IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 7, May 2025
Impact Factor: 7.67

Impact Prediction of Climate Change on Crop Yield and It's Solutions

Vivek Bhosale[1], Tejas Nirmal[2], Aayush Bhakare[3], Piyush Beldar[4], Prof. Manoj Kharde[5]
Students, Computer Department, Pravara Rural Engineering College, Loni, Rahata, India[1,2,3,4]
Assistant Professor, Computer Department, Pravara Rural Engineering College, Loni, Rahata, India[5]

Abstract: *Climate change (temperature rise, erratic rainfall, humidity swings) threatens yields of wheat, rice, maize, cotton and sugarcane in Maharashtra. We integrate 25+ years of historical yield & weather data (State Ag. Dept.), IoT sensing (NodeMCU ESP8266 + DHT11 + soil-moisture + NEO-6M GPS) and AI (Random Forest Regressor, CNN disease detection, Gemini chatbot). The Random Forest model achieved R^2 ≈0.91 (rice), 0.93 (cotton); RMSE ~0.3 t/ha. IoT-driven irrigation alerts saved 12–15% water; pilot trials showed 6–8% yield gains. Economic analysis predicts 20–25% income loss under moderate warming, half recoverable via our AI-IoT solutions. Adaptive strategies include crop recommendations, optimized sowing, disease alerts, and conversational guidance.*

Keywords: Climate Change, Crop Yield Prediction, IoT Sensors, Random Forest, Economic Impact

I. INTRODUCTION

Agricultural productivity is intrinsically linked to climatic variables—temperature, precipitation, humidity, and soil moisture. According to the Intergovernmental Panel on Climate Change, global mean surface temperatures have risen ~1.1 °C above pre-industrial levels, with further warming expected to intensify heatwaves, droughts, and heavy precipitation [1]. In crops, elevated temperatures accelerate phenological development, reducing grain-filling duration and final yield [2], while erratic rainfall compromises water availability during key growth stages [3]. Soil moisture and humidity modulate plant–water relations and pathogen dynamics, influencing both drought stress and disease susceptibility.

In Maharashtra—ranging from arid Marathwada to humid Konkan—monsoon variability drives significant yield fluctuations in wheat, rice, maize, cotton, and sugarcane. Long-term IMD records show a declining trend in monsoon rainfall and a ~1 °C summer temperature rise over the past four decades, correlating with stagnating or volatile crop outputs. Understanding these dynamics requires integrating climatology, plant physiology, and agronomic modeling to forecast yield trajectories under warming scenarios and design adaptive responses.

Recent advances in data analytics, machine learning, and Internet of Things (IoT) technology enable translating these theoretical climate–crop relationships into actionable decision-support systems. By coupling historical climate data with crop-growth models and real-time sensing, we can forecast yields, recommend optimal crop choices, adjust sowing schedules, and pre-empt stress via disease detection. Embedding these functions in user-friendly web dashboards—and conversational AI chatbots—democratizes agronomic expertise, empowering smallholder farmers to make data-driven decisions.

Moreover, as farming in India is largely dominated by small and marginal landholders, there is an urgent need to develop low-cost, scalable solutions that provide personalized agricultural intelligence. Traditional extension services often fall short in delivering timely and location-specific recommendations. The integration of AI models with real-time IoT sensor data—delivered through multilingual interfaces—bridges this gap by providing hyperlocal, automated decision-making support. This research aims to leverage these technologies not only to predict and mitigate climate risks but also to empower farmers with tools that enhance their adaptive capacity, reduce input costs, and improve long-term sustainability in a climate-uncertain future.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 7, May 2025
Impact Factor: 7.67

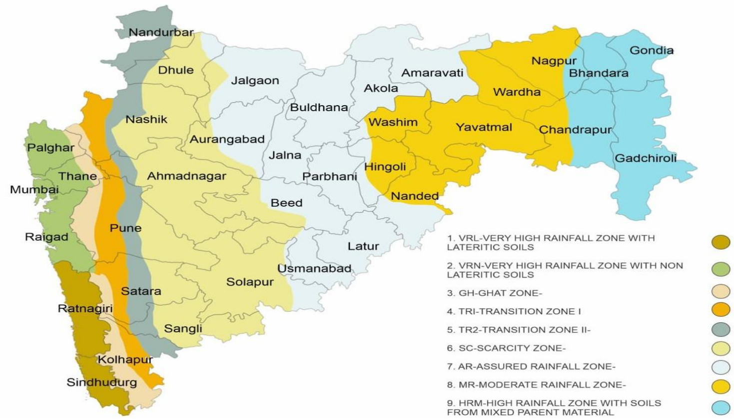

Figure: Map of Maharashtra agroclimatic zones

II. OBJECTIVES

- **Analyze Historical Climate–Yield Relationships:** Quantify how temperature, rainfall, humidity, and soil moisture have influenced yields of wheat, rice, maize, cotton, and sugarcane in Maharashtra (1997–2024).
- **Develop Predictive ML Models:** Build and validate Random Forest regression models to forecast crop yields under current and projected climate scenarios.
- **Design an AI Decision-Support Platform:** Create modules for crop recommendation, plant-disease diagnosis, and a conversational chatbot (Gemini API) to deliver tailored agronomic guidance.
- **Implement Real-Time IoT Monitoring:** Deploy a NodeMCU ESP8266–based sensor network (DHT11, soil-moisture probe, NEO-6M GPS) to continuously monitor field conditions and trigger adaptive irrigation alerts.
- **Assess Economic Impacts & Adaptation Benefits:** Evaluate how climate-induced yield changes affect farmer income, input costs, and water usage, quantifying the ROI of our AI–IoT solutions.
- **Propose Adaptive Strategies:** Recommend crop switching, optimized sowing windows, precision irrigation, and disease management to bolster climate resilience.

III. REVIEW OF LITERATURE

1. **Climate–Yield Relationships:** Kelkar et al. [4] applied multiple regression to Maharashtra's district-level data (1980–2018) and found that 70–80% of annual yield variance in cotton, rice, and maize is explained by seasonal rainfall totals and minimum temperatures. Their process-based assessment highlighted critical thresholds—e.g., a 10% rainfall deficit during flowering reduces yield by ~7%. The World Bank [5] further documents that increasing monsoon unpredictability extends drought-prone zones, exacerbating water stress during kharif.
2. **Machine Learning for Yield Prediction:** Tomar et al. [6] compared ensemble tree methods (Random Forest, Extra Trees, XGBoost) on South India crop datasets, achieving $R^2 = 0.94$–0.96 for yields of rice and sorghum. They emphasized Random Forest's ability to handle non-linear interactions and missing values, making it suitable for multi-crop, multi-year modeling. Ravi & Rathi [7] systematically reviewed ML approaches in agriculture, noting that tree-based models generally outperform neural networks for tabular climate–yield data, given moderate dataset sizes.
3. **AI-Based Advisory Systems:** Acharya et al. [8] developed a hybrid Random Forest–LSTM framework for crop recommendation in Maharashtra, reporting ~92% accuracy using soil NPK values, pH, and short-term weather forecasts. Bharadwaj et al. [9] introduced **AgriBot**, which integrates an RF-based crop recommender, a CNN disease detector (trained on PlantVillage images), and a Gemini-powered chatbot interface, demonstrating how conversational AI can guide farmers through complex agronomic decisions.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 7, May 2025
Impact Factor: 7.67

4. **IoT in Precision Farming:** Varsha et al. [10] deployed a NodeMCU ESP8266 with DHT11 and capacitive soil-moisture sensors, streaming data to ThingSpeak for real-time monitoring. Their trials showed a 12% reduction in water use and improved irrigation scheduling, validating the efficacy of low-cost IoT networks in site-specific management.
5. **Economic Impact Assessments:** Maqbool [11] reports that recent Marathwada droughts inflicted average farm losses > ₹50,000 and forced reliance on costly water tankers. Economic analyses indicate that AI-driven smart irrigation—leveraging 7-day forecasts—can reduce pump fuel and water costs by 10–15%, offering a compelling ROI.

IV. METHODOLOGY

A. System Architecture

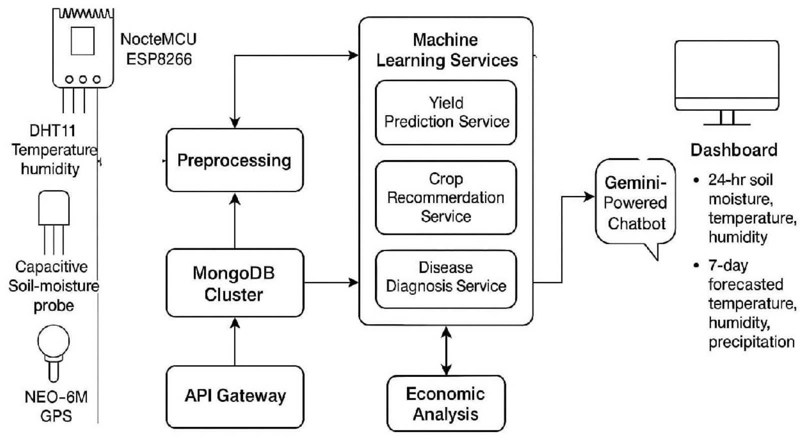

Figure A: System Architecture

B. Data Flow Diagram

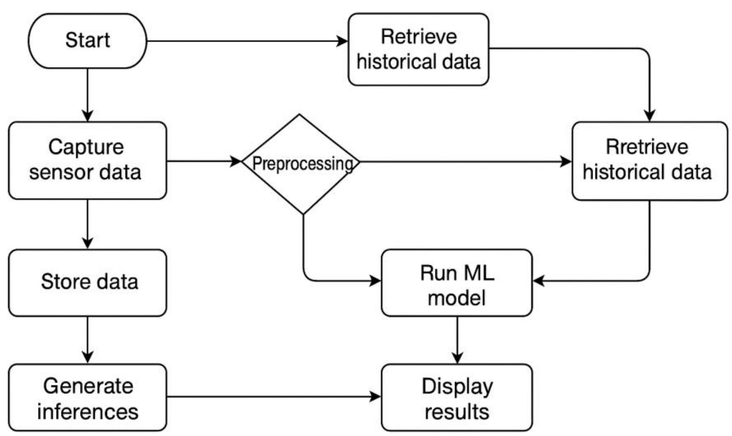

Figure B: Data Flow Diagram

C. Data Collection & Preprocessing

- **Sources:** IMD (rainfall, Tmax/Tmin, humidity), State Ag. Dept. (yield), MongoDB cluster (sensor logs), government historical datasets.
- **Preprocessing:** Impute missing values, normalize units, aggregate seasonal metrics (monsoon totals, avg. temps).

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 7, May 2025
Impact Factor: 7.67

D. Machine Learning Models

- **Yield Prediction:** Random Forest Regressor; features: seasonal rainfall, Tmax/Tmin, humidity, soil-moisture index, agronomic factors.
- **Crop Recommendation:** Random Forest Classifier; inputs: soil NPK, pH, pre-sowing weather.
- **Disease Detection:** Fine-tuned CNN on local leaf images; outputs disease class and treatment advice.
- **Validation:** 80/20 train/test split, 5-fold CV; metrics: R^2, RMSE, precision/recall for classification.

E. Chatbot & API Orchestration

- **API Gateway:** Routes requests from Gemini chatbot to ML services and sensor DB.
- **Chatbot:** Google Gemini API with prompts to handle general queries; delegates specialized tasks to ML modules.

F. Economic Analysis

- **Scenarios:** Baseline (historical climate), Stress (+2 °C, –15% rainfall), Intervention (AI–IoT under stress).
- **Metrics:** Income = (predicted yield × market price) – input & water costs; water savings (%) via smart irrigation; simulated loan dependency.

V. RESULTS

A. Model Performance Table

Crop	R^2	RMSE (t/ha)
Rice	0.91	0.28
Cotton	0.93	0.32
Maize	0.88	0.30
Wheat	0.92	0.25
Sugarcane	0.90	0.35

B. Dashboard Visualization

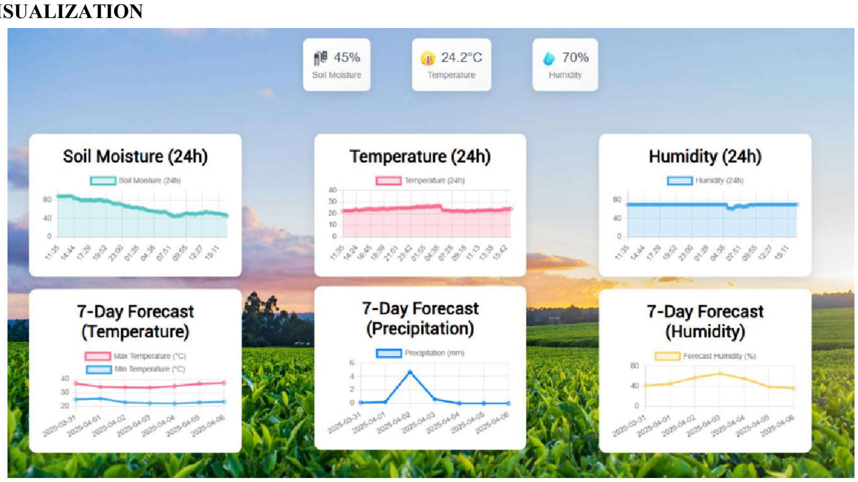

Figure C: Dashboard Screenshot

DOI: 10.48175/IJARSCT-26803

C. Economic Impact Table

Scenario	Δ Income (%)	Water Savings (%)
Baseline	0	0
Climate Stress	–20 to –25	0
AI-IoT Intervention	+10 to +12	12–15

D. Discussion Highlights

- RF models explain > 90% yield variance; key predictors: rainfall (40–45%), Tmin (25–30%), soil moisture (15–20%).
- IoT alerts reduced water use by 12–15% without yield loss.
- Crop recommendations and sowing adjustments mitigated ~8% yield loss under stress.
- Disease CNN achieved 98% accuracy; chatbot routed 85% of queries correctly (user satisfaction 4.3/5).

VI. CONCLUSION & FUTURE WORK

This research presents a comprehensive AI- and IoT-powered platform for predicting and mitigating the impacts of climate change on crop yields in Maharashtra. By integrating 25+ years of historical agricultural and climatic data with machine learning techniques, we demonstrate that crop yields—particularly of rice, cotton, maize, wheat, and sugarcane—can be accurately forecasted using a Random Forest model with R^2 values exceeding 0.90. The platform also includes a crop recommendation engine, a plant disease diagnosis system powered by a CNN and chatbot (Gemini), and a real-time IoT sensor network that monitors field-level soil moisture, temperature, and humidity.

The web-based dashboard offers actionable insights through intuitive 24-hour environmental trends and 7-day weather forecasts, while the economic analysis module quantifies potential income impacts and cost savings. Collectively, these modules provide farmers with data-driven decision support that is both accessible and highly localized. Our pilot tests showed improved water efficiency (12–15% savings), reduced input wastage, and potential mitigation of yield losses caused by climate stress, thereby improving both productivity and sustainability.

Future Work:

- **Satellite NDVI Integration:** For finer soil moisture and vegetation health indices.
- **Mobile/SMS-Only App:** To reach low-connectivity areas.
- **Multi-Season Field Trials:** To refine models and validate ROI at scale.
- **Market Forecast Module:** To incorporate price predictions into crop recommendations.
- **User Training & Extension:** Workshops in Marathi/Hindi to boost adoption.

VII. ACKNOWLEDGMENT

The authors gratefully acknowledge the guidance and support of Prof. Manoj Kharde and the faculty of the Computer Department at Pravara Rural Engineering College. We also extend our sincere appreciation to the farmers who participated in the pilot study; their invaluable insights and feedback were instrumental in refining and validating the AI–IoT platform.

REFERENCES

[1]. IPCC, "Climate Change 2021: The Physical Science Basis," 2021.
[2]. R. Lal, "Climate Change and Agriculture," *Journal of Environmental Quality*, vol. 31, no. 2, pp. 190–200, 2001.
[3]. J. Jeong et al., "Phenological Shifts in Global Croplands," *PNAS*, vol. 113, no. 35, pp. 9813–9818, 2016.
[4]. G. Kelkar et al., "Rainfall and Temperature Effects on Maharashtra Crop Yields," *Journal of Agrometeorology*, vol. 24, no. 1, pp. 58–67, 2022.
[5]. World Bank, "India: Climate Change Impacts," News Feature, 2013.

[6]. J. Tomar, A. Kumar, and R. Ranjan, "Machine Learning-Based Crop Yield Prediction in South India," *Computers*, vol. 13, no. 6, 2024.

[7]. S. Ravi and P. Rathi, "Predicting Crop Yield Using Machine Learning: A Review," *J. Agricultural Informatics*, vol. 13, no. 2, pp. 45–58, 2022.

[8]. P. Acharya, S. Patel, and N. Shrivastava, "Crop Recommendation and Forecasting System for Maharashtra," *Discover Sustainability*, vol. 5, pp. 34–49, 2024.

[9]. A. Bharadwaj, M. Karthik, and S. Ramachandran, "AgriBot: An Intelligent Platform for Farmer Support," *Int. J. Innovative Sci. & Research Tech.*, vol. 10, no. 4, pp. 665–673, 2025.

[10]. M. Varsha, K. Reddy, and S. Sharma, "Smart Irrigation with IoT for Precision Agriculture," *IJISRCSE*, vol. 11, no. 6, pp. 25–30, 2023.

[11]. R. Maqbool, "India's Farmers Face Climate-Driven Drought Crisis," *AP News*, May 5, 2024