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Remote Sensing, GIS and Machine Learning for Agricultural Drought Intelligence: Evidence from California, Northern Nigeria and Rajasthan

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Abstract: Agricultural drought remains one of the most significant environmental challenges affecting food security, water resource availability, and agricultural productivity, particularly in semi-arid regions. Recent advances in remote sensing, Geographic Information Systems (GIS), and machine learning have provided innovative approaches for monitoring, predicting, and managing drought conditions with greater spatial and temporal accuracy. This study evaluates the effectiveness of integrating remote sensing, GIS, and machine learning techniques for agricultural drought intelligence using evidence from California (United States), Northern Nigeria, and Rajasthan (India). A quantitative research design based on secondary data was adopted, utilizing Landsat and MODIS satellite imagery, meteorological records, vegetation indices, and geospatial datasets published up to 2018. Descriptive statistics, correlation analysis, multiple regression, and machine learning algorithms, including Random Forest and Support Vector Machine, were employed to assess drought detection and prediction performance. The findings indicate that integrating remote sensing with GIS significantly enhances drought monitoring, while machine learning algorithms improve prediction accuracy by effectively analyzing complex environmental datasets. Comparative analysis further reveals regional differences in drought severity, technological capacity, and environmental conditions, highlighting the importance of location-specific drought management strategies. The study concludes that combining remote sensing, GIS, and machine learning provides a reliable framework for agricultural drought intelligence, supporting evidence-based decision-making, sustainable water resource management, and climate-resilient agricultural planning in drought-prone regions.

Keywords: Agricultural drought, Remote sensing, Geographic Information Systems (GIS), Machine learning, Precision agriculture, Landsat, MODIS.

1. INTRODUCTION

Agricultural drought is one of the most serious environmental challenges in food production, water security and rural livelihoods worldwide. Agricultural drought is based on the supply of available moisture to the soil and is different from meteorological drought, which is when there is insufficient moisture. The frequency, duration and intensity of drought events have been aggravated over many agricultural regions of the world due to increasing climate variability, rising temperatures, changing precipitation patterns and unsustainable water resource management. These challenges pose a threat to agricultural productivity, food security, ecosystem sustainability, and economic development especially in the arid and semi-arid areas where rainfall variability is naturally high (Mishra & Singh, 2010; Dai, 2011). Timely detection, monitoring and prediction of agriculture drought have therefore emerged as a pressing need for governments, researchers and agriculture stakeholders to better prepare for and enhance agriculture climate resilience.

To leverage agricultural drought intelligence, remote sensing is an indispensable tool that is delivering objective, consistent environmental information from various geographical areas. High resolution satellite imagery from sensors like Landsat, MODIS and other Earth observation sensors provide a valuable resource for monitoring vegetation dynamics, water stress, crop conditions, and environmental change. Vigor and thermal conditions of vegetation related to water stress have been assessed using vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), and Vegetation Temperature Condition Index (VTCI), which have been widely used to determine the severity of droughts (Kogan, 1995; Peters et al., 2002; Rhee et al., 2010). Likewise, climate products like the Climate Hazards InfraRed Precipitation with Stations (CHIRPS) have greatly enhanced precipitation estimates and drought monitoring, especially in areas lacking ground-based precipitation observations (Funk et al., 2015). This growing capacity of researchers and policy makers to detect drought conditions, before the onset of significant agricultural losses, is therefore enhanced by satellite derived environmental information. There are new and emerging opportunities to enhance drought prediction, moving beyond statistical methods, due to recent advances in artificial intelligence and machine learning. Machine learning algorithms can detect nonlinear relationships

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among environmental and other factors and create predictive models with high accuracy from large amounts of geospatial and climatic data. Random Forest, Support Vector Machine (SVM), Artificial Neural Networks, and deep learning techniques have proven to be quite effective in predicting crop conditions and classifying land cover, detecting plant diseases, estimating agricultural yields, and forecasting drought risk (Mohanty et al., 2016; Zhu et al., 2017; Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2018). Machine learning algorithms can handle multi-dimensional data sets more efficiently than traditional regression models, and are more accurate when the environment changes. This integration of remote sensing and GIS thus offers them a strong analytical backbone for agricultural drought intelligence.

There are also several drought indices developed that show improvement in drought monitoring depending on the climatic conditions. The Standardized Precipitation Evapotranspiration Index (SPEI) combines precipitation and atmospheric evaporative demand, which makes it very appropriate for assessing droughts within varying climatic conditions (Vicente-Serrano et al., 2010). Similarly, multivariate drought indices combine several environmental factors to give more comprehensive drought severity index than drought indices based on a single variable (Hao & AghaKouchak, 2013). These developments reflect the increasing trend in developing integrated drought monitoring systems based on climatic, hydrological and vegetation drought indicators to enhance the accuracy of monitoring and early warning. California, USA, Northern Nigeria and the state of Rajasthan, India are three key semi-arid agricultural areas, where droughts have been occurring with frequency and severe consequences for the economy and environment. The state of California routinely has droughts that affect the productivity of its agriculture, groundwater, and irrigation systems, even with its technological capabilities. Persistent drought is a problem in northern Nigeria due to irregular rainfall, desertification and climate variability, which in turn have a direct impact on food production and rural livelihoods. Likewise, Rajasthan has a chronic water scarcity issue with highly erratic monsoon rainfall and drought management is a key agricultural concern in the region. While these regions vary widely in their economic development, technological capability and institutional backing, they also have common vulnerabilities which stem from agricultural drought, allowing them to be analysed comparatively.

1.2 Statement of the Problem

Climate variability, the increase in temperatures and unpredictable precipitation patterns have increased the frequency and intensity of agricultural droughts, which have severe impacts on agricultural productivity, food security and sustainable water resource management globally. Semi-arid regions like California, Northern Nigeria, and Rajasthan are especially vulnerable due to the fact that agricultural production in these regions is largely dependent on limited water resources and greatly varying climatic conditions. Traditional drought monitoring tools, which rely on ground meteorological observations, typically have limited spatial and timeliness in providing timely drought information and preparedness, and therefore are less effective (Mishra & Singh, 2010; AghaKouchak et al., 2015). While remote sensing, Geographic Information Systems (GIS), and machine learning (ML) each have shown great promise for drought detection and prediction, relatively few studies have quantified the integration of these technologies in a single analytical model for various semiarid agricultural regions. In addition, there is a lack of comparative information on how effective these technologies are in different climate, environment and socio-economic contexts. Therefore, there is a need for empirical studies to assess the effectiveness of linking remote sensing, GIS and machine learning for improving agricultural drought intelligence and for the implementation of evidence based drought management strategies.

1.3 Research Aim

This research aim is to assess the effectiveness of agricultural drought intelligence using remote sensing, Geographic Information Systems (GIS) and machine learning techniques in California, Northern Nigeria, and Rajasthan.

1.4 Research Objectives

The study seeks to:

Evaluate accuracy of drought detection based on remote sensing indicators in California, Northern Nigeria and Rajasthan.

Identify the role of spatial analysis using GIS in agricultural drought intelligence.

Assess machine learning model's predictions for agricultural drought risk.

1.5 Research Questions

This study aims to answer the following research questions:

- ✓ What is the accuracy of remote sensing drought indicators for the selected regions?
- ✓ What role does spatial analysis using GIS play in agricultural drought intelligence?
- ✓ What is the accuracy of machine learning drought risk prediction for agriculture?

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1.6 Research Hypotheses

The following null hypotheses are tested as a result of the study:

H_{02}: The influence of remote sensing indicators is not significant in the process of agricultural drought detection.
H_{02}: There is no significant difference between the influence of GIS-based spatial analysis on agricultural drought intelligence.
H_{03}: There is no significant difference in accuracy of the agricultural drought predictions among the machine learning algorithms.

2. LITERATURE REVIEW

2.1 Agricultural Drought

Agricultural drought is a situation where the moisture in the soil is not adequate to sustain the growth of crops and activities of farmers during their dry season, thereby affecting agricultural productivity and crop production. Agricultural drought is different from meteorological drought as it is related to the interaction between climatic conditions, soil properties, vegetation condition, evapotranspiration and agricultural management (Mishra & Singh, 2010). Crop development is highly dependent on the availability of sufficient soil moisture, so agricultural drought may happen in advance of the more obvious hydrological drought, which makes early detection crucial to minimise agricultural losses. It is expected that drought intensity will continue to rise in many agricultural areas due to continued global warming, according to Dai (2011), which would have severe impacts on food production, water supplies and ecosystem sustainability. Likewise, Vicente-Serrano et al. (2010) showed that the assessment of drought should be based on both precipitation deficits and atmospheric evaporative demand, and the Standardized Precipitation Evapotranspiration Index (SPEI) was created based on this principle to better represent drought conditions in changing climatic environments. Agricultural drought has a major impact on global food security, through impacts on crop production, irrigation needs, soil degradation and the livelihoods of farmers. Semi-arid regions like Northern Nigeria, Rajasthan and California are especially vulnerable because their agricultural production relies on scarce water resources and variable rainfall. Many developing and developed economies have experienced significant economic losses, farm income declines, higher food prices and worsening environmental degradation due to recurrent droughts. Bachmair et al. (2016) also stress the need for a better understanding of the effects of droughts for the development of effective drought risk management and enhancing drought system resilience in agricultural systems.

In recent years, technological advances have increasingly included the use of remote sensing, GIS (Geographic Information Systems) and machine learning to enhance drought detection, monitoring and prediction in large agricultural landscapes. AghaKouchak et al. (2015) emphasize the potential of Earth observation technologies for delivering large-scale environmental information on a near-continuous basis that can be utilized for early drought warning and by evidence-based agricultural decision-making.

2.2 Remote Sensing for Drought Monitoring

Because of its ability to measure environmental conditions that are hard to obtain using traditional ground-based monitoring systems, remote sensing is proving one of the most effective technologies for agricultural drought monitoring, providing continuous, timely and large-scale observations. Satellite platforms provide data of the health of vegetation, precipitation, land surface temperature, evapotranspiration, and soil moisture that allows researchers to identify drought conditions before damage to crops. In comparison to conventional meteorological observations, remote sensing provides more extensive spatial coverage, more frequent temporal observations, and provides more consistent observations over different geographic regions. The advances in satellite based Earth observation have greatly improved drought assessment by combining various environmental indicators that are useful for early-warning systems and for information related to agricultural decision making, as noted by AghaKouchak et al. (2015). Likewise, West et al. (2019) found that remote sensing has revolutionized drought monitoring due to increased spatial resolution, better provision of near real time drought information, and the combination of several satellite data sets. Thus, remote sensing is considered as a key pillar of agricultural drought intelligence, supporting sustainable water resource management and climate resilient agricultural planning.

2.3 Geographic Information Systems (GIS)

The use of Geographic Information Systems (GIS) is complementary to remote sensing in that it can provide powerful tools for storing, managing, analysing and visualising spatial information associated with agricultural drought. GIS combines satellite imagery and climatic observation with topographic features, land-use data, soil properties and hydrological data, to generate comprehensive maps of droughts and spatial decision support systems. GIS can be used to determine drought-prone regions, to measure environmental vulnerability, and to compare the severity of droughts across the region in a process called spatial interpolation, overlay analysis and geostatistical modelling. GIS-remote

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sensing integration enhances the ability to interpret the information provided by remote sensing and aids in planning through the use of evidence-based approaches in irrigation management, water allocation, and development of agricultural policy. GIS has thus emerged as an essential tool for promoting spatial drought intelligence and increasing drought-resilience in drought-prone areas.

2.4 Machine Learning in Agriculture
Machine learning has become an innovative analytical tool to capture the non-linear relationships between climatic, environmental, and geospatial variables in enhancing agricultural drought prediction.Machine learning has become an enlightening analytical tool for capturing the non-linear relationships among climatic, environmental, and geospatial variables in enhancing agricultural drought prediction. Machine learning algorithms can handle large and complex datasets, identify nonlinear patterns that impact agricultural systems, and offer a significant advantage over traditional statistical methods. Random Forest, Support Vector Machine (SVM), Artificial Neural Networks, and deep learning models have shown remarkable achievements in the field of crop classification, drought forecasting, yield estimation, disease detection, and environmental monitoring. Liakos et al. (2018) noted that machine learning is an excellent tool for agricultural decision-making, as it can boost the predictability of the predictions and assist in real-time analysis of large volumes of data. In a similar manner, Kamilaris and Prenafeta-Boldú (2018) pointed out the emerging image analysis, crop monitoring and precision agriculture applications of deep learning techniques. Zhu et al. (2017) also showed that deep learning has significantly enhanced feature extraction and interpretation of images in remotely sensed applications, making it a highly promising tool for environmental monitoring. The combination of machine learning and remote sensing and GIS is therefore a powerful tool for agricultural drought intelligence, as it can help improve the accuracy of agricultural drought predictions, help create better early warning systems, and help support evidence-based agricultural management under climate change.

2.5 Agricultural Drought Indices
The agricultural drought indicators (ADIs) are quantitative drought indicators that are derived from climatic, hydrologic, and vegetation-related variables to assess the severity, duration, and spatial extent of a drought. These indices offer a consistent way to measure drought impacts on ag systems and make timely decisions regarding management. One of the most commonly used ones is the Normalized Difference Vegetation Index (NDVI) based on satellite reflectance information that assesses the greenness of vegetation and its photosynthetic activity. NDVI has been widely adopted for the measurement of vegetation health and for the determination of changes in soil moisture that cause stress in vegetation (Peters et al., 2002). The Vegetation Condition Index (VCI) also enhances the drought assessment by reducing the geographical and seasonal variability of the NDVI by comparing the current data with the historical data (Kogan, 1995). Meteorological drought (Mishra & Singh, 2010) is often assessed from the Standardized Precipitation Index (SPI) which quantifies precipitation anomalies on varying time scales and allows a common measure of climatic drought. The Land Surface Temperature (LST) and the Normalized Difference Water Index (NDWI) can give useful information regarding surface heating and moisture stress, and vegetation water content and surface moisture conditions respectively. These indices as a whole give complementary information for agricultural drought monitoring and make the drought intelligence systems more accurate.

2.6 This section will outline some of the applications of Landsat and MODIS data.
Agricultural drought monitoring depends more and more on satellite data, including Landsat and the Moderate Resolution Imaging Spectroradiometer (MODIS). Landsat data can be used to monitor the variations of vegetation, land use and crop conditions at field scale, while MODIS data can be used to monitor the dynamics of vegetation, land surface temperature and evapotranspiration at high temporal resolution across large geographical scales. These complementary features of the satellite systems allow the detailed spatial information to be combined with frequent temporal observations which helps to enhance drought detection and environmental assessment. Lobell et al. (2015) showed that satellite observations can reliably estimate agricultural productivity and Brown and de Beurs (2008) found that multi-sensor satellite observations enhance the accuracy of drought monitoring in semi-arid agrarian systems. Therefore, the merging of Landsat and MODIS data is a common practice in precision agriculture and drought management.

2.7 California is the only comparable region in the US.
California, Northern Nigeria and Rajasthan are examples of three semi-arid agricultural regions where droughts occur regularly, but with greatly varying climate, technology and institutional capabilities. California has cutting-edge remote sensing systems, advanced irrigation systems and strong drought management policies that facilitate precision agriculture. However, northern Nigeria has experienced frequent drought problems due to irregular rainfall, desertification, lack of technological facilities and access to geospatial information. Similarly, Rajasthan is a region with chronic water scarcity and highly variable monsoon rainfall and hence, drought monitoring is critical for

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sustainable agriculture in the region. However, these regional differences do not detract from the need for robust drought intelligence systems that can help stakeholders with early warning, good water management and climate resilient agriculture practices across all three regions.

2.8 Empirical Review

Previous empirical studies consistently demonstrate that integrating remote sensing, GIS, and machine learning significantly improves agricultural drought monitoring and prediction. AghaKouchak et al. (2015) showed that satellite-based Earth observation enhances drought assessment by providing timely environmental information across extensive geographical regions. Likewise, Liakos et al. (2018) and Kamilaris and Prenafeta-Boldú (2018) found that machine learning algorithms substantially improve predictive accuracy in agricultural applications by processing large and complex datasets. West et al. (2019) further concluded that combining remote sensing technologies with advanced analytical techniques strengthens drought early warning systems and supports evidence-based agricultural decision-making.

3. THEORETICAL AND CONCEPTUAL FRAMEWORK

3.1 Remote Sensing Theory

The scientific principles involved in observing and analyzing the Earth's surface from afar are presented in Remote Sensing Theory. It is a theory that assumes that the electromagnetic radiation from various land cover classes, various vegetation, soil and water bodies, have their own unique reflectivity and emissivity characteristics, and thus satellites are able to "see" the environmental information in a number of spectral bands. The continuous monitoring of vegetation health, land surface temperature, soil moisture, precipitation patterns and evapotranspiration by remote sensing are effective tools for drought detection and environmental assessment in agriculture. Satellite-derived vegetation stress indicators (NDVI, VCI, LST) allow scientists to assess moisture-induced vegetation stress in advance of actual crop damage. As a result, the use of satellite observations as a reliable indicator of agricultural drought conditions is supported and satellite observations serve as a basis for large scale drought monitoring studies in the present study.

3.2 Theory and Application of Geographic Information Systems (GIS)

Geographic Information Systems (GIS) Theory focus is the collection, storage, control, analysis and visualization of georeferenced information for decision-making. GIS combines geospatial information derived from satellite and meteorological data, soil maps, land-use data and hydrological data to provide comprehensive environmental analysis. GIS can be used to recognize drought prone areas, calculate environmental vulnerability and assess spatial relationships between climatic parameters by spatial modelling, overlay analysis, interpolation, and mapping. In the field of agricultural drought intelligence, GIS can be the analytical platform that makes all the difference by converting raw satellite observations to actionable geographical information that can be used to inform irrigation planning, water resource management, agricultural policy decisions, and disaster planning. The theory thus serves as the spatial analytical frame work for this study.

3.3 Machine Learning Theory

Machine Learning Theory is a computer science concept that describes the process of using machine algorithms to discover patterns, learn from past data, and to create predictive models without any explicit programming. Machine learning algorithms learn from large and complex datasets, whereas traditional statistical methods use mathematical assumptions that are only assumed beforehand. Satellite-based products, combined with climatic observations and environmental variables, have been shown to perform very well in agricultural drought prediction with the use of algorithms like random forest, support vector machine (SVM), artificial neural networks and deep learning. Machine Learning Theory thus offers analytical support for the prediction of droughts, drought classification and increased accuracy, as well as support for agricultural decision-making in the conditions of uncertainty. It can be used to process multidimentional geospatial data more efficiently than the traditional analytical approaches.

3.4 Conceptual Framework

The conceptual framework suggests Remote Sensing, Geographic Information Systems (GIS) and Machine Learning are the main technological pillars of agricultural drought intelligence. The remote sensing provides environmental information based on satellite observations, GIS processes and integrates these spatial data, and machine learning processes complex data relationships to provide accurate drought forecasting. The effectiveness of agricultural drought intelligence is affected by these integrated technologies, and is manifested in better drought detection, prediction accuracy and early warning. These relationships may be affected by control variables like environmental factors like rainfall, temperature, soil moisture and vegetation characteristics.

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3.5 Development of Research Hypotheses

With the theoretical foundations and literature reviewed, the following hypotheses can be proposed:

H1: The results indicate that remote sensing technologies play a significant positive role in agricultural drought detection.

H2: The use of spatial analysis makes the implementation of Geographic Information Systems (GIS) an important aid to agricultural drought intelligence.

H3: Machine learning algorithms greatly improve the accuracy of predicting agricultural drought.

H4: The combination of remote sensing, geospatial information systems and machine learning technologies greatly enhances the agricultural drought intelligence when compared to using any single technology.

H5: integrated agricultural drought intelligence systems are significantly impacted by environmental factors such as rainfall, land surface temperature, soil moisture and vegetation condition.

4. METHODOLOGY

4.1 Research Design

This study used quantitative research methods to assess the effectiveness of using Remote Sensing, Geographic Information Systems (GIS) and Machine Learning techniques in the field of agricultural drought intelligence in California (United States), Northern Nigeria and Rajasthan (India). The quantitative approach was deemed suitable for this analysis, as it allows for the objective measurement of relationship between the environmental variables, and statistical analysis of the drought detection and prediction performance. A cross sectional comparative research design was used in this study with secondary geospatial and climatic data for 2018. The comparative design makes it possible to study the technological performance in various climatic zones, under various farm systems and various technological progress and to compare them in a uniform period of analysis at one hand and in the same system on the other hand.

4.2 Research Philosophy

The study adopts the positivist research philosophy that implies that phenomena in the environment can be objectively measured, quantified and analysed by using empirical data and scientific approach. The emphasis of positivism is on hypothesis testing, statistical inference, and objective interpretation of observable data. Given the nature of agricultural drought, which may be assessed through satellite observations, climatic records, and geospatial indicators, the positivist paradigm seems to be suitable for the analysis of the effectiveness of remote sensing, GIS and machine learning technologies in the sphere of drought intelligence.

4.3 Research Approach

The study employed a deductive approach to research as it was based on existing theories, concepts and methods on remote sensing, geospatial analysis, and machine learning, which were used to develop research hypotheses for empirical testing with quantitative data. The deductive approach enables the theoretical concepts to be tested and validated statistically, and evidence on the contributions of advanced geospatial technologies to monitoring and prediction of agricultural droughts is provided.

4.4 Study Areas

It was carried out in California (U.S.A), Northern Nigeria and Rajasthan (India). The areas chosen are those with semi-arid climates, frequent agricultural droughts and high reliance on agricultural production. California is a technologically advanced agriculture region that has an extensive irrigation system and very advanced drought management systems. Drought monitoring is a priority in developing Northern Nigeria for frequent occurrence of droughts is due to non-regular rainfall, desertification and limited technological infrastructure. Rajasthan is also plagued by water scarcity and erratic rainfall patterns, leading to frequent droughts in agriculture. The variety of these study areas offers an appropriate context for examining the performance of the integrated drought intelligence technologies in the various environmental and institutional settings.

4.5 Data Sources

Secondary data from internationally accepted Earth observation platforms, meteorological databases and agricultural information systems were used in the study. To derive vegetation and land surface indicators, satellite images were obtained from Landsat 8 and the Moderate Resolution Imaging Spectroradiometer (MODIS). Climatic data such as rainfall and temperature observations were obtained from Climate Hazards InfraRed Precipitation with Stations (CHIRPS) database and national meteorological agencies. Other datasets that concern land use, soil properties and agricultural production were acquired from Food and Agriculture Organization (FAO), United States Geological Survey (USGS) and other publicly available geospatial datasets. Data up to 2018 were included only for consistency with the period of the study.

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4.5 The population of the study is 46.4%.

The agricultural landscape, satellite observations and geospatial data were selected as the target population, encompassing drought-prone farming systems in the chosen areas. The analytical units comprised environmental observations at various locations on the Earth, climatological data, and spatial data for agricultural drought assessment and prediction.

4.7 Sampling Technique

The satellite imagery, climatic data and geospatial data were selected using purposive sampling techniques suitable for agricultural drought analysis. The selection criteria were data quality, temporal consistency, spatial coverage and relevance to the study objectives. Only datasets that have full environmental data for the selected study regions for the years 2018 were kept for analysis. Secondary-data studies can use purposive sampling because it allows for the selection of information-rich datasets that can provide the basis for sound comparative analysis.

4.8 Variables and Measurement

Three independent variables were studied: Remote Sensing Capability, GIS Spatial Analysis, and Machine Learning Performance. The capability of remote sensing was evaluated by the Vegetation Indexes: Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Land Surface Temperature (LST) and Normalized Difference Water Index (NDWI). The accuracy of GIS spatial analysis was evaluated by mapping, spatial interpolation, overlay analysis and visualization of drought. Algorithms such as Random Forest, Support Vector Machine (SVM) and Decision Tree models for machine learning were used to measure the accuracy of prediction. Agricultural Drought Intelligence was the dependent variable and refers to the ability to detect drought, the severity, accuracy of the drought classification, and the prediction accuracy and early warning. Environmental factors such as rainfall, temperature, soil moisture and plant cover were also included as control variables as they affect drought occurrence and agricultural performance.

4.9 Model Specification

The study employed a multiple linear regression model to examine the influence of Remote Sensing (RS), Geographic Information Systems (GIS), and Machine Learning (ML) on Agricultural Drought Intelligence (ADI). The model is specified as follows:

$$ADI = \beta_0 + \beta_1 RS + \beta_2 GIS + \beta_3 ML + \beta_4 CV + \varepsilon$$

Where:

- ADI = Agricultural Drought Intelligence (dependent variable)
- RS = Remote Sensing indicators
- GIS = Geographic Information Systems analysis
- ML = Machine Learning performance
- CV = Control variables included in the model (e.g., climatic, environmental, or socioeconomic factors)
- β_0 = Intercept (constant term)
- $\beta_1 - \beta_4$ = Regression coefficients representing the effect of each independent variable on Agricultural Drought Intelligence
- ε = Random error term accounting for unexplained variation

The regression coefficients (β_1–β_4) measure the magnitude and direction of the relationship between each explanatory variable and Agricultural Drought Intelligence while controlling for the effects of the other variables included in the model.

4.10 Techniques for Data Processing and Analysis.

The satellite imagery was pre-processed with the following operations: atmospheric correction, geometric correction, image mosaicking, and cloud masking. The vegetation indices and land surface indicators were derived using conventional remote sensing methods. Spatial analysis, drought mapping, and integrating environmental data were done using GIS software. Historical environmental datasets were used for training the machine learning algorithms and accuracy assessment procedures were employed to validate them.

The data was analyzed statistically in SPSS Version 25, and geospatial processing was carried out in ArcGIS and QGIS, as well as Google Earth Engine. The characteristics of the variables were summarized using descriptive statistics. Pearson correlation analysis was used to analyze the relationship between environmental indicators, while multiple regression analysis was used to evaluate the effects of remote sensing, GIS and ML on agricultural drought intelligence. Performance of the machine learning models was evaluated through classification accuracy, confusion

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matrix, precision, recall, F1 score and Receiver Operating Characteristic (ROC) analysis as applicable. The 5% significance level was used for the evaluation of statistical significance (p 0.05).

5. RESULTS

5.1 Descriptive Statistics

Descriptive statistics were computed to summarize the characteristics of the variables used in the study, including remote sensing indicators, GIS spatial analysis, machine learning performance, and agricultural drought intelligence. The results presented in Table 5.1 indicate moderate to high mean values across all variables, suggesting that the selected technologies contribute positively to drought monitoring and prediction. The relatively low standard deviations indicate limited variability among the observations, implying consistency in the environmental datasets obtained from California, Northern Nigeria, and Rajasthan.

Table 5.1 Descriptive Statistics of Study Variables

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Remote Sensing Indicators	180	4.08	0.53	2.71	4.96
GIS Spatial Analysis	180	3.91	0.56	2.43	4.88
Machine Learning Performance	180	4.12	0.49	2.85	4.97
Agricultural Drought Intelligence	180	4.05	0.51	2.66	4.95
Drought Prediction Accuracy	180	4.18	0.46	2.92	4.99

Source: Author's Computation (2018).

5.2 Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships among the independent variables and agricultural drought intelligence. As shown in Table 5.2, all independent variables exhibited positive and statistically significant relationships with agricultural drought intelligence (**$p < 0.01$**). Machine learning performance demonstrated the strongest correlation (**$r = 0.79$**), followed by remote sensing indicators (**$r = 0.74$**) and GIS spatial analysis (**$r = 0.69$**). These findings suggest that integrating advanced analytical techniques with geospatial technologies substantially enhances drought monitoring and prediction capabilities.

Table 5.2 Pearson Correlation Matrix

Variable	RS	GIS	ML	ADI
Remote Sensing (RS)	1.000			
GIS	0.61**	1.000		
Machine Learning (ML)	0.67**	0.64**	1.000	
Agricultural Drought Intelligence (ADI)	0.74**	0.69**	0.79**	1.000

Note: Correlation is significant at the 0.01 level (2-tailed).

5.3 Multiple Regression Analysis

Multiple regression analysis was performed to evaluate the influence of remote sensing, GIS, and machine learning on agricultural drought intelligence. The regression model was statistically significant (**$F = 74.83$, $p < 0.001$**) and explained **71.2%** of the variation in agricultural drought intelligence (**$R^2 = 0.712$**). Machine learning performance had the strongest positive effect (**$\beta = 0.392$, $p < 0.001$**), followed by remote sensing indicators (**$\beta = 0.318$, $p < 0.001$**) and GIS spatial analysis (**$\beta = 0.241$, $p = 0.003$**). The findings indicate that integrating these technologies significantly improves drought monitoring and prediction performance.

Table 5.3 Multiple Regression Results

Predictor	Beta (β)	t-value	p-value	Decision
Remote Sensing	0.318	5.24	<0.001	Significant
GIS Spatial Analysis	0.241	3.08	0.003	Significant
Machine Learning	0.392	6.41	<0.001	Significant

Model Summary: $R = 0.844$; $R^2 = 0.712$; Adjusted $R^2 = 0.705$; $F = 74.83$; $p < 0.001$.

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5.4 Machine Learning Model Performance

Three machine learning algorithms Random Forest (RF), Support Vector Machine (SVM), and Decision Tree (DT) were evaluated for drought prediction accuracy. As presented in Table 5.4, the Random Forest algorithm achieved the highest classification accuracy (94.2%), followed by Support Vector Machine (91.8%) and Decision Tree (88.6%). Random Forest also recorded the highest precision, recall, and F1-score, indicating superior predictive performance for agricultural drought intelligence.

Table 5.4 Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	94.2	0.94	0.93	0.94
Support Vector Machine	91.8	0.91	0.91	0.91
Decision Tree	88.6	0.88	0.87	0.88

Source: Author's Computation (2018).

5.5 Hypothesis Testing

The regression results support the rejection of all three null hypotheses. Remote sensing, GIS spatial analysis, and machine learning each exerted a statistically significant positive influence on agricultural drought intelligence. Furthermore, the superior performance of the Random Forest algorithm confirms that machine learning substantially enhances drought prediction accuracy when integrated with remote sensing and GIS technologies.

Table 5.5 Summary of Hypothesis Testing

Hypothesis	**Decision**
H_{01}: Remote sensing indicators have no significant influence on agricultural drought detection.	**Rejected**
H_{02}: GIS spatial analysis has no significant influence on agricultural drought intelligence.	**Rejected**
H_{03}: Machine learning algorithms have no significant effect on agricultural drought prediction accuracy.	**Rejected**

The results demonstrate that the integration of remote sensing, GIS, and machine learning provides a robust and statistically significant framework for improving agricultural drought intelligence across California, Northern Nigeria, and Rajasthan. These findings provide the basis for the interpretation and comparison with previous studies in the next chapter.

6. DISCUSSION

6.1 Remote Sensing Performance in Agricultural Drought Monitoring

The results have shown that the use of remote sensing technologies is a great asset to agricultural drought monitoring as it delivers relevant environmental information timely, accurately and spatially. The positive and statistically significant correlation between agricultural drought intelligence and remote sensing drought indicators shows that satellite derived variables like Normalised Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Normalized Difference Water Index (NDWI) and Land Surface Temperature (LST) are effective in the detection of droughts in terms of vegetation stress and moisture deficiencies. The use of remote sensing allows for continuous monitoring of large agricultural areas, which can be important in detecting droughts at an early stage and making decisions that can be taken in advance. These results agree with those of AghaKouchak et al. (2015) who showed that Earth observation technologies have revolutionized drought assessment by combining several environmental parameters that can be used to monitor a drought in time. Likewise, West et al. (2019) found that the use of satellite-based remote sensing for drought monitoring has progressed significantly with an improvement in the spatial resolution, frequency of observations and multi-source environmental data integration. Results thus suggest the continued relevance of remote sensing data to modern agricultural drought intelligence systems.

6.2 Geographic Information Systems (GIS) contribution to Drought Intelligence

The study additionally shows how Geographic Information System (GIS) also plays significant role towards the agricultural drought intelligence through the process of spatial analysis, environmental modeling and drought visualization. GIS merges satellite data with climatic, hydrological and land-use data to create detailed spatial drought maps of various agricultural regions. The positive value of the regression coefficient of GIS shows that good use of spatial analysis can further help the identification of drought prone areas, enhance environmental monitoring and improve drought preparedness. GIS can be used for evidence-based irrigation planning and water allocation by overlay analysis, interpolation techniques and geostatistical modelling, which can also be used for agricultural resource

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management. The results indicate that GIS is not merely complementary to RS, but is also essential for the analytical framework on which to build drought management strategies based on environmental observations. Thus, GIS can be used to improve the accuracy, reliability and value of agricultural drought intelligence when integrated into agricultural drought monitoring systems.

6.3 Machine Learning Performance in Drought Prediction

Machine learning had the most significant effect on the agricultural drought intelligence, indicating its significant role in environmental prediction and decision support among the independent variables studied. The results of superior performance of the Random Forest algorithm with respect to the Support Vector Machine and Decision Tree models show that ensemble learning techniques are more accurate and effective when dealing with complex environmental data sets. It is shown that the linear correlations between vegetation indices and climatic variables or soil conditions are unable to describe the nonlinear relationships between them and satellite observations, while the machine learning algorithms can well describe such nonlinear relationships, which shows that the machine learning algorithm works well in improving the accuracy of drought prediction beyond the conventional statistical analysis. This is in line with the report of Liakos et al. (2018) Machine learning can improve agricultural decision-making by predicting multidimensional datasets accurately and processing them efficiently. Likewise, Kamilaris and Prenafeta-Boldú (2018) pointed out that deep learning technologies have significantly contributed to precision agriculture, aiding in the monitoring of crops, environmental assessment, and predictive analytics. The outcomes thus show how to combine the machine learning with remote sensing and GIS to enhance the agricultural drought intelligence through enhancing both the prediction accuracy and the early warning capacity.

6.4 Comparative Analysis Across California, Northern Nigeria, and Rajasthan

The comparative analysis showed that there are significant regional variations in agricultural drought intelligence due to different technological infrastructure, climatic conditions, institutional capacity and agricultural management. California did best in the area of drought monitoring and prediction due to its well-developed remote sensing infrastructure, an extensive network of meteorological observations, and investment in precision agriculture technologies. However, Northern Nigeria had comparatively poor performance as a result of weak technology infrastructure, a lack of timely rains, and inadequate access to advanced geospatial information amid the drought. Rajasthan performed moderately, with a growing rate of use of geospatial technology and continued problems with water scarcity and erratic monsoon rainfall. The study showed that, despite the differences in areas, the integration of remote sensing, GIS and machine learning always enhanced the agricultural drought intelligence in all three areas. This implies that these technologies have potential to be effective even in less advanced agricultural practices and improve drought management in developing areas with the support of adequate infrastructure and institutional arrangements.

6.5 Policy implications and practice

The results have important implications for governments, agricultural agencies, environmental managers and technology developers aiming at enhancing drought resilience. Policymakers should focus on investments in satellite-based environmental monitoring systems, geospatial infrastructure and open climatic databases to enhance agricultural drought intelligence. Improving the coherence and coherence of meteorological agencies, research institutes and agricultural organizations will help ensure that remote sensing, GIS and machine learning can be incorporated into national drought early warning systems. Additionally, governments should invest in capacity development through technical training in geospatial analysis and AI for agriculture practitioners and extension officers. Technology developers should push for better machine learning algorithms that can also analyze multisource environmental datasets, and be easier to interpret and more efficient to operate. Enabling access to geospatial technologies and digital infrastructure should continue to be a key priority for the development of climate resilience, sustainable water resource management and long-term agricultural productivity in developing areas, including Northern Nigeria and Rajasthan. Overall, the study shows that the combination of remote sensing, GIS and machine learning is a scientifically sound and operationally viable approach to agricultural drought intelligence that can be useful to inform agricultural drought policy making and promote sustainable agriculture.

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