Project Report
On
AI-Based Downscaling and Crop Resilience Mapping

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ABSTRACT

Climate change has significantly impacted agricultural productivity through unpredictable rainfall and rising temperatures. Global climate datasets are often available at coarse spatial resolutions, limiting their usefulness for local agricultural planning.

This project presents an AI-based downscaling framework to convert coarse climate data into fine-resolution local estimates and integrate them with crop yield data to generate crop resilience maps. Machine learning models are trained using historical climate and crop datasets to predict yield variations and assess crop resilience under changing climatic conditions. The results provide actionable insights for farmers, planners, and policymakers.

1. Introduction

Agriculture is highly sensitive to climatic factors such as temperature and rainfall. Traditional climate models operate at coarse resolutions (25–100 km grids), which are insufficient for district- or village-level agricultural decision-making.

Downscaling bridges this gap by translating large-scale climate information into fine-scale local predictions. When combined with AI and crop yield data, it enables the assessment of **crop resilience**, i.e., the ability of crops to withstand climate variability.

2. Objectives and Specifications

Objectives

- Perform AI-based downscaling of climate variables
- Predict crop yield using climate features
- Quantify crop resilience using predicted vs actual yield
- Generate crop resilience maps and visualizations

Specifications

- Temporal scale: Multi-year historical data
- Spatial scale: District-level or grid-level
- Climate variables: Rainfall, Avg/Max/Min Temperature
- Models: Machine Learning (Random Forest / XGBoost)

3. Literature Review

Climate downscaling is essential for converting coarse-resolution global climate model outputs into locally relevant information. Traditional statistical downscaling methods, such as linear regression and bias correction, are widely used but suffer from limitations due to their reliance on linear assumptions. These methods often fail to capture complex and non-linear relationships among climate variables, especially under extreme or changing climatic conditions.

Recent studies demonstrate that machine learning–based downscaling techniques provide improved accuracy by effectively modeling non-linear interactions between climate variables like rainfall and temperature. Algorithms such as Random Forest, Support Vector Machines, and Neural Networks have shown superior performance in generating fine-resolution climate estimates compared to conventional approaches.

Machine learning has also been extensively applied in crop yield prediction, where climate variables play a critical role in determining agricultural productivity. AI-based models outperform traditional models by identifying key climate patterns that influence crop growth and yield variability.

While AI techniques have been successfully used for climate downscaling and yield prediction independently, integrated crop resilience mapping remains a relatively unexplored area. Most existing studies do not combine downscaled climate data with yield response to assess crop resilience at local scales. This project addresses this gap by developing an integrated AI-based framework for downscaling and crop resilience assessment.

4. Methodology and Techniques

Overall Workflow

1. Data collection
2. Data preprocessing
3. Climate downscaling using ML
4. Crop yield prediction
5. Resilience index calculation
6. Visualization and mapping

Techniques Used

- Data normalization and feature engineering
- Supervised learning models
- Time-series trend analysis
- Statistical performance evaluation

5. Dataset Description

Climate Dataset

- Source: NASA POWER
- Variables:
  - Rainfall (mm)
  - Average Temperature (°C)
  - Maximum Temperature (°C)
  - Minimum Temperature (°C)

Crop Dataset

- Source: Government / FAOSTAT
- Variables:
  - Crop name
  - Area harvested
  - Yield (kg/ha)
  - District / Region

6. Model Description

Downscaling Model

- Input: Coarse-resolution climate variables
- Output: Fine-resolution climate estimates
- Algorithm: Random Forest / XGBoost

Crop Yield Prediction Model

- Inputs: Downscaled climate variables
- Output: Predicted crop yield
- Evaluation Metrics: RMSE, R^2 score

Resilience Index

Resilience Index=Actual YieldPredicted Yield\text{Resilience Index} = \frac{\text{Actual Yield}}{\text{Predicted Yield}}Resilience Index=Predicted YieldActual Yield

Classification:

- Highly Resilient (≥ 0.75)
- Moderately Resilient (0.50 – 0.75)
- Vulnerable (< 0.50)

7. Implementation

- Programming Language: Python
- Libraries: Pandas, NumPy, Scikit-learn, Matplotlib
- Steps:
  - Load and clean datasets
  - Train ML models
  - Predict yields
  - Compute resilience index
  - Generate plots and maps

8. Results

- Accurate downscaling of climate variables achieved
- Crop yield prediction shows strong correlation with rainfall and temperature

- Certain crops demonstrate higher resilience under moderate temperature ranges
- Visualizations include:
    - Yield vs Year time-series
    - Resilience class distribution
    - District-wise resilience maps

9. Conclusion

This project successfully demonstrates the effectiveness of an **AI-based framework for climate downscaling and crop resilience mapping**. By transforming coarse-resolution climate data into fine-scale local estimates, the proposed approach addresses a key limitation of traditional climate models and enhances their applicability for agricultural analysis and decision-making.

The integration of machine learning techniques enables accurate modeling of the complex and non-linear relationships between climatic variables and crop yield. The results indicate that factors such as rainfall variability and temperature extremes have a significant impact on crop productivity, and their influence can be effectively captured using AI-based models. Compared to conventional statistical approaches, the implemented machine learning models show improved predictive performance and robustness.

The crop resilience mapping component provides valuable insights by quantifying how different crops respond to climatic stress. Regions and crops exhibiting higher resilience can be identified, while vulnerable areas can be prioritized for intervention. This information is particularly useful for farmers, planners, and policymakers in developing climate-adaptive agricultural strategies.

Overall, the project establishes a scalable and data-driven framework that supports **climate-smart agriculture**. The methodology can be further extended by incorporating satellite imagery, real-time weather data, and high-performance computing resources to enhance spatial resolution and prediction accuracy. Such advancements would enable early warning systems and support long-term agricultural sustainability under changing climatic conditions.