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Assessment of Climate Change Patterns in Karnataka Using Machine Learning Approaches

Divyashree H S
Department of Computer Science and Engineering
Research Scholar (4PS20PCS03) , Visvesvaraya Technological University,Belagavi)
P.E.S College of Engineering , Mandya - 571401
divyasannamma1987@gmail.com

Dr.Girisha Raju
Professor
Department of Computer Science and Engineering ,
P.E.S College of Engineering , Mandya - 571401
write2girish@gmail.com

Dr.Piyush Kumar Pareek
Nitte Meenakshi Institute of Technology , Bengaluru
Piyush.kumar@nmit.ac.in

Abstract

Karnataka's diverse agro-climatic zones—from Coastal and Malnad to North and South Interior—have experienced notable hydro-climatic variability over recent decades. Robust, district-scale evidence is essential to understand changing rainfall and temperature patterns, extremes, and their implications for agriculture, water resources, and risk management. This article develops a machine-learning (ML) workflow to assess climate-change patterns in Karnataka by integrating long historical observations with bias-corrected global climate model outputs. We synthesize recent evidence on Indian rainfall trends and ML downscaling, then propose a practical pipeline for data curation, feature engineering, model training, and interpretability tailored to the state context. The approach emphasizes transparent benchmarking, uncertainty awareness, and operational usability for planners. A discussion of expected findings and validation strategies illustrates how ML models can complement conventional trend analyses, offering improved spatial specificity for intra-state planning. The study contributes (i) a Karnataka-focused synthesis of recent literature, (ii) an end-to-end ML assessment framework for regional climate applications, and (iii) guidance on integrating ML outputs into adaptation decisions.

Keywords: Karnataka; climate change; monsoon rainfall; machine learning; downscaling; trend analysis; hydrometeorology

Introduction

Karnataka spans markedly different rainfall regimes, from high-precipitation coastal belts to drought-prone interior districts. Agriculture, water supply, and urban drainage are highly sensitive to the spatiotemporal distribution of monsoon rainfall and temperature. Recent seasons have shown both localized deficits and surpluses, underscoring the need for district-scale diagnostics of trends, variability, and extremes. While statistical trend tools (e.g., Mann–Kendall, Sen's slope) remain valuable, they can be complemented by machine learning to capture non-linearities, teleconnections, and regime shifts that manifest at seasonal to multi-decadal scales.

Across India, advances in ML-based prediction and downscaling have improved skill in reproducing daily rainfall distributions and capturing complex processes missed by linear methods. Ensemble and hybrid deep-learning models, coupled with bias-corrected global climate simulations, offer a route to finer-scale assessments aligned to district planning horizons. Yet, Karnataka-specific synthesis remains fragmented across agro-climatic sub-regions and methods. Consolidating that evidence and operationalizing an ML pipeline for the state can accelerate sectoral planning.

This study takes a practice-oriented view: we curate recent evidence on Indian rainfall trends and ML downscaling and then propose a Karnataka-ready workflow for data ingestion, feature engineering, model building, and evaluation. The design principles emphasize reproducibility, interpretability, and measurable utility for line departments (agriculture, water resources, urban development). By anchoring the workflow to open, auditable datasets and rigorous validation, the intent is to balance innovation with trustworthiness.

Finally, we outline how outputs—trend maps, anomaly probabilities, and scenario envelopes—can feed water allocation, reservoir operation heuristics, sowing advisories, and urban flood preparedness. The goal is not only better prediction, but also decision-grade climate intelligence that acknowledges uncertainty and supports adaptive management.

Literature Survey

Recent work shows ML can complement statistical downscaling by capturing non-linearities and improving multi-model ensemble predictions of daily climate variables. A Scientific Reports study demonstrates that ML approaches enhance ensemble performance for daily precipitation, directly addressing stationarity and linearity limitations common in traditional downscaling. (Nature)

A 2023 Journal of Climatology study evaluates ML-based multi-model ensembles for climate applications and reports improved handling of spatiotemporal dependence structures relative to single-model baselines, underscoring ML's role in climate-change assessments where complex drivers and interactions matter. (Royal Meteorological Society)

National-scale rainfall change diagnostics highlight methodological best practices relevant to Karnataka. A 2023 study in *Hydrology Research* appraises Indian rainfall trend methods and demonstrates how choice of test and time window influences inference about change, reinforcing the need to triangulate classical trend tests with ML-assisted pattern discovery. (Journal of Farm Sciences)

Karnataka-focused evidence is emerging. A 2023 Springer article applies an innovative trend analysis to semi-arid districts, finding seasonally differentiated tendencies and emphasizing that monsoon-season trends can differ from post-monsoon behaviour—an important nuance for crop calendars and tank irrigation scheduling. (SpringerLink)

Complementing this, a 2023 article in the *Journal of Farm Sciences* analyzes historical and projected rainfall for South Interior Karnataka, integrating observations with projections to expose evolving seasonal distributions relevant to sowing and irrigation planning. (Journal of Farm Sciences)

On methods, neural and neuro-fuzzy approaches have been applied to Indian rainfall prediction problems, showing feasibility for quantitative forecasts and local customization, which supports sub-basin-level applications within Karnataka. (Taylor & Francis Online)

Hybrid deep-learning models (e.g., CNN-LSTM) have demonstrated improvements for multi-region Indian rainfall, emphasizing the value of multi-scale feature extraction and temporal memory—useful when translating large-scale drivers (ENSO/IOD) into district rainfall anomalies. (JATIT)

Methodological progress in downscaling CMIP6 rainfall over India shows that algorithm choice (ANN, K-NN, regression) and predictor selection materially affect local skill, guiding feature engineering and model selection for Karnataka districts. (Indian Academy of Sciences)

Bias-corrected CMIP6 evaluations report significant regional changes over peninsular India, indicating increased rainfall in parts of the southwest and peninsular zones; such diagnostics frame scenario design and stress testing for Karnataka. (ScienceDirect)

Finally, the ML community's parallel work on energy/carbon tracking (e.g., Carbontracker) is relevant for operational deployments of climate ML at scale, encouraging transparent, efficient modeling pipelines when institutionalizing such tools. (arXiv)

Research Methods and Discussion

Study area and data. The workflow targets Karnataka's four meteorological sub-regions: Coastal, Malnad, North Interior, and South Interior. Historical gridded rainfall and temperature (e.g., IMD) are collated with station data where available. Large-scale drivers (ENSO, IOD), land-surface indices, and orographic descriptors provide exogenous features. For future assessments, bias-corrected CMIP6 daily precipitation from multiple GCMs is ingested to build scenario ensembles aligned with mid-century horizons.

Pre-processing and quality control. Rigorous checks address missingness, inhomogeneities, and breakpoints. Classical trend diagnostics (modified Mann–Kendall; robust slope estimators) are computed per district and season to provide a statistical baseline, consistent with national-scale best practices. Features are standardized; temporal splits respect seasonality and serial dependence to avoid information leakage.

Modeling strategy. We compare three families: (i) tree-based ensembles (Random Forest/Gradient Boosting) for interpretability and robustness; (ii) recurrent or hybrid deep-learning models (LSTM/CNN-LSTM) for sequence learning and spatial context; and (iii) simple baselines (climatology, ARIMA-like) to anchor gains. Hyperparameters are tuned with nested cross-validation; models are tested on withheld years and, where possible, unseen districts to evaluate generalization.

Metrics and validation. Performance is summarized with MAE/RMSE for amounts, equitable threat scores for occurrence, and rank metrics for anomaly classification (e.g., terciles for deficit/normal/excess). Reliability diagrams and Brier skill quantify probabilistic skill. Spatial verification compares pattern correlations across districts and seasons. Sensitivity analyses test robustness to feature subsets (e.g., removing ENSO/IOD), and multi-model ensembles are combined using ML meta-learners to exploit complementary strengths documented in prior studies. (Nature)

Interpretability and use. Shapley-value summaries and partial dependence profiles reveal how synoptic predictors and antecedent moisture influence district-scale rainfall. For planning, outputs are delivered as (i) seasonal risk maps (probability of deficit/excess), (ii) extremal indicators (threshold exceedance likelihoods), and (iii) scenario envelopes (near-term decadal windows using bias-corrected CMIP6). Integration pathways include sowing advisories, tank/reservoir operation guidelines, and urban storm-water capacity checks.

Expected findings and implications. Based on Karnataka-focused and national evidence, we expect heterogeneity: semi-arid districts may show weak or no monsoon-season trend but clearer post-monsoon signals; coastal and Malnad zones may retain high totals yet exhibit shifting intra-seasonal distributions. ML downscaling should improve district-level daily distribution fidelity, aiding flood and drought preparedness. Embedding the pipeline within departmental workflows enables iterative refinement as additional station data and crowd-sourced observations become available. The approach is designed to be operationally maintainable and auditable, encouraging long-term institutional adoption.

Conclusion

Machine learning provides a pragmatic complement to conventional climate diagnostics for Karnataka, enabling district-scale assessment of changing rainfall patterns and extremes. By uniting robust pre-processing, transparent model benchmarking, and actionable probabilistic outputs, the proposed workflow supports sector decisions in agriculture, water resources, and urban resilience. Recent advances in ML-based downscaling and ensemble learning, combined with bias-corrected CMIP6 projections, make it feasible to create decision-grade maps and risk indicators tailored to Karnataka's sub-regions. Future work should prioritize expanding high-quality station networks, integrating hydrologic impact models (streamflow, recharge), and co-designing products with agencies to ensure sustained uptake. Operational governance—covering model updates, uncertainty communication, and efficiency of ML pipelines—will be essential as these tools transition from pilots to routine planning instruments.

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