Climate Change Impact on Food Security Using NASA POWER Data

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Abstract

Climate change has emerged as a critical global challenge affecting agricultural productivity and food security. This project analyzes climate variability across multiple Indian cities using NASA POWER data, focusing on rainfall trends and climate risk assessment. By integrating climate indicators with machine learning techniques, a food security risk index is developed to classify regions into varying levels of food insecurity. The results highlight the significant influence of rainfall variability on food security and demonstrate the effectiveness of data-driven climate analysis.

1 Introduction

Climate change significantly alters rainfall patterns, temperature, and extreme weather events, directly impacting agriculture and food availability. India, due to its diverse climatic zones, is particularly vulnerable. This project aims to assess climate-induced food security risks using authentic satellite-based climate data.

2 Objectives

- Analyze climate data from NASA POWER
- Study rainfall variability across Indian cities
- Develop a Climate Risk Score
- Create a Food Security Risk Index
- Visualize climate trends
- Predict food security status using machine learning

3 Data Source

The data used in this project is obtained from NASA POWER (Prediction Of Worldwide Energy Resources), which provides high-resolution, satellite-derived climate data.

Selected Cities

City	State	Climate Type
Prayagraj	Uttar Pradesh	Indo-Gangetic Plain
Jaipur	Rajasthan	Arid / Semi-Arid
Mumbai	Maharashtra	Coastal
Patna	Bihar	Flood-Prone
Bengaluru	Karnataka	Moderate / Plateau

4 Data Preprocessing

CSV files downloaded from NASA POWER were cleaned by removing metadata rows. Only the parameter `PRECTOTCORR_SUM` (corrected total precipitation) was selected. Annual rainfall values were extracted and city metadata was added. All datasets were merged into a single dataframe.

5 Feature Engineering

5.1 Rainfall Normalization

Rainfall values were normalized using Min-Max scaling to allow fair comparison across regions.

5.2 Climate Risk Score

Climate risk was calculated as the deviation of normalized rainfall from the mean rainfall. Higher deviation indicates greater climate instability.

6 Food Security Risk Index

A composite food security risk score was computed using weighted climate indicators:

$$FoodSecurityRisk = 0.5 \times ClimateRisk + 0.3 \times TemperatureStress + 0.2 \times LowRainfallPenalty$$

Classification

- Severe Insecurity: Score ≥ 0.66
- Moderate Insecurity: Score $0.33 - 0.66$
- Relatively Secure: Score < 0.33

7 Data Visualization

The following visualizations were created:

- Rainfall trend line plots
- City-wise rainfall comparison bar charts
- Climate risk heatmaps
- Feature importance plots
- Confusion matrix

8 Machine Learning Model

A Random Forest Classifier was used to predict food security status due to its robustness and interpretability. The model was trained using rainfall and climate risk indicators and evaluated using accuracy, precision, recall, and F1-score.

9 Results

The model successfully classified food security levels across cities. Climate Risk Score emerged as the most important feature, confirming the strong link between climate variability and food security.

10 Conclusion

This study demonstrates that climate variability significantly impacts food security. The integration of NASA POWER data with machine learning provides a reliable framework for climate risk assessment. The approach can support policymakers in planning climate-resilient agricultural strategies.

11 Future Scope

- Include temperature and humidity parameters
- Add crop yield data
- Expand analysis to more cities
- Apply advanced deep learning models

12 Tools and Technologies

Python, Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, NASA POWER Dataset, Kaggle Notebook.

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