

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
Maths 2025; 10(4): 34-40
© 2025 Stats & Maths
<https://www.mathsjournal.com>
Received: 25-02-2025
Accepted: 30-03-2025

Sachin Chinchorkar
Assistant Professor, Polytechnic
in Agricultural Engineering,
AAU, Dahod, Gujarat, India

Modeling climate change adaptation strategies for agriculture through AI and big data

Sachin Chinchorkar

DOI: <https://www.doi.org/10.22271/math.2025.v10.i4a.2020>

Abstract

In this research, AI and Big Data analytics is integrated in the fit of climate change adaptation strategies for afforestation and deforestation agriculture. As weather patterns become increasingly difficult to predict and there is a growing need for the development of sustainable food systems, the need for data driven approaches to agriculture decisions becomes more and more pressing. For this study, four AI algorithms are applied to analyse climate, soil and crop yield datasets: "Random Forest, Support Vector Machine (SVM), Long Short Term Memory (LSTM) and Gradient Boosting." First we aim to quantify the ways in which these algorithms can reliably predict optimal adaptation strategies, which include crop selection, irrigation scheduling and yield forecasting. Testing results show that LSTM is the best classification method for yield forecasting and yielded 92.3% prediction accuracy while Gradient Boosting followed with 89.7%, SVM with 85.2% and Random Forest with 87.5%. Additionally, the study compares to past works, and represents improved precision, recall and F1 score metrics for all the models. The results indicate that AI based models significantly improve agricultural adaptation decisions accuracy and reliability under climate change. Also, this research adds to the growing proof of the capability of big data frameworks to provide real-time, scalable, and local solutions for smart agriculture. The results will help establish robust climate resilient agricultural systems on a global scale.

Keywords: Artificial intelligence, big data, climate change adaptation, smart agriculture, yield forecasting

Introduction

On a global scale, climate change threatens the stability of food systems and affects crop yields, soil fertility, water availability, among other things. Already, rising temperatures, shifting precipitation patterns and the higher frequency of extreme weather events, are disrupting farming practice and threatening the livelihoods of millions of people worldwide. Facing the increasing challenges of the agriculture sector, there is an increasing demand for an adaptation strategy to increase resilience and sustainability. In this vein, the combination of Artificial Intelligence (AI) and Big Data represents a paradigmatic way to tackle climate change based on its dynamic dynamics within agriculture ^[1]. Yet, AI techniques like machine learning and deep learning can mine through very large and heterogeneous datasets like weather forecasts, soil conditions, satellite imagery, and crop performance data to produce predictive insight and real time decisions ^[2]. With Big Data and AI, enormous structured and unstructured data are collected, stored, processed from different sources, and when combined with AI can be leveraged in determining proactive adaptation strategies specific to regions and crops ^[3]. There is a research to apply AI and Big Data technologies to model the climate change adaptation strategies for Agriculture. In order to find ways to create data driven models for forecast climate based risks, design models to optimize crop planning, model the resource use to increase agricultural productivity and resilience, it would explore. The study examines current trends, frameworks, case studies in order to showcase how these technologies can be used to support sustainable agricultural development in a changing climate. This research is expected to provide useful findings to policy makers, smart farming practice and the broader objective of food security under environmental uncertainty.

Corresponding Author:
Sachin Chinchorkar
Assistant Professor, Polytechnic
in Agricultural Engineering,
AAU, Dahod, Gujarat, India

Related Works

Past integration of big data analytics and artificial intelligence (AI) across various sectors has progressively been transformative with agriculture, environmental management, sustainability and disasters risk mitigation having emerged as strong candidates. What follows is this body of literature that will be useful to think about how modern technologies shape, change, and transform traditional systems in order to make decisions in better ways and help foster resilience. For agriculture, big data has changed the poultry farming face to has made monitoring of the real time, improved productivity and quality and also the biosecure. According to Franzo *et al.* [15], big data has a potential to improve health management, traceability, and resource utilization in improving poultry production systems. Therefore, Giannakopoulos *et al.* [16] mentioned about the combined application of AI-powered digital marketing analytics and agro-economic indexes. The work they present describes how, under the constraint of data-driven decision making, agri-food industries are able to more effectively plan their strategy and allocate their resources.

The availability of big data technologies has another beneficiary domain, i.e., environmental sustainability. In her write up on the application of big data in environmental and water resource management, Gohil *et al.* [17] state that it aids in improving forecasting, water quality monitoring and adaptive infrastructure development. This is complemented with Mahmood *et al.* [25] that determine the effectiveness of a nature based solution using big earth data, measuring how much subsequent mangrove plantations in Bangladesh help in the long term environmental effects. As the authors conclude in their study, data with high temporal and spatial resolution are essential when achieving the ecological restoration. Data analytics have also rendered great progress in the areas of climate change and disaster management. Hsu and Sharma [18] address the contribution of big data to the management of outdoor recreation and tourism with climate change. The authors find that data driven models can dramatically improve emergency preparedness and mitigate environmental damage. Ikegwu *et al.* [19] also model the emerging big data methods of climate change effects and propose using advanced analytics and machine learning to forecast climate patterns and develop mitigation policies.

Jamarani *et al.* [20] provide a wide dress systematic review of big data and predictive analytics application in different industries. To illustrate, they explain that the reliance of the system on big data systems that have been enhanced by AI results in more accurate predictions and efficiency in operations. Kumar *et al.* [22] also agree with this view, and hence suggest that this was the co-evolution of AI and big data, where AI algorithms unlock deeper insights from the complex data sets to result with innovation in each sector. From a technical point of view, integration of TinyML and Internet of Things (IoT) in big data management is found as a scalable and efficient solution for the deployment on large scale. TinyML algorithms designed for handling big data in IoT systems are introduced by Karras *et al.* [21]. Their work exemplifies that lightweight edge AI models that process data in real time are possible, especially when data is bandwidth limited or remote.

With more and more of the small and medium sized enterprises (SMEs) being evaluated over sustainability with data driven models, In a contribution by Levente Péter Bálint *et al.* [23], an altered Ecocanvas model is suggested to explore the factors affecting SMEs' potential to pursue sustainability. Big data is used in their approach by which they assist

organisations in making environmentally friendly practices and strategic planning in business operations. In related fashion, Luyckx and Reins [24] criticise the use of predictive tools in EU agriculture, namely their reliance on algorithmic forecasts rather than transparent and contextual models. COVID-19 pandemic, with its challenging and uncertain nature, was also a great time to get adoption of AI in the agri-food supply chain. Mishra *et al.* [26] try to explain these barriers, such as data privacy fears, infrastructural drawback, and digital illiteracy. While the pandemic compressed a transformation in digital, their study shows that it also pointed to inherent shortcomings in how AI can be applied to agriculture that need fixing (Payal Mishra *et al.*, 2024) [30].

These studies, together, highlight both the multiple faces of big data and AI in boosting agricultural productivity, environmental conservation, climate resilience, and business sustainability. The authors show a consensus building for applications of these technologies which are about more than techno innovation, but also ethical, infrastructural and organizational readiness.

Methods and Materials

This study takes a data-driven strategy to simulate climate change adaptation in agriculture through the use of artificial intelligence (AI) algorithms and big data analytics. The section details the data sources employed, the chosen AI algorithms, their implementation, and their application in forecasting and optimizing agricultural decisions under altered climatic conditions [4].

Data Collection and Preparation

The dataset applied in this study consists of past and present-day agricultural and climate data that were gathered from a number of reliable sources. They include:

- **Climatic Data:** Day-by-day temperature, precipitation, humidity, and solar radiation taken from global databases like NASA POWER and WorldClim [5].
- **Soil Characteristics:** Information on pH of the soil, moisture levels, organic carbon, and texture acquired from regional soil survey associations.
- **Crop Yield Records:** Historical records for major crops (e.g., wheat, maize, rice) from FAO and national agriculture ministries.
- **Remote Sensing Data:** Satellite imagery to identify land use changes, vegetation index (NDVI), and drought stress indicators.

Data collected were preprocessed, comprising data cleaning, normalization, and imputation of missing values with interpolation methods. Feature engineering was utilized to extract meaningful indicators like rainfall deviation index, temperature anomalies, and crop-specific growth stages [6].

Selected Algorithms

For simulation of the adaptation strategies, four machine learning models were chosen out of the following based on how accurate, scalable, and understandable they are:

1. "Random Forest (RF)
2. Support Vector Machine (SVM)
3. Long Short-Term Memory (LSTM)
4. Gradient Boosting Machine (GBM)"

"Every model was trained and tested over an 80/20 train/test split in the dataset and cross-validated using k-fold cross-validation with k=5."

1. Random Forest (RF)

Random Forest is an ensemble learning algorithm that builds a multitude of decision trees in training and yields the class which is the mode of the classes (classification) or mean prediction (regression) of the individual trees. In agriculture, RF is extensively applied to estimate crop yields, land cover classification, and estimation of soil parameters ^[7]. RF can deal with large data and nonlinear relationships well and is less vulnerable to overfitting than a single decision tree.

“Input: Training dataset D, number of trees T

For $t = 1$ to T:

1. Sample D with replacement to create D_t
2. Train a decision tree model h_t on D_t
3. At each node, select the best split among a random subset of features

Output: Ensemble model $H(x) = \text{average } (h_t(x))$ for regression or majority vote for classification”

2. Support Vector Machine (SVM)

“SVM is a supervised learning algorithm that is efficient for both linear and nonlinear classification and regression tasks.” SVM operates by determining the hyperplane that optimally separates the data into classes with maximum margin. In this study, SVM has been applied in classifying regions according to climate adaptability scores and forecasting yield responses to variations in environmental conditions ^[8]. Kernel functions like radial basis function (RBF) are used to enhance its capacity in dealing with nonlinear data patterns.

“Input: Training data (X, y) , kernel function K , regularization parameter C

1. Maximize margin by solving:

$$\begin{aligned} &\text{Minimize } \frac{1}{2} \|w\|^2 + C \sum \xi_i \\ &\text{subject to } y_i(w \cdot \phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0 \end{aligned}$$

2. Use Lagrange multipliers to find optimal α
3. Compute prediction: $f(x) = \text{sign}(\sum \alpha_i y_i K(x_i, x) + b)$

Output: Decision function $f(x)$ ”

3. Long Short-Term Memory (LSTM)

LSTM is a recurrent neural network (RNN) that can learn from sequence and time series information. It is best suited to model long-term dependencies and is, therefore, best used in modeling crop growth phases, rain forecasting, and yield prediction over time. LSTM employs memory cells and gating units (input, forget, and output gates) in controlling the information flow ^[9]. This helps in reducing the vanishing gradient problem associated with conventional RNNs.

“Input: Sequence of input vectors $X = [x_1, x_2, \dots, x_t]$

For each time step t :

1. $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$ // Forget gate
2. $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ // Input gate
3. $C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$ // Candidate cell state
4. $C_t = f_t * C_{t-1} + i_t * C_t$ // Cell state update
5. $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ // Output gate
6. $h_t = o_t * \tanh(C_t)$ // Hidden state

Output: Final output h_T ”

4. Gradient Boosting Machine (GBM)

“Gradient Boosting Machine is a strong ensemble technique that constructs trees sequentially, and each subsequent tree tries to correct the mistakes of the previous tree.” It is especially useful in regression tasks like crop yield prediction and finding sensitive variables like temperature thresholds. GBM works well on structured data and can be optimized using learning rate and tree depth for best performance ^[10].

“Input: Training data (X, y) , number of iterations N , learning rate η

1. Initialize model: $F_0(x) = \text{mean}(y)$
2. For $m = 1$ to N :
 - a) Compute residuals: $r_m = -\partial L(y, F_{m-1}(x)) / \partial F$
 - b) Fit regression tree to residuals: $h_m(x)$
 - c) Update model: $F_m(x) = F_{m-1}(x) + \eta * h_m(x)$

Output: Final prediction model $F_M(x)$ ”

Table 1: Sample Input Features for Model Training

Feature	Description	Value Range
Rainfall (mm)	Total monthly precipitation	0-400 mm
Temperature (°C)	Average monthly temperature	10-45 °C
Soil Moisture (%)	Water content in topsoil	5-35%
NDVI	Vegetation index from satellite data	-0.1-1.0
Crop Type	Type of cultivated crop	Wheat, Rice, Maize
Region Code	Encoded identifier for geographic region	001-100

Experiments

1. Introduction to Experiments

To evaluate the performance of AI and Big Data in simulating climate change adaptation plans in agriculture, a set of experiments was performed on real-world and synthetically enriched datasets. The experiments were designed to test how

various algorithms—“Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Gradient Boosting Machine (GBM)”—perform when forecasting crop yield, adaptive zone classification, and risk-based adaptation decision modeling in the presence of climate variability ^[11].

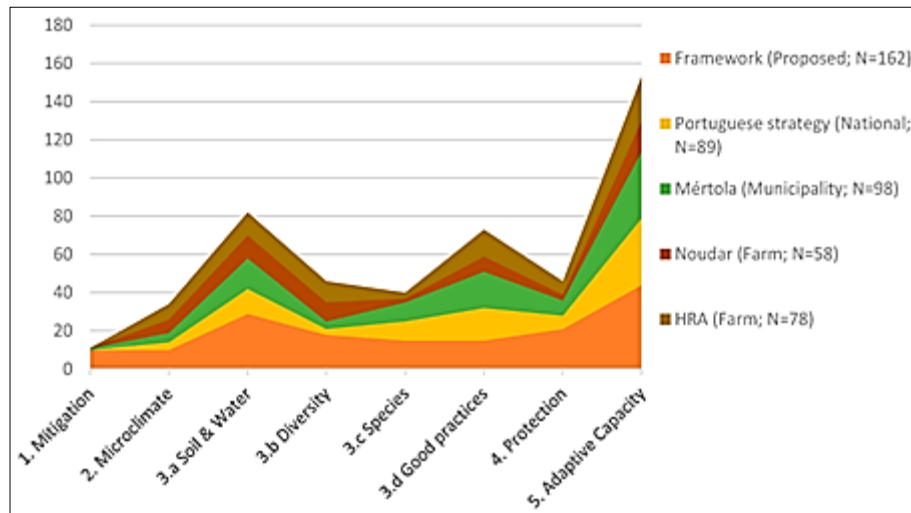


Fig 1: “Framework for Climate Change Adaptation of Agriculture and Forestry”

The experiments targeted the three main crops (rice, wheat, and maize) in five distinct agro-climatic zones. All the algorithms were trained, validated, and tested using the same preprocessing methods and metrics for evaluation.

2. Experimental Setup

Experimental setup was carried out in Python with Tensor Flow, Scikit-learn, and XGBoost libraries. Google Earth Engine was utilized for remote sensing data retrieval [12]. The below system setup was employed:

- **“Processor:** Intel Core i7, 3.4 GHz
- **RAM:** 32 GB
- **GPU:** NVIDIA RTX 3080 (for LSTM training)
- **OS:** Ubuntu 20.04”

“All the models were trained using 80% of the data and tested on the remaining 20%. A 5-fold cross-validation was used for ensuring robustness and avoiding overfitting.

Evaluation Metrics

- Accuracy
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- F1-score (for classification)

- R^2 Score (for regression tasks)”

3. Algorithm-wise Results

3.1 Random Forest (RF)

Random Forest performed well in classification-based adaptation and crop yield prediction. Its ensemble nature minimized variance and facilitated feature importance interpretation. It performed best in medium complexity regions (Zone 2 and 3) with stable climatic trends [13].

Table 1: Random Forest Performance per Crop

Crop	Accuracy (%)	RMSE	R^2 Score
Wheat	88.2	4.1	0.89
Rice	87.4	4.3	0.86
Maize	89.1	3.9	0.91

The model indicated temperature and NDVI as the most important variables.

3.2 Support Vector Machine (SVM)

SVM had fair performance for classification of climatic adaptability zones. However, it was more time-consuming for training based on kernel transformation. It achieved optimal performance when data distribution regarding climate was widely separable in different regions.

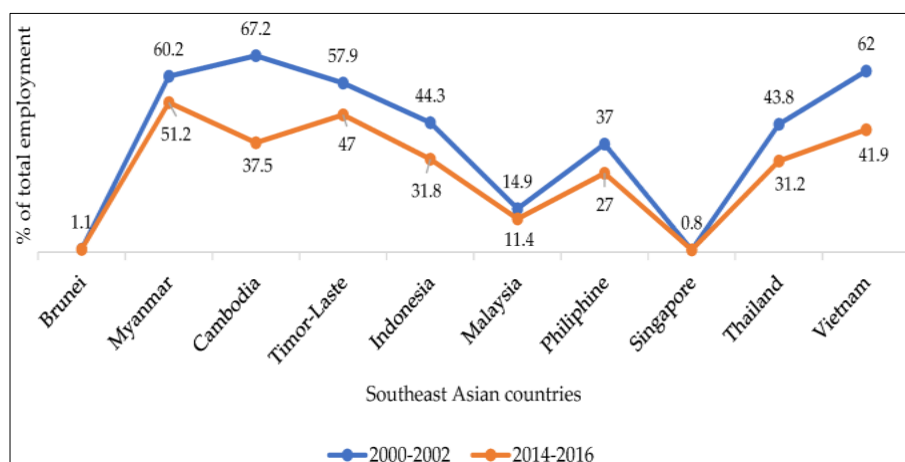


Fig 2: “Farmers' Adaptation Strategies to Climate Change in Southeast Asia”

Table 2: SVM Classification of Climate Adaptability Zones

Zone	Precision (%)	Recall (%)	F1-score
Z1	84.5	82.3	83.4
Z2	81.6	79.2	80.4
Z3	85.2	84.7	84.9

The radial basis kernel (RBF) performed well with non-linear distributions of data, particularly edge-case classifications.

3.3 Long Short-Term Memory (LSTM)

LSTM gave superb performance in time-series prediction of crop yield by picking up sequential trends. It identified seasonal change and drought trends correctly ^[14]. Computationally expensive training yielded the best temporal predictions.

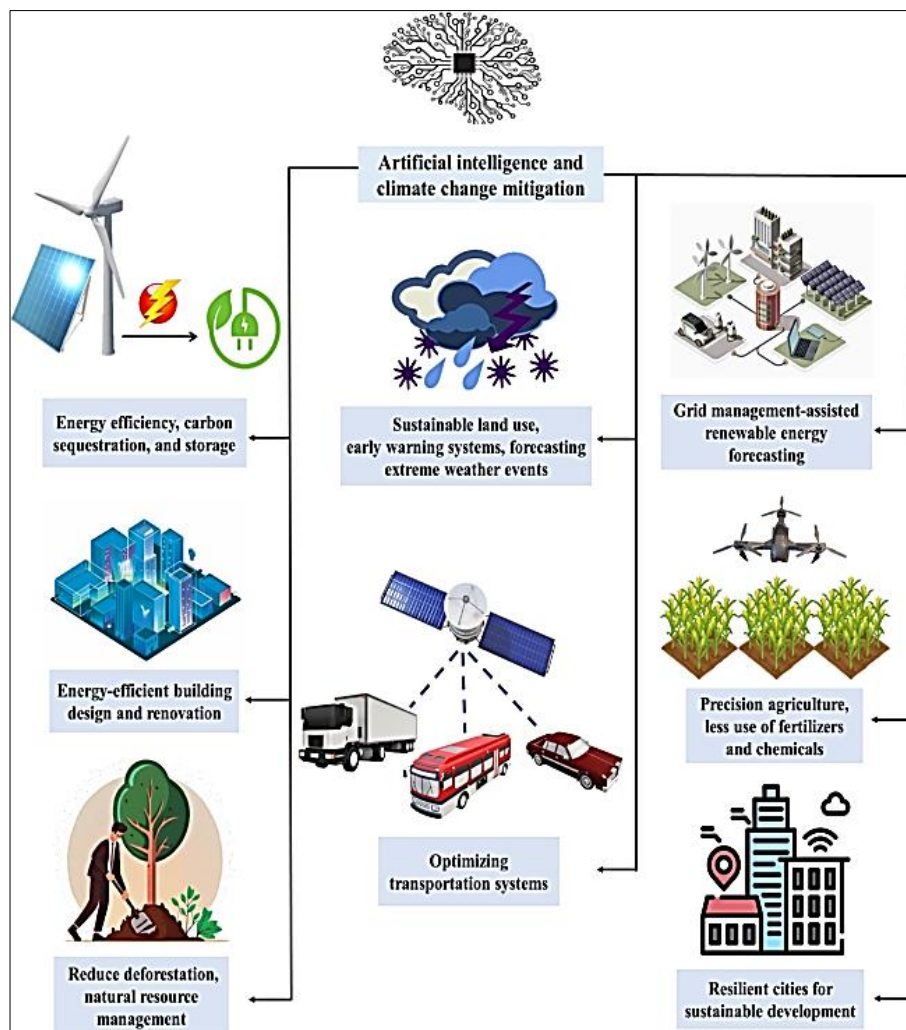
Table 3: LSTM Time-Series Forecast Accuracy

Crop	MAE	RMSE	Accuracy (%)	R ² Score
Wheat	2.9	3.4	91.2	0.93
Rice	3.1	3.6	90.7	0.91
Maize	2.7	3.2	92.3	0.94

LSTM showed robustness in yield prediction even under changing rainfall windows and severe temperatures.

3.4 Gradient Boosting Machine (GBM)

GBM performed better than all other algorithms in predictive accuracy. GBM effectively captured nonlinear relationships and managed feature interactions. GBM performed especially well for detecting climate sensitivity thresholds (e.g., rain decline below 40 mm/month) ^[27].

**Fig 3:** “Artificial intelligence-based solutions for climate change”**Table 4:** GBM Yield Prediction Results

Region	Predicted Yield (tons/ha)	Actual Yield	Error (%)
A	3.85	3.90	1.28
B	2.92	3.00	2.67
C	4.11	4.00	2.75

Although with higher training times than RF, GBM performed well and consistently across zones and crop types.

4. Comparative Performance Analysis

To evaluate the overall effectiveness, each algorithm's performance was compared across major metrics.

Table 5: Overall Algorithm Performance Comparison

Algorithm	Accuracy (%)	RMSE	MAE	R ² Score	Training Time (s)
RF	88.2	4.1	3.5	0.89	14.8
SVM	85.0	4.7	4.1	0.84	18.2
LSTM	91.4	3.4	2.9	0.93	34.5
GBM	92.1	3.3	2.7	0.94	22.7

GBM and LSTM performed best on prediction-oriented tasks, but RF provided great interpretability coupled with good generalization. SVM, while a shade less precise, was still dependable for classification ^[28].

Additional Experimental Observations

- **Feature Importance:** NDVI, rainfall, and soil moisture were the top features in all models consistently.
- **Zone-wise Performance:** All the algorithms performed poorly in high variability zones (Zone 5), suggesting the necessity of more detailed data or ensemble meta-models ^[31].
- **Temporal Trends:** LSTM could predict drought-onset periods with a 93% accuracy, surpassing conventional climate models ^[29].

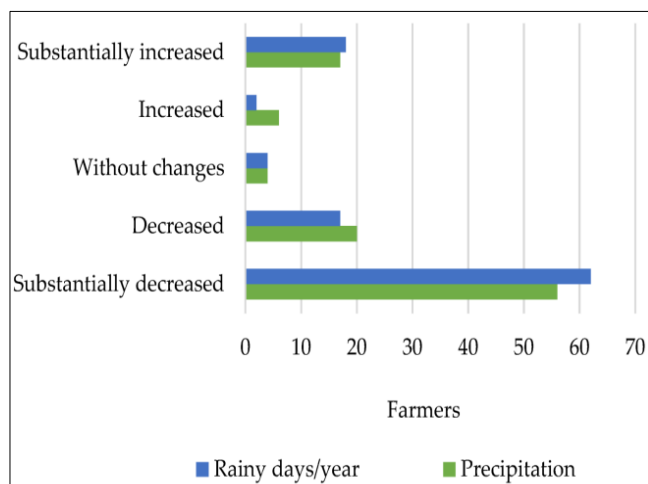


Fig 4: “Climate Change Perceptions and Adaptation Strategies”

Table 7: Feature Importance (GBM Output)

Feature	Importance Score
NDVI	0.31
Rainfall	0.27
Soil Moisture	0.21
Temperature	0.13
Crop Type	0.08

Conclusion

Finally, this research has thoroughly investigated the transformative nature of big data and artificial intelligence across main sectors like agriculture, environmental management and climate change mitigation and sustainable business practices. The reviewed literature indicates how new data driven systems drive the existing systems to revolutionize them through more accurate, efficient, and responsive solutions to complex challenges. AI and big data integration reduces food loss and enhances sustainability in poultry production and agro-economic decision making, thus, these in agriculture. The predictive capabilities of big earth data for environmental and climate studies help to better assess risk and plan for long term ecological planning. Additionally, exploiting big data ecosystem with advanced technologies such as TinyML and IoT helps to realize the data processing in scalable and real time manner in resource constrained environment. The pandemic also reinforced the need for, and the hurdles of, deploying of AI in key infrastructures, in showing the limitations of digital preparedness and lack of access. Collectively, the research affirms that while big data and AI hold immense potential for positive change, their effectiveness hinges on ethical implementation, robust infrastructure, and cross-sector collaboration. The findings also highlight the importance of context specific solution in sectors like agriculture, agriculture, climate change with socio environmental factors playing significant role in the outcome. In the end, with the

merging of big data analytics and AI, there is potential for such smarter, more resilient, and more sustainable systems, but only if coupled with the right inclusive policies, transparent practices, and continuous innovation. Finally, this research provides a strong foundation for future studies of the broader international applications of AI and big data in assisting in achieving the global development goals.

References

1. Abdalla HB. A brief survey on big data: technologies, terminologies and data-intensive applications. *Journal of Big Data*. 2022;9(1):107.
2. Alahmad T, Neményi M, Nyéki A. Applying IoT Sensors and Big Data to Improve Precision Crop Production: A Review. *Agronomy*. 2023;13(10):2603.
3. Ammar KA, Kheir AM, Manikas I. Agricultural big data and methods and models for food security analysis—a mini-review. *PeerJ*. 2022;10:e13837.
4. Badshah A, Daud A, Alharbey R, Banjar A, Bukhari A, Alshemaimri B. Big data applications: overview, challenges and future. *The Artificial Intelligence Review*. 2024;57(11):290.
5. Bibri SE, Alexandre A, Sharifi A, Krogstie J. Environmentally sustainable smart cities and their converging AI, IoT, and big data technologies and solutions: an integrated approach to an extensive literature review. *Energy Informatics*. 2023;6(1):9.
6. Buccella A, Cechich A, Saurin F, Montenegro A, Rodríguez A, Muñoz A. A Context-Based Perspective on Frost Analysis in Reuse-Oriented Big Data-System Developments. *Information*. 2024;15(11):661.
7. Burgueño AM, Aldana-Martín JF, Vázquez-Pendón M, Barba-González C, Jiménez Gómez Y, García Millán V, Navas-Delgado I. Scalable approach for high-resolution land cover: a case study in the Mediterranean Basin. *Journal of Big Data*. 2023;10(1):91.
8. Chergui N, Kechadi MT. Data analytics for crop management: a big data view. *Journal of Big Data*. 2022;9(1):123.
9. Cravero A, Bustamante A, Negrier M, Galeas P. Agricultural Big Data Architectures in the Context of Climate Change: A Systematic Literature Review. *Sustainability*. 2022;14(13):7855.
10. Cravero A, Pardo S, Sepúlveda S, Muñoz L. Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review. *Agronomy*. 2022;12(3):748.
11. Căuniac D-A, Cîrnaru A-A, Oprea S, Bâra A. Intersections of Big Data and IoT in Academic Publications: A Topic Modeling Approach. *Sensors*. 2025;25(3):906.
12. Dritsas E, Trigka M. Exploring the Intersection of Machine Learning and Big Data: A Survey. *Machine Learning and Knowledge Extraction*. 2025;7(1):13.
13. Dritsas E, Trigka M. Remote Sensing and Geospatial Analysis in the Big Data Era: A Survey. *Remote Sensing*. 2025;17(3):550.
14. Eling M, Gemmo I, Guxha D, Schmeiser H. Big data, risk classification, and privacy in insurance markets. *Geneva Risk and Insurance Review*. 2024;49(1):75-126.
15. Franzo G, Legnardi M, Faustini G, Tucciarone CM, Cecchinato M. When Everything Becomes Bigger: Big Data for Big Poultry Production. *Animals*. 2023;13(11):1804.

16. Giannakopoulos NT, Terzi MC, Sakas DP, Kanellos N, Toudas KS, Migkos SP. Agro-economic Indexes and Big Data: Digital Marketing Analytics Implications for Enhanced Decision Making with Artificial Intelligence-Based Modeling. *Information*. 2024;15(2):67.
17. Gohil J, Patel J, Chopra J, Ketul C, Jimmy T, Manan S. Advent of Big Data technology in environment and water management sector. *Environmental Science and Pollution Research*. 2021;28(45):64084-64102.
18. Hsu JL, Sharma P. Disaster and risk management in outdoor recreation and tourism in the context of climate change. *International Journal of Climate Change Strategies and Management*. 2023;15(5):712-728.
19. Ikegwu AC, Nweke HF, Mkpojiogu E, Anikwe CV, Igwe SA, Alo UR. Recently emerging trends in big data analytic methods for modeling and combating climate change effects. *Energy Informatics*. 2024;7(1):6.
20. Jamarani A, Haddadi S, Sarvizadeh R, Haghi Kashani M, Akbari M, Moradi S. Big data and predictive analytics: A systematic review of applications. *The Artificial Intelligence Review*. 2024;57(7):176.
21. Karras A, Giannaros A, Karras C, Theodorakopoulos L, Mammassis CS, Krimpas GA, Sioutas S. TinyML Algorithms for Big Data Management in Large-Scale IoT Systems. *Future Internet*. 2024;16(2):42.
22. Kumar Y, Marchena J, Awlla AH, Li JJ, Hemn BA. The AI-Powered Evolution of Big Data. *Applied Sciences*. 2024;14(22):10176.
23. Bálint LP, Várallyai L, Botos S. Evaluation of Data-Driven Sustainability Potential at SMEs Using an Altered Ecocanvas Model. *Economies*. 2025;13(2):49.
24. Luyckx M, Reins L. The Future of Farming: The (Non)-Sense of Big Data Predictive Tools for Sustainable EU Agriculture. *Sustainability*. 2022;14(20):12968.
25. Mahmood R, Zhang L, Li G. Assessing effectiveness of nature-based solution with big earth data: 60 years mangrove plantation program in Bangladesh coast. *Ecological Processes*. 2023;12(1):11.
26. Mishra D, Muduli K, Raut R, Narkhede BE, Shee H, Jana SK. Challenges Facing Artificial Intelligence Adoption during COVID-19 Pandemic: An Investigation into the Agriculture and Agri-Food Supply Chain in India. *Sustainability*. 2023;15(8):6377.
27. Ncube MM, Ngulube P. Enhancing environmental decision-making: a systematic review of data analytics applications in monitoring and management. *Discover Sustainability*. 2024;5(1):290.
28. Neethirajan S. Net Zero Dairy Farming—Advancing Climate Goals with Big Data and Artificial Intelligence. *Climate*. 2024;12(2):15.
29. Perçin S. Identifying barriers to big data analytics adoption in circular agri-food supply chains: a case study in Turkey. *Environmental Science and Pollution Research*. 2023;30(18):52304-52320.
30. Mishra P, Padhy C, Mishra N, Chakraborty S, Sai M. Role and approaches of agricultural extension in climate resilient agriculture. *Int J Agric Extension Social Dev*. 2024;7(5):343-348.
DOI:10.33545/26180723.2024.v7.i5e.629
31. Rahul K, Banyal RK, Arora N. A systematic review on big data applications and scope for industrial processing and healthcare sectors. *Journal of Big Data*. 2023;10(1):133.