection risk. The model's predictions are presented through a React frontend supported by a FastAPI backend, allowing users to view district-level risk information and related visualizations.

However, satellite detections do not always represent confirmed forest fires. Agricultural burning and other heat sources may contribute to the dataset labels. In addition, one weather sampling point per district may not capture local differences in terrain, vegetation, and weather conditions.

The reported results indicate useful predictive ranking performance on the evaluated dataset, but they do not establish that the system prevents forest fires or improves real-world emergency response. Further validation using independently verified fire records, finer spatial data, and additional test periods is needed before operational use.

CONCLUSION

ForestGuard AI provides a web-based approach to predicting next-day satellite fire-detection risk across 13 districts of Uttarakhand, India. By combining historical weather data, satellite fire detections, geographical information, and machine-learning techniques, the system estimates district-level risk and presents the results through an interactive web application. The comparison of Logistic Regression, Random Forest, and Histogram Gradient Boosting enables the selection of a suitable prediction model based on validation performance. Risk classification, district-level visualizations, and weather forecast integration help users identify areas that may require closer monitoring.

The system demonstrates the potential of combining environmental data and machine learning to support forest-fire monitoring and decision-making.

However, satellite detections do not always represent confirmed forest fires, and the model's improvement over a district-and-month baseline was not statistically conclusive in the reported analysis. Therefore, ForestGuard AI should be considered a decision-support system rather than a replacement for field verification or official fire-monitoring procedures. Future improvements may include verified fire records, finer geographical data, and further validation across locations and forecast periods.

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