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Predicting climate factors based on big data analytics based agricultural disaster management

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A R T I C L E I N F O

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A B S T R A C T

Aggressive, unexpected, and catastrophic changes in the environment-induced or impacted by the cultivation of land, crops, and cattle are known as agricultural disasters. In agriculture, the volume of data unpredictability, processing, and data management standards for interoperability are significant concerns. While natural catastrophes are still a considerable problem, the enormous amount of data available has opened up new avenues for coping. Accordingly, big data analytics has profoundly changed the way people respond to disasters in the agriculture sector. In this paper, the **Data handling model using big data analytics (DHM-BDA)**explores the role of big data in managing agricultural disasters and highlights the technical status of delivering practical and efficient disaster management solutions. DHM-BDA is used to address the essential sources of big data that include climatic causes and associated successes and developing technological problems in different disaster management phases. In addition, it aids in the monitoring, mitigation, alleviation, and acceptance of agricultural catastrophes and the process of recovery and rebuilding. The simulation findings have been executed, and the suggested model enhances the prediction ratio of 98.9%, decision-making level of 97.8%, data management of 96.5%, production ratio of 95.6%, and risk reduction ratio of 97.1% compared to other existing approaches.

1. Overview of agricultural disaster management using big data analytics

Agriculture is a multifaceted system within which changes are driven by the joint effects of environmental, economic, political, and social forces. Agriculture is one of the most disaster-affected sectors (Guo et al., 2020). Agricultural production is negatively impacted by any unexpected environmental variations or changes in physical conditions (Manogaran et al., 2018). This gets emphasized in the case of floods, cyclones, and droughts consequential in disturbance of publics' livelihood and adding to the damage, risk, and stress of disasters as a significant part of the populace depends on agriculture for its livelihood (Hassani et al., 2019). There are considerable crop losses due to pests, diseases, animals, etc. Agricultural Disaster Management System (ADMS) design and implementation are complex and challenging for most agricultural applications (Meechang et al., 2020). A holistic approach consisting of broadly related technologies and related business data can be used for agricultural big data (Manogaran and Lopez, 2018). The absence of single-source data is insufficient to decide accurately (Nguyen et al., 2018). Data from numerous sources, such as soil-based data, intercultural management data, climatic data, data from the long-term census, information gathering, crop patterns, and agribusiness data, are obtained (Sekaran et al., 2020). Digital agriculture blends information technology, computer learning, Engineering Design,

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Environmental Studies, HR, Risk Management, and Disaster Response (Sarker et al., 2019). The purpose of emergency response is to deliver quick aid to keep people alive, enhance their health, and boost their spirits. It deals with crop management inputs, such as seeds, pesticides, agrochemicals, soils, agriculture, and weather (Nguyen et al., 2017). This can have a long-lasting impact on crops, forest growth, and arable land, including crops requiring time to ripen. Their long-term effects on agriculture and the environment will be less than learned to prepare for and recover from natural events and disasters. As the economy increases, people's food demand grows (Zhang and Liu, 2019). Thus, the control of agricultural goods has become an additional significant (Wu et al., 2018). Technology is the only key to increasing agricultural production (Tantalaki et al., 2019). Big data analytics can suit growing agricultural output and address future challenges (Al-Turjman and Alturjman, 2018). Big data analytics have enormous implications and expectations for future agriculture's disaster management field (Zilberman, 2019). The data is transmitted to the server utilizing the communication technology for general radio packets (GPRS) and 4G/5G network cards for data transfers (Al-Turjman, 2019a). On 2G and 3G networks, the GPRS mobile communications standard allows for reasonably fast data transfers. A mobile communications standard called General Packet Radio Service (GPRS) runs on 2G and 3G cellular networks to allow for reasonably fast data transfers using packet-based technology. The new concept of "Smart farming" refers to farm managers using Big Data, robotics, and Drones to enhance product quantity and quality while optimizing human labor needs.

Agricultural Disaster Management, agricultural development, mobile data creation, social networking, GPS system-aided location-based data, satellite image, and intelligent card data are researched to solve the challenges (Delgado et al., 2019). The detonation of this sensitive information with extensive data guarantees that practical agricultural crisis management problems are prevented as part of the research methodology (Al-Turjman, 2019b). Other barriers hamper increasing development, such as a slowdown in growth, arable land scarcity, changing climate, freshwater scarcities, energy prices, and rapid urbanization (Lee et al., 2019). Cloud computing, big data, and intelligent technologies and instruments like the Internet of Things (IoT) increase agricultural production within those limits (Ever et al., 2020). New technologies aim to build and push robots and artificial intelligence through IoT and Big Data Analysis in agriculture (Unay-Gailhard and Bojnec, 2020). Smart agriculture uses extensive data assessments, sensors, and GPS systems (Aujla et al., 2017). Precision agriculture uses information and communication systems, new machinery equipment for crop growth intercultural activities, intelligent environment control, processing, post-harvest administration and marketing management, IoT, and big data analytics (Lioutas et al., 2019). In order to increase the predictability and efficiency of farm operations, market farming focuses on collecting data and interpreting it using computing technology. Smart agriculture is crucial for handling threats, disasters, challenges, and risks and ensuring sustainability in climate change, crop diseases, and pest attacks (Chaudhary et al., 2018). Digital agriculture can produce precise information on the status of the crop, soil, animal, fish, and intercultural management requirements, which can easily manage farms properly (Drohan et al., 2019). By giving customers with knowledge about the origins and safety of their food at the point of purchase, digital agriculture will provide them more influence. Better decision-making, more accurate management, and automated action via the employment of robots and advanced machinery will alter farming. Using big data technologies in agriculture is possible to attain digital agriculture's objective (Abdel-Basset et al., 2020). Big-data analysis and IoT can quickly solve various agricultural challenges such as disasters, drought, and climate Changement through the management of multiple algorithms, methods, and policies (Feng et al., 2019). The increasing social impact of natural disasters has shown that extreme weather events such as bushing fires, severe storms, cyclones, floods, and earthquake events in Australia caused increased mental illness, alcoholicity, domestic violence, chronic disease, and short-term unemployment.

Most problems for farmers may be met by technology. They can contribute even more accurately to climate prediction, water use reduction, yield increase, and net profit margins. Big data can provide farmers with high-quality and desirable crops. A lot of data is obtained from different agriculture sectors and points. Stored and stored for decision making on the machine for use and reuse (Sankar et al., 2020). In all respects, hardware and software tools are helped by sensors to handle agriculture with modern technology (Zhang et al., 2019). Computer algorithms allowed for agronomic mixing prescription (Nie et al., 2020). Computers allowed the agro-business network to take human capital, stock, logistics, machinery, procurement, and sale of the system and benefit from agricultural products (Mall et al., 2019). Agricultural automation has been established by robotic technology, intelligent farm data, and environmental intelligence programs (Hemalatha et al., 2018).

The paper's main contribution is,

- Designing the DHM-BDA model for handling agricultural disasters highlights the technical status of bringing practical and effective disaster management solutions.
- Evaluating the statistical model of weather forecasting and climate factors modeling using the different regression methods.
- Numerical results were carried out and compared to other existing approaches; the proposed DHM-BDA model enhanced the prediction, decision-making, data management, production, and risk reduction ratio.

The remaining papers are organized in the following way: Sections 1 and 2 discuss the introduction and existing methods for the management of agricultural disasters. Section 3 proposes the DHM-BDA Model, and section 4 has conducted experimental results. Section 5 finally concludes the article on the research.

2. Literature survey

Yunqiang Liu et al. (2019a) suggested a comprehensive multi-index evaluation of agricultural drought and flood disasters with the entropy information dissemination model (MICE-EIDM). The approach investigates the influence of environmental, economic, and social effects on disasters and discusses inadequate knowledge and catastrophe risk in the field. First, the analyses show that, first and second, agricultural drought and floods are affected in the study region and that flooding risks are more significant than drought. Secondly, the threats of drought and surge events are distinct regarding the change in catastrophe severity. Thus, the disaster risk evaluation will instinctively and thoroughly represent the laws and features of disasters and the importance of applying disaster avoidance and reduction in the area based on resolving inadequate knowledge and considering extensive disaster causes.

Meng Dai et al. (2020) proposed the standardized precipitation index (SPI) to characterize agricultural drought risk. Copula functions measure the joint return times of many drought grades and durations under various agricultural drought situations. In addition, risk factors of drought (resilience, susceptibility, and exposure) are used to explain drought risk. The joint return time and risk factors are then determined in every window, and the agricultural drought dynamics are investigated based on a moving window. Results have shown: (1) the SPI period of four months is most adequate to define agricultural drought based upon Pearl River Basin (PRB) agricultural damage; (2) the system of risk factors is best suited to the Joint Return cycle for the Agricultural Drought Risk Assessment; (3) most present PRB substantial challenges of increasing irrigation and the Pearl River Delta has decreased drought risk.

Dong Liu et al. (2019b) discussed The Weighted Mahalanobis Distance and Grey Relative Assessment (MTS-GRA-TOPSIS) to evaluate the resilience of the CRAWSR system. The findings revealed that the existing strength was relatively low and improved. Detailed countermeasures and recommendations were suggested, comprising raising water supplies and soil, returning to forest agricultural land, minimizing land use for agricultural irrigation, managing various industries' growth, and enhancing agricultural water conservation and industrialization. Specific measures and proposals were proposed. Industrial agriculture is the intensive, large-scale cultivation of both crops and animals, which frequently includes the routine, risky use of medicines on animals or artificial fertilizer on crops. The evaluation results obtained via the MTS-GRA-TOPSIS model could be verified and applied to develop the related capital development strategies for their efficiency and reliability.

Omid Rahmati et al. (2020) introduced the Machine learning models (MLM) for spatial modeling of agricultural droughts. In addition to the machine-learning methods, a key risk map is developed, which aims to adopt a robust drought contingency planning action in this field and other areas where drought is a persistent challenge, involving its impact on main practical facets of economic and environmental and social viability. This paper contributes in a novel scientific way to the creation of an agricultural drought hazard system using numerous advanced machine learning models, like boosted regression trees (BRT), classification and regression trees (CART), multivariate adaptive regression splines (MARS), random forest (RF), support vector machine (SVM), and flexible discriminant analysis (FDA). RF succeeded other models led by good performance models such as CART, SVM, and MARS.

Gohil, J et al. (Gohil et al., 2021) introduced Big Data influences on the Internet. Progress in mainstream computing power has significantly increased its feasibility while gradually making it even more practical to implement. Finally, the current challenges and restrictions on big data are discussed, and correct solutions appear successful.

Wang. C et al. (Wang et al., 2022) offers a technical metric analysis of the body of work that has been done over the past ten years on various types of disasters and the utilization of big quantities. The annual growth of publication outcomes, the related topical categories, and the productivity study requirements were specified for the data assessment.

Sebestyén. V et al. (Sebestyén et al., 2021) analyzing the potential connections between the most recent Big Data application papers has shown how the System of Systems approach or climate computing improves knowledge integration. The analysis demonstrates how data and models concentrating on particular facets of sustainability can be combined to explore the intricate issues of climate change.

The survey shows that existing techniques are challenged with solving these problems. This article proposes the DHM-BDA model for effective decisions and data management in a severe catastrophic event. This section briefly discusses the model proposed by DHM-BDA.

3. Data handling model using big data analytics (DHM-BDA)

Agriculture is a significant development in the growth of sedentary civilization, which led to food surpluses for domesticated species that enabled people to live in cities. Spending the majority of the year in one place for extended periods of time is known as a sedentary lifestyle. Sedentary hunter-gatherer civilizations are also widespread in history and the archaeological record, however agricultural societies are more commonly associated with sedentary sedentism. A rapid, coordinated state response from the outset is required to respond to an agricultural emergency that threatens to lose crops or animal species. Data modelling is a method for creating a clear image of a software application and the data pieces it contains by using symbols and words to represent the data and how it flows. When developing new databases or updating outdated software, data structures serve as a guide. The urbanization process, persistent poverty, and ecosystem degradation create disaster risks. Hydro-meteorological and geophysical disasters are known as natural disasters. Hydrometeorological hazards, such as floods, droughts, landslides, and storm surges, can directly threaten lives and have an effect on livelihoods by destroying transportation infrastructure, electrical grids, commercial buildings, and agricultural land. Definitions of different forms of a hydrometeorological disaster have been established, including floods, droughts, cyclones, fires, and heatwaves. Environmental degradation is one of the fundamental causes leading to the danger of natural disasters for agriculture, forestry, and farmlands. Environmental degradation is the deterioration of the environment caused by the use up of resources such as soil, air, and water, the loss of ecosystems, and the extinction of wildlife. Contrary to industrialized agriculture, which relies on monocultures, subsistence agriculture makes use of polycultures, which are plots where various crop varieties are grown together. The best way to maximize crop productivity on a small plot of land is to plant polycultures. Extreme weather conditions, particularly drought, are one of several factors that contribute to land degradation. It is also brought on by human activities that harm or deteriorate soil quality and land usability. Although industrialized agriculture has succeeded in producing large quantities of food, there are problems in agriculture that threaten the future of food production. The loss of agricultural land and the reduction in crop and livestock production are two major problems in agriculture. Livestock has historically also provided transportation, leather, wool, and other raw products. Livestock serve as a source of high-quality protein and energy foods as well as a component of integrated, renewable plant and animal agriculture systems. The ecological and psychological aspects are the climate, vegetation, diseases, and availability of water. The human factors are the use of medication and the provision of housing and skills. Cattle, goats, and sheep are the main animals used in mechanisation. Agricultural residues, unharvested crops, and harvest-related losses are all included in the losses. Production of livestock: waste and inefficiencies in the transformation of grass and feed into animal products.

Sustainable development traditional definitions centered on the balancing of agricultural and environmental productivity. It is essential to expand the concept of sustainable development beyond reducing environmental impacts; this should address vulnerability management and enhanced natural disaster mitigation and response capability. As such, the matrix of sustainable agricultural development should include the aspect of disaster risk mitigation. The Sustainable Agriculture Matrix (SAM), which offers objective and open measurements of agricultural sustainability at the national level, can assist organizations and governments in monitoring progress, promoting accountability, identifying areas that need improvement, and guiding national policies and initiatives. Hydrometeorological disasters must be mitigated with intensity by improving climate and weather knowledge, forecasts, early warning systems, and suitable land and natural resource management methods. Hence, this paper introduces the DHM-BDA framework for effective decision-making in agriculture disaster management and climate and weather forecasting with cloud computing and IoT. Furthermore, a different regression model has been suggested for data management in the agricultural field.

Fig. 1 shows the proposed DHM-BDA model. The vast amount of agricultural data involves using BDA to extract useful information and produce correct decisions. The primary computational platforms are cloud computing, the internet, computer development, and theories or concepts. The farmer and associated organization can derive an economical cost from very high data volumes by allowing high-speed capturing, discovering, and analyzing of agricultural data. The soil features and their effect on crop production are an essential component of crop management systems at a specific location. Both physical and chemical properties include soil properties. All soils contain organic material, water, air, or mineral shards. Together, these elements create the soil's structure, shape, permeability, chemical composition, and color. Big data can usually be divided into four steps in agriculture: (1) data capture, (2) storage, (3) data transformation, (4) data analysis, (5) marketing of data. Data capture collects vast quantities of heterogeneous data available by the department of agriculture, government, etc., from different sources, such as remote mapping, weather stations, field characteristics, and cropping patterns. The emergency management cycle demonstrates how the public sector, private sector, and civil society prepare to lessen the effects of disasters soon after they occur and

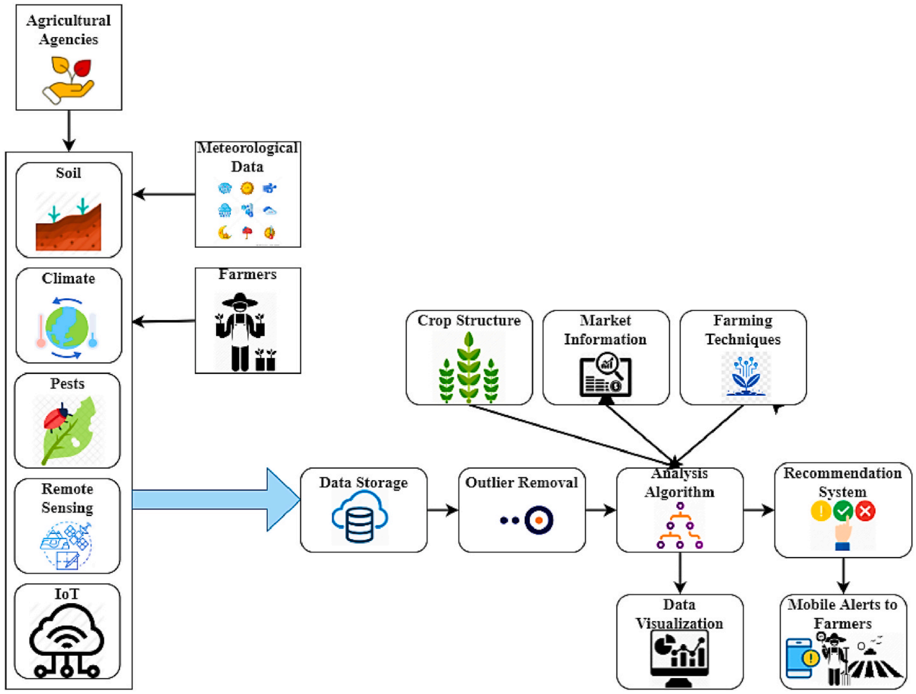

Fig. 1. Proposed DHM-BDA

take steps to recover from them. Data storage is the main challenge in the enormous data-driven application becoming common in NoSQL technologies. NoSQL databases keep information in documents, in opposed to relational database systems. We classify them as "not merely SQL" and divide them into various flexible data model groups as a consequence. Examples of NoSQL database types include pure textual databases, crucial stores, broad databases, and data modeling. Data processing is a stage in integrating many data representing the same parameter into a single reliable monitor. Data analytics extracts value from the data collected and interprets results articulating value into information. Data marketing ties the empirical outcomes obtained to the processes to be followed. Big Data Analytics is used to answer local crop questions such as irrigation methods, crop selection, yield prediction, and fertilizer selection. Farmers may be provided with mobile alerts about selecting crops and good agriculture practices to adapt them to analysis. The data visualization can better explain the result produced after the analysis.

Fig. 2 shows the Agricultural Disaster Management Cycle. In disaster management, four phases are equally important: preparation, response, recovery, and mitigation. Effective preparation and response to disasters are the goals of disaster management. To limit the damage that disasters create, resources must be strategically organised. Additionally, it entails a methodical strategy to handling the obligations of catastrophe prevention, readiness, response, and recovery. Land exploitation, infrastructure construction, rising urbanisation, and technological advancement have all increased demand on natural resources. Minimizing harmful and destructive impacts of disasters on agriculture or other elements at stake will be decreased by comfort. The interventions range from engineering projects such as bridges, protective floors, drilling grounds, and safe building designs and non-structural measures such as community risk assessment, risk reduction planning in the Community, public knowledge of food safety programs, savings in groups, cooperatives, crop insurance, and national disaster management agencies and stabilization and mitigation of disasters. Food safety is crucial to preventing foodborne illness and improving human wellbeing. Food-related illnesses have increased globally over time, having a detrimental impact on both developing and developed countries' economies and on their citizens' health. Interventions in mitigation and

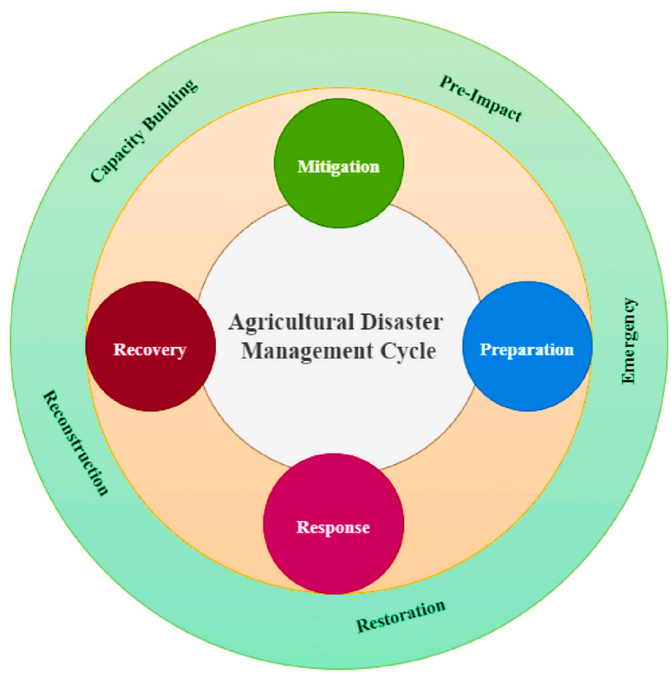

Fig. 2. Agricultural disaster management cycle.

prevention have a strong correlation with development planning. Preparation requires steps to ensure that sufficient and efficient action occurs during crises, such as community decisions on agricultural production, coordinated and systemic measures, tank sluice exercises, public awareness, early collection, late planting, control of seeds, etc. Preparation encompasses measures taken before a disaster. Emergency responses are actions intended to ensure survival and avoid further escalation of the situation. This includes storage of tanks, drainage canals, transporting products for urgent repair, damage needs and capability assessment, food, non-food relief support, and medical assistance.

The recovery process requires rehabilitation and reconstruction and is carried out to prevent and reduce vulnerability rather than just bringing it back.

Fig. 3 shows smart farming. The utilization of information and communication technology and Big data analytics in Smart Farming is still in an initial development phase. The term "smart farming" refers to the management of farms using IoT, robotics, drones, and AI to improve product quality and quantity while minimizing the need for human labour. The phenomenon of big data analytics drives digital agriculture, wherein substantial data volumes with a wide variety can be captured, analyzed, and utilized for making a decision. With the advent of IoT, intelligent sensors, cloud computing, and real-time data generation, conventional farming will transform into a new data-driven and data-enabled smart agriculture. The Agriculture Facility consists of the RFID system, sensors (temperature, light, pressures, humidity, plant growth, CO2), GPRS wireless, intelligent information processing, and cloud computing. The digital tool provides information on food processing, weather, fertilizers, seeds, pesticides, crop combinations, etc. Apart from agriculture-related content, the tablet offers other data like e-governance, education, rainwater harvesting, and elementary healthcare. The farmers can interact through a dedicated call center created for the purpose. The Smart Farming idea is beginning to emerge, with farmers using modern information dissemination technology to boost production volumes and quality while optimizing their labor. Smart sensors provide documentation for precision farming, which helps farmers track and maximize crop production and keep up with changing environmental influences. By positioning sensors to maintain assets and decrease environmental impacts, farmers can micro-understand their crops.

Fig. 4 shows the decision-making process based on BDA. Well-structured and employed decisions subsidize straightly to the bottom line by depressing storage, transportation, sourcing, disposal, and stock out expenses. The diverse potential benefits of data-reinforced decision-making have encouraged researchers to consider the probable incorporation of big data in agricultural disaster management. The consequences denote that practical data analytics approaches usually use prescriptive and predictive methods rather than descriptive. Big data and predictive analysis on two sustainability features, comprising social and environmental characteristics. The raw data of historical facts are collected, described, and examined using descriptive statistics. It analyzes and defines historical events and creates them understandable and interpretable by humans. Prescriptive analytics is the process of using data to determine the optimal course of action. This type of analysis, which takes into consideration all relevant factors, yields recommendations for the subsequent stages. As a result, scenario planning is a powerful tool for making decisions based on data. Prescriptive analytics monitors substitute decisions based on descriptive and predictive analytics utilizing predictive and descriptive analytics, mathematical, multicriteria decision-making, or simulation optimization systems. Correct rigid analytics applications can lead to optimal and effective decision-making. Businesses that rely on three distinct types of analytics to aid in decision-making: actionable insights, which explain what should happen moving forward, predictive analytics, which shows us what could happen, and analyze the possibility, which explains whatever has actually happened.

This paper discusses the instance of a zero-dimensional energy-balance system of the Earth's climate. In a zero-dimensional energy balance model, the disease of the Earth's surface, as averaged throughout the entire planet, is used to represent the Earth's climate system. The modest simulations of the Earth's atmosphere can aid in comprehending global warming better. The model depends on linear differential equations:

$$D \cdot \frac{dT}{dt} = F - \lambda \cdot T \tag{1}$$

As shown in equation (1), where T signifies the global mean surface temperature perturbation, D indicates the Earth's climate system heat capacity, F denotes a term capturing a linear combination of every radiative force factor, t represents time, and λ is a constant response variable. Disparities in these models have been utilized and deliberate wisely in climate physic. The model term indicates that if any radiant force increases, then amplified levels of CO2 in the atmosphere, should equally correspond to the energy of the climate system due to a radiative financial plan reaction.

Fig. 5 shows the Big data for the prediction of climate change. The

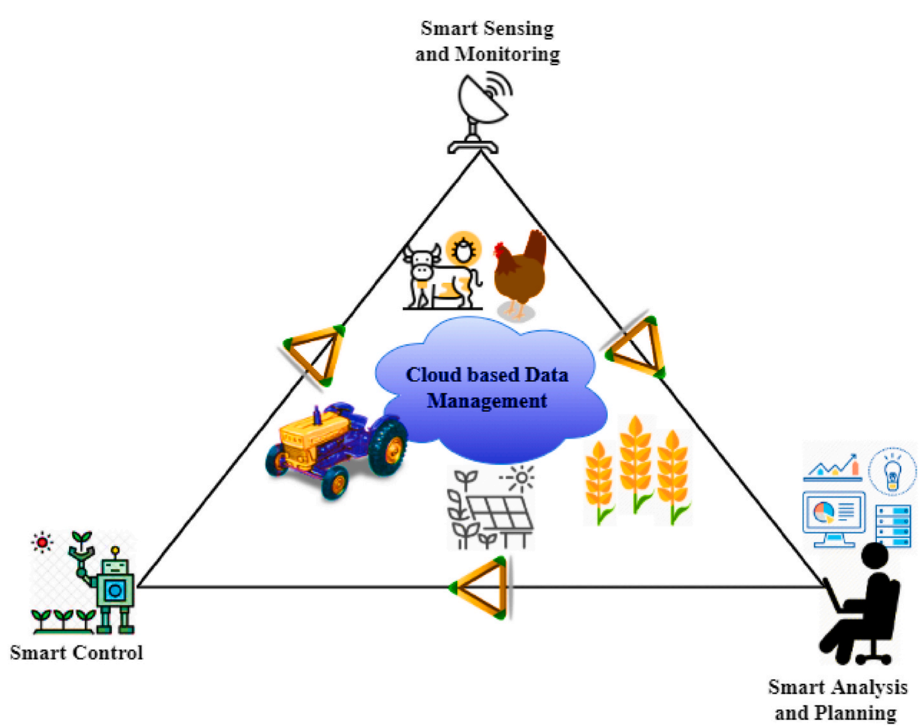

Fig. 3. Smart farming.

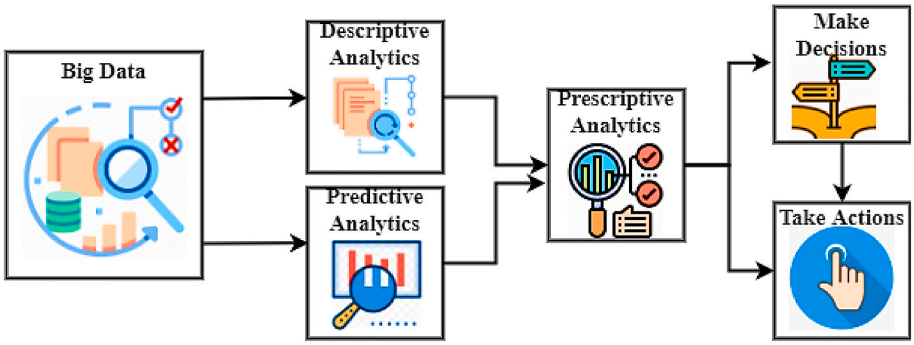

Fig. 4. Decision-Making Process based on BDA.

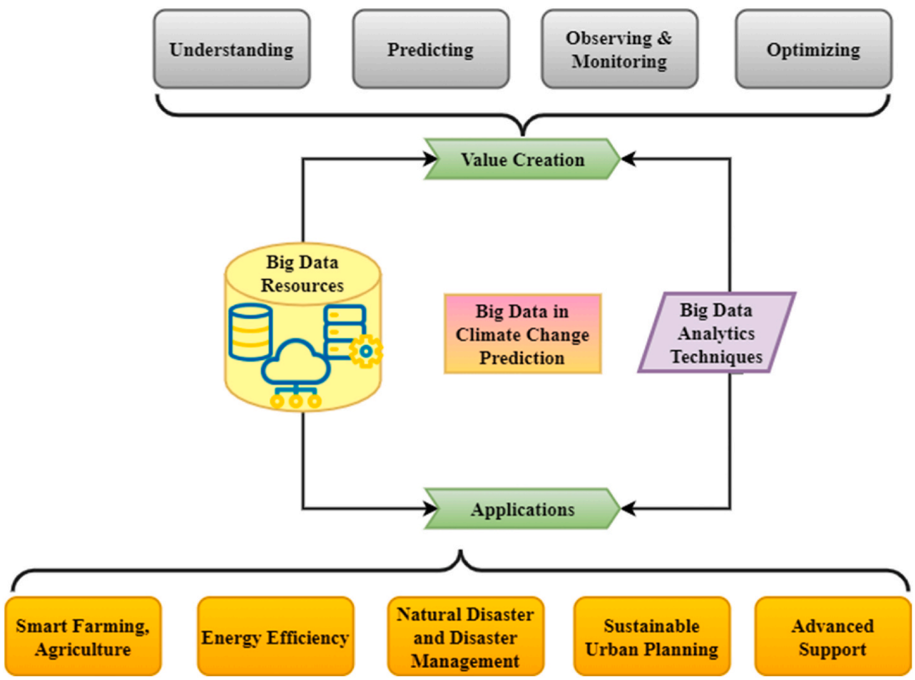

Fig. 5. Big data for prediction of climate change.

big data applications in climate change prediction have two essential components: big data analytics techniques and extensive climate data resources. This paper classifies value creation as well as the particular application. It is pointed out that Big Data on Climate Change generally functions in four facets of creating value for adequate access to applications and clear guiding principles: monitoring and observation, understanding, optimization, and prediction, while applications are divided into five areas: smart agriculture and agriculture, energy efficiency, disease analysis, and natural disasters.

Let's consider Y is the independent variable and$X$ is the dependent variable. Let $x_1, x_2, \ldots x_m$ be m-observations recorded on X variable. Let's consider $y_1, y_2, \ldots y_m$ be m- observations recorded on Y variable. Under the suppositions of the linear relationship among X and Y, the simple regression model of X on Y,

$$X = \beta + \alpha Y + \varepsilon \tag{2}$$

The unidentified parameters β and α are assessed by the least square (reducing the remaining sums of squares (W)). The random variable (ε) is presumed to trail standard distributions with mean 0 and unit standard deviations. The evaluation of β and α are determined by allowing for function $W = \sum (x_j - \widehat{x}_j)^2$, which is to be diminished.

The calculation of β and α are found by resolving partial derivatives $\frac{\partial W}{\partial \beta} = 0$ and $\frac{\partial W}{\partial \alpha} = 0$ correspondingly, which are given below:

$$\widehat{\beta} = b = \overline{x} - \widehat{\alpha}\overline{y}, \ \widehat{\alpha} = a = \frac{m \sum x_j y_j - \sum x_j y_j}{m \sum y_j^2 - \left(\sum y_j\right)^2} \tag{3}$$

The fitted model for expression (2) is $X = b + \ a \ Y$ and is utilized to determine the approximation of $X(\widehat{X})$ for given Y. The fitted model reliability to (2) is tested by computing remaining $(X - \widehat{X})$. A fit model explains the association between a dependent variables and one or more predicting factors. There are numerous models you can fit, including binary logistic regression, linear regression model, analysis of variance (ANOVA), covariance analyses (ANCOVA), and simple linear regression.

Using regression analysis, researchers can evaluate the importance of each predictor to the relationship as well as the strength of the relationship between an outcome (the dependent variable) and an amount of predictor variables. Commonly, the impact of many other predictors has been statistically eliminated. Multiple regression models are utilized to examine more than two parameters. Let $Y_1, Y_2, \ldots Y_l$ be l-parameters the regression model of three parameters, by supposing Y_1 dependent and other independent parameters expressed by

$$Y_1 = \alpha_1 + \alpha_2 Y_2 + \alpha_3 Y_2 + \varepsilon \tag{4}$$

The unidentified variables $\alpha_1, \ \alpha_2$ and α_3 are to be calculated by the least square approach (i.e., reducing the remaining sums of squares (W)). The random variable (ε) is presumed to trail standard distributions with mean 0 and unit standard deviations.

Let m-observations be verified on the parameters Y_1, Y_2 and Y_3. The overall correlation coefficient indicated as p_{12}, p_{13} and p_{23} are computed utilizing the subsequent expression,

$$p_{ji} = \frac{m\sum Y_{jt}Y_{it} - \left(\sum Y_{jt}\sum Y_{it}\right)}{\sqrt{m\sum {Y_{jt}}^2 - \left(\sum Y_{jt}\right)^2}\sqrt{{Y_{it}}^2 - \left(\sum Y_{it}\right)^2}};\ j \neq i = 1,2,3\ and\ t = 1,2,3,\ldots m \tag{5}$$

The sample variances W_1^2, W_2^2, and W_3^2 are obtained using the following expression

$$W_j^2 = \frac{m\sum y_j^2 - \left(\sum y_j\right)^2}{m^2};\ j = 1,2,3\ and\ t = 1,2,3,..m \tag{6}$$

The correlation matrix for the three variables is provided as

$$P = \begin{bmatrix} 1 & p_{12} & p_{13} \\ p_{21} & 1 & p_{23} \\ p_{31} & p_{32} & 1 \end{bmatrix} \tag{7}$$

The approximations α_1, α_2 and α_3 are obtained by considering function $W = \sum(Y_1 - \widehat{Y}_1{}^2)$, which is to be reduced. The estimations of α_1, α_2 and α_3 are determined by resolving partial derivatives $\frac{\partial W}{\partial \alpha_1} = 0$, $\frac{\partial W}{\partial \alpha_2} = 0$ and $\frac{\partial W}{\partial \alpha_3} = 0$ correspondingly. The assessments are provided as

$$\widehat{\alpha}_1 = b = \widehat{Y_1} - \widehat{\alpha}_2\overline{y_2} - \widehat{\alpha}_3\overline{y_3}\widehat{\alpha}_2 = a_1 = \frac{-w_1P_{12}}{w_2P_{11}}\ and\ \widehat{\alpha}_3 = \frac{-w_1P_{13}}{w_3P_{11}} \tag{8}$$

The fitted model for expression (4) is $Y_1 = b + a_1Y_2 + a_1Y_3$ and is utilized to determine an estimation of $X_1(\widehat{X}_1)$ for given Y_2 and Y_3 . The fitted model reliability to (4) is tested by computing remaining $(X - \widehat{X})$.

This paper suggested a model using Map-Reduce for big data processing and the linear regression method for data calculation. The current ensemble climate and weather predicting systems offer precise statements about the ambiguity in daily and seasonal, indicating to progress a model to enhance modeling, visualization technologies, and statistical analysis for distributing the ensemble outcomes. Linear regression is utilized for forecasting future patterns from the past data item. The data gathered are stored in the database using data storage functions, where the vector y containsn numerical values (y_1; y_2; y_3 :::; y_{m-1}, y_m), and m is the number of feature values of every data item in the dataset, andexpression9demonstrates a standard model for the data process.

$$\widehat{x} = f(y) + \xi \tag{9}$$

and Equation (10) demonstrates the algorithm utilized to model x as a function of y:

$$\widehat{x}_j = b_0 + b_1y_j + \xi \tag{10}$$

Utilizing the following equations, the regression coefficient is computed

$$\overline{yx} - \overline{yx} = \frac{1}{M}\sum_{j=1}^{M}\left(y_j - \overline{y}\right)\left(x_j - \overline{x}\right) \tag{11}$$

$$b_1 = \frac{\overline{yx} - \overline{yx}}{x^2 - \overline{x}^2} \tag{12}$$

$$b_0 = \overline{y} - b_1\overline{y} \tag{13}$$

The data size of the y and b_1 vectors are equivalent to the dimensions in the feature space, and the error term is the variance among the natural and forecasted values of the target variable. The x is utilized to specify the predicted value of the target parameter by the method where $x = b_0 + b_1y$.

The objective is to reduce the variance of actual and the forecasted values for every data item,

$$f(q) = \frac{1}{M}\sum_{j=1}^{M}\xi_j^2 \tag{14}$$

The results have been estimated utilizing this model by relating diverse climate, weather, and rainfall values; when the past data values rise, it reduces the execution period as per normal execution. Thus, the proposed DHM-BDA method improves the prediction, decision making, data management, production, and risk reduction ratio compared to other existing methods.

4. Simulation analysis

In the article, DHM-BDA discusses the role of big data in the management of agricultural disasters and highlights how practical and effective disaster management systems are reasonably obtainable. In this respect, using Big Data Analytics, human populations have transformed the application of agricultural disaster management tools to mitigate human misery and economic losses. The results were based on the performance measurements such as production, risk reduction, data management, decision-making, and prediction ratios.

4.1. Production ratio

In the field of agriculture, big data have a tremendous opportunity. A thorough understanding of big data will help us overcome fundamental challenges for all forms of conventional farming technology to boost crop quality and production. To increase the yield of a certain crop or group of crops, which are frequently genetically engineered, conventional farming uses synthetic pesticides and fertilisers. This technique degrades a landscape's ecology and necessitates a sizable input of chemical and energy. The critical influence of the application of big data in agriculture was benchmarking, research, model prediction, visualization, marketing, and management. This technology can be used in agriculture to accumulate and compare vast volumes of data derived from many agriculture stages. Big data analytics and IoT-based agriculture production monitoring system analyze crop atmosphere and deliver a method to enhance decision-making efficiency by examining harvest statistics and predicting agriculture production utilizing IoT sensors. Fig. 6 shows the production ratio using the suggested DHA-BDA model.

(i) Risk Reduction Ratio

Disaster risk reduction in the agricultural value chain is an emerging research area that can effectively mitigate disaster risks. A fundamental agricultural product is produced in the field, moved along a "value chain" of actors and activities, and finally consumed. Value is added to the product at each stage. Understanding agriculture disaster risk for all aspects of the farm value chain will boost disaster risk mitigation policy design and development. Diversification has a significant role to play in reducing disaster risk in agriculture. Diversification usually refers to introducing farming systems to new crops and livestock. By increasing the product prospects of farmers, this approach reduces vulnerability. Two major natural disasters that impact agriculture and irrigation are drought and flood. Big data-based strategies can be recognized at diverse levels to decrease these disasters' impacts. Fig. 7 illustrates the disaster risk reduction ratio using the suggested DHM-BDA model.

(ii) Effectiveness of Data Management

The agricultural extensive data management framework can automatically capture and produce detailed management information reports on development, replication, marketing, market demand, and

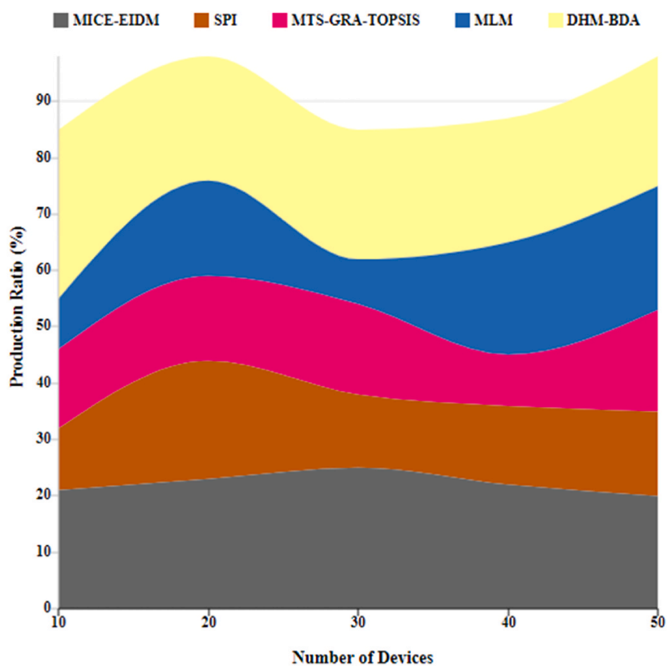

Fig. 6. Production ratio.

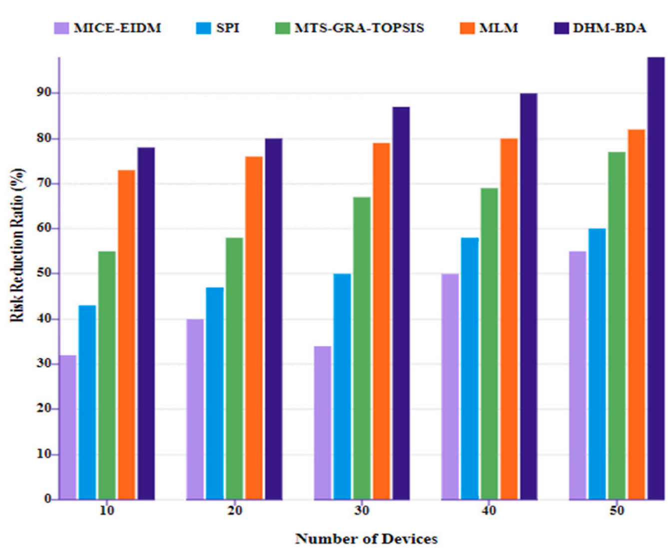

Fig. 7. Risk reduction ratio.

other facets of agriculture in some areas. It provides consistent data on production and sales alerts and wise decision-making for farm divisions and farmers to ensure consistent stockpiling and intellectual extensive data administration on agriculture production. From data management, flat-file management, and finally spatial database management, GIS spatial data organisation has evolved. Massive data management tools are provided by spatial data management, the multi-user current operation management of permissions for data visits and co-current access, and structural database cluster applicability. Master Data Management (MDM) solutions are corporate software packages that assist the connected to system, linking, and syncing of data base across heterogeneous sources of information through logical reconciliation of master data. Fig. 8 illustrates the effectiveness of the data management ratio using the suggested DHM-BDA model.

(iii) Level of decision-making

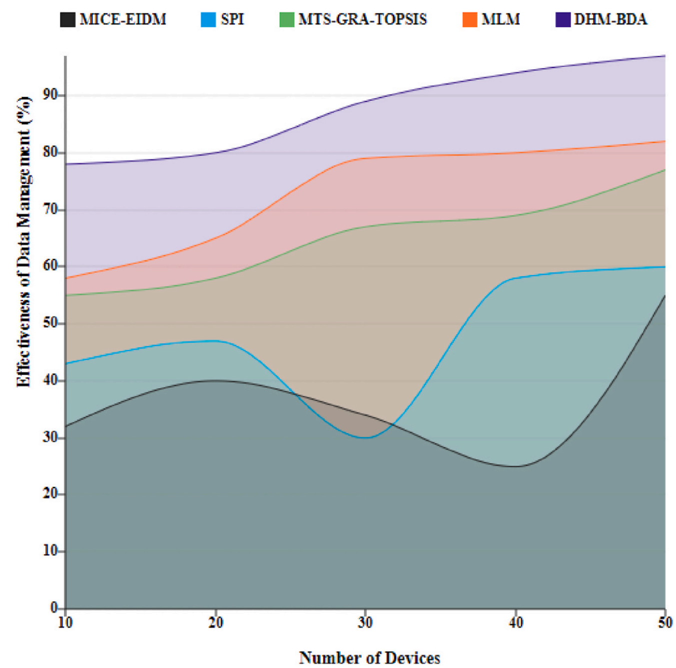

Fig. 8. Effectiveness of data management ratio.

In agriculture decisions, large-scale data analysis and analytical technology will include crop development, production, soil, and climate as part of crop development. Economic, environmental, and sustainable growth makes agricultural decision-makers more accurate, real-time, and effective. Adequate and precise data offers the required technological provision for developing a rural incorporated data services system to create a rural structured information system. Therefore it is expected to enhance the efficiency of the decision-making progression on agricultural disasters and reimbursement by decreasing the number of in-situ visits, reducing costs, and controlling delays. Farmers can access the Big agricultural data to make an informed decisions (crop choice, irrigation, etc.). Fig. 9 demonstrates the decision-making level

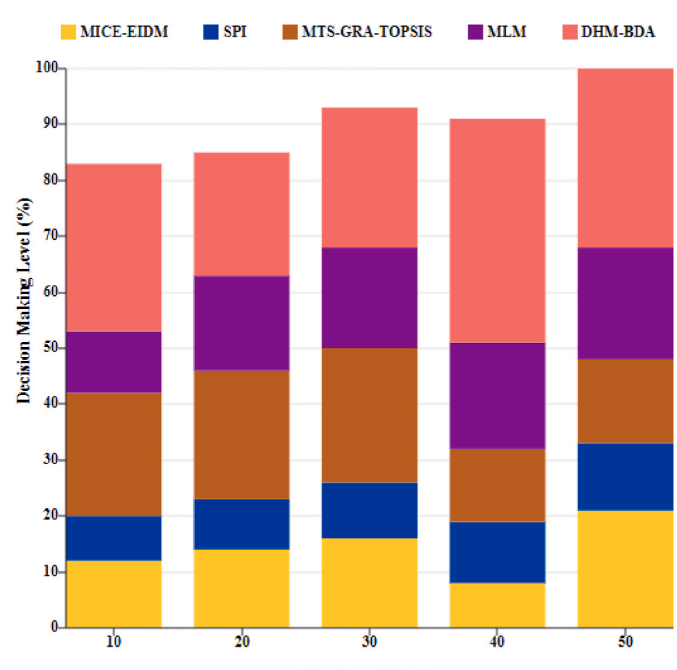

Fig. 9. Decision making level.

using the suggested DHM-BDA model.

(iv) Prediction Ratio

Weather plays a major role in agriculture and impacts crop growth, production, and yield. Weather aberrations can destroy crops and cause soil erosion. It depends on the weather to export produce from the field to the market, and poor weather can negatively affect crop quality during transport or storage. The kinds of plants that can thrive there depend on the climate of the region. Temperature and precipitation both affect plant development. Plants may not grow well if there is too much or too little precipitation, or whether it is too hot or too cold. The problem can be divided, mapped on each machine, and then aggregated back together in the end. Advanced algorithms are used in modern agriculture to describe patterns and behaviors that predict pesticide invasion and microscopic diseases. Predictive agricultural analytics educate farmers about how pesticides can be managed. In the farming industry, statistical tools and data processing are used to treat hazardous insects scientifically. Fig. 10 demonstrates the prediction ratio using the suggested DHM-BDA model.

In comparison to existing comprehensive multi-indices assessments using an entropy information diffusion model (MICE-EIDM), a standardized precipitation index (SPI), Mahalanobian distance, and grey relation analyses, the DHM-BDA proposal for agricultural disaster management and climate factor modeling enhances prediction, decision-making, data management, production, and risk reduction ratio. The experimental results were carried out, and the proposed model increased the preview ratios by 96.8%, 95.6%, and the risk reduction ratio by 97.1%, compared to other existing methods. The analysis also improved the decision-making level by 99.9%.

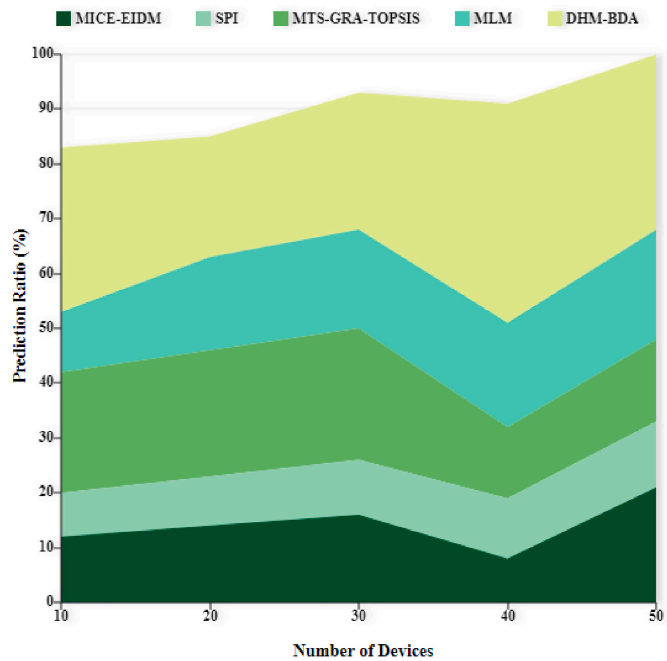

Fig. 10. Prediction ratio.

5. Conclusion

Digital data and tools have provided a chance to collect data from different sources directly and indirectly, which affect crop yields. Big data is a capable data storage platform. The use of predictive models helps analyze and manage data, which can be a major step in emerging an efficient farm support system for making decisions. Intelligent technologies in agriculture allow farmers to adopt IoT-powered farm-specific decisions. Data from various factors covered in this paper are available. This paper develops high-speed networks and high-performance computing environments, particularly for the agricultural information infrastructure. The establishment of agricultural information resources based on BDA can better interpret data through improved, quick, and remote sensing of major farm data in a deeper and broader context. Working to achieve general agricultural systems resilience may be an effective way of reducing disaster risk. The experimental findings were carried out. The suggested model improves the prediction ratio by 98.9%, the decision-making level by 97.8%, the data management ratio by 96.5%, the production ratio by 95.6%, and the risk reduction ratio from other existing methods by 97.1%.

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Author’s contributions

All Author are contributed to the design and methodology of this study, the assessment of the outcomes and the writing of the manuscript.

Data availability

Not Applicable.

Code availability

Not applicable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abdel-Basset, M., Mohamed, R., Elhoseny, M., Chang, V., 2020. Evaluation framework for smart disaster response systems in uncertainty environment. Mech. Syst. Signal Process. 145, 106941.
Al-Turjman, F., 2019a. Cognitive routing protocol for disaster-inspired internet of things. Future Generat. Comput. Syst. 92, 1103–1115.
Al-Turjman, F., 2019b. A rational data delivery framework for disaster-inspired internet of nano-things (IoNT) in practice. Cluster Comput. 22 (1), 1751–1763.
Al-Turjman, F., Alturjman, S., 2018. Intelligent Positioning for Precision Agriculture (PA) in Smart-Cities. Intelligence in IoT-enabled Smart Cities, p. 189.
Aujla, G.S., Kumar, N., Zomaya, A.Y., Ranjan, R., 2017. Optimal decision making for big data processing at edge-cloud environment: an SDN perspective. IEEE Trans. Ind. Inf. 14 (2), 778–789.
Chaudhary, R., Aujla, G.S., Kumar, N., Rodrigues, J.J., 2018. Optimized big data management across multi-cloud data centers: software-defined-network-based analysis. IEEE Commun. Mag. 56 (2), 118–126.
Dai, M., Huang, S., Huang, Q., Leng, G., Guo, Y., Wang, L., et al., 2020. Assessing agricultural drought risk and its dynamic evolution characteristics. Agric. Water Manag. 231, 106003.
Delgado, J., Short, N.M., Roberts, D.P., Vandenberg, B., 2019. Big data analysis for sustainable agriculture. Front. Sustain. Food Syst. 3, 54.
Drohan, P.J., Bechmann, M., Buda, A., Djodjic, F., Doody, D., Duncan, J.M., et al., 2019. A global perspective on phosphorus management decision support in agriculture: lessons learned and future directions. J. Environ. Qual. 48 (5), 1218–1233.
Ever, E., Gemikonakli, E., Nguyen, H.X., Al-Turjman, F., Yazici, A., 2020. Performance evaluation of hybrid disaster recovery framework with D2D communications. Comput. Commun. 152, 81–92.
Feng, P., Wang, B., Li Liu, D., Yu, Q., 2019. Machine learning-based integration of remotely-sensed drought factors can improve the estimation of agricultural drought in South-Eastern Australia. Agric. Syst. 173, 303–316.
Gohil, J., Patel, J., Chopra, J., Chhaya, K., Taravia, J., Shah, M., 2021. Advent of Big Data technology in environment and water management sector. Environ. Sci. Pollut. Control Ser. 1–19.
Guo, J., Wu, X., Wei, G., 2020. A new economic loss assessment system for urban severe rainfall and flooding disasters based on big data fusion. Environ. Res. 188, 109822.
Hassani, H., Huang, X., Silva, E., 2019. Big Data and climate change. Biodata Coginitive Comput. 3 (1), 12.

Hemalatha, P., Dhanalakshmi, K., Matilda, S., Anand, M.B., 2018. Farmbot-a smart agriculture assistor using internet of things. Int. J. Pure Appl. Math Special Iss. 119 (10), 557–566.
Lee, J.W., Jung, C.G., Chung, J.H., Kim, S.J., 2019. The relationship among meteorological, agricultural, and in situ news-generated big data on droughts. Nat. Hazards 98 (2), 765–781.
Lioutas, E.D., Charatsari, C., La Rocca, G., De Rosa, M., 2019. Key questions on the use of big data in farming: an activity theory approach. NJAS - Wageningen J. Life Sci. 90, 100297.
Liu, Y., You, M., Zhu, J., Wang, F., Ran, R., 2019a. Integrated risk assessment for agricultural drought and flood disasters based on entropy information diffusion theory in the middle and lower reaches of the Yangtze River, China. Int. J. Disaster Risk Reduc. 38, 101194.
Liu, D., Qi, X., Li, M., Zhu, W., Zhang, L., Faiz, M.A., et al., 2019b. A resilience evaluation method for a combined regional agricultural water and soil resource system based on Weighted Mahalanobis distance and a Gray-TOPSIS model. J. Clean. Prod. 229, 667–679.
Mall, R.K., Srivastava, R.K., Banerjee, T., Mishra, O.P., Bhatt, D., Sonkar, G., 2019. Disaster risk reduction including climate change adaptation over south Asia: challenges and ways forward. Int. J. Disaster Risk Sci. 10 (1), 14–27.
Manogaran, G., Lopez, D., 2018. Spatial cumulative sum algorithm with big data analytics for climate change detection. Comput. Electr. Eng. 65, 207–221.
Manogaran, G., Lopez, D., Chilamkurti, N., 2018. In-Mapper combiner based MapReduce algorithm for processing of big climate data. Future Generat. Comput. Syst. 86, 433–445.
Meechang, K., Leelawat, N., Tang, J., Kodaka, A., Chintanapakdee, C., 2020. The acceptance of using information technology for disaster risk management: a systematic review. Eng. J. 24 (4), 111–132.
Nguyen, N.T., Liu, B.H., Pham, V.T., Liou, T.Y., 2017 Sep 26. An efficient minimum-latency collision-free scheduling algorithm for data aggregation in wireless sensor networks. IEEE Syst. J. 12 (3), 2214–2225.
Nguyen, N.T., Liu, B.H., Chu, S.I., Weng, H.Z., 2018 Dec 3. Challenges, designs, and performances of a distributed algorithm for minimum-latency of data-aggregation in multi-channel WSNs, 1. In: IEEE Transactions on Network and Service Management, 16, pp. 192–205.
Nie, X., Fan, T., Wang, B., Li, Z., Shankar, A., Manickam, A., 2020. Big data analytics and IoT in operation safety management in under water management. Comput. Commun. 154, 188–196.
Rahmati, O., Falah, F., Dayal, K.S., Deo, R.C., Mohammadi, F., Biggs, T., et al., 2020. Machine learning approaches for spatial modeling of agricultural droughts in the south-east region of Queensland Australia. Sci. Total Environ. 699, 134230.
Sankar, S., Srinivasan, P., Luhach, A.K., Somula, R., Chilamkurti, N., 2020. Energy-aware grid-based data aggregation scheme in routing protocol for agricultural internet of things. Sustain. Comput.: Informatic. Syst. 28, 100422.
Sarker, M.N.I., Islam, M.S., Ali, M.A., Islam, M.S., Salam, M.A., Mahmud, S.H., 2019. Promoting digital agriculture through big data for sustainable farm management. Int. J. Innovat. Appl. Stud. 25 (4), 1235–1240.
Sebestyén, Viktor, Czvetko, Timea, Abonyi, János, 2021. The applicability of big data in climate change research: the importance of system of systems thinking. Front. Environ. Sci. 9 (1) https://doi.org/10.3389/fenvs.2021.619092.
Sekaran, K., Meqdad, M.N., Kumar, P., Rajan, S., Kadry, S., 2020. Smart agriculture management system using internet of things. Telkomnika 18 (3), 1275–1284.
Tantalaki, N., Souravlas, S., Roumeliotis, M., 2019. Data-driven decision making in precision agriculture: the rise of big data in agricultural systems. J. Agric. Food Inf. 20 (4), 344–380.
Unay-Gailhard, İ., Bojnec, Š., 2020. Public support effect on natural disaster management: a case study of ice storms in forests in Slovenia. Land Use Pol. 95, 103811.
Wang, Caili, Gao, Yuwen, Aziz, Asad, Ogunmola, Gabriel, 2022. Agricultural disaster risk management and capability assessment using big data analytics. Big Data 10, 246–261. https://doi.org/10.1089/big.2020.0411.
Wu, W., Lin, W., Hsu, C.H., He, L., 2018. Energy-efficient hadoop for big data analytics and computing: a systematic review and research insights. Future Generat. Comput. Syst. 86, 1351–1367.
Zhang, C., Liu, Z., 2019. Application of big data technology in agricultural Internet of Things. Int. J. Distributed Sens. Netw. 15 (10), 1550147719881610.
Zhang, D., Pan, S.L., Yu, J., Liu, W., 2019. Orchestrating Big Data Analytics Capability for Sustainability: A Study of Air Pollution Management in China. Information & Management, 103231.
Zilberman, D., 2019. Agricultural economics as a poster child of applied economics: big data & big issues. Am. J. Agric. Econ. 101 (2), 353–364.