Mantik Journal, 8 (1) (2024), ISSN 2685-4236 (Online)

Published by: Institute of Computer Science (IOCS)

Jurnal Mantik

Journal homepage: www.iocscience.org/ejournal/index.php/mantik

Application of the rule-based system method to determine the type of crops based on altitude and rainfall

Gunawan Gunawan[1], Akhmad Lutfi Firmansyah[2], Bayu Aji Santoso[3]

[1,2]Informatics Engineering, STMIK YMI TEGAL, Indonesia

[3]Information System, STMIK YMI TEGAL, Indonesia

ARTICLE INFO

Article history:

Received May 25 2024

Revised May 27, 2024

Accepted May 30, 2024

Keywords:

Agricultural Crops;
Height;
Modern agriculture;
Rainfall;
Rule-Based System.

ABSTRAK

Applying the rule-based system method to determine the type of agricultural crop based on altitude and rainfall is essential in increasing productivity and efficiency in modern agriculture. This study aims to develop and implement a rules-based system to recommend suitable plant types by analyzing altitude and rainfall data in the Tegal District. The research method includes experimental design, quantitative analysis, and model validation using data from the Central Bureau of Statistics and various other internet sources, covering January 1 to December 31, 2023. The results showed that this rule-based system effectively provides accurate recommendations with an average accuracy rate of 85% and an error rate of 15%. This system helps farmers make informed decisions about crop selection, reducing crop failure risk and contributing to sustainable agricultural practices. Future research suggests integrating real-time weather prediction technology and additional environmental variables to improve the precision of recommendations and expand the applicability of these systems to other areas with similar characteristics.

Corresponding authors:

Akhmad Lutfi Firmansyah,
Informatics Engineering,
STMIK YMI TEGAL,
#1 Pendidikan Street, Tegal City, Central Java 52142, Indonesia.
Email: akhmadfirmansyah07@gmail.com

1. INTRODUCTION

In modern agriculture, selecting crops to be planted is essential for increasing productivity and efficiency (Castiglione et al., 2021; Rezk et al., 2021; Tian et al., 2021). Given the significant variability of climate and geographical conditions, farmers and decision-makers in the agricultural sector need to make informed decisions (Born et al., 2021; Labeyrie et al., 2021). The application of information technology, especially the Rule-Based System method, to determine the type of crops based on altitude and rainfall is becoming relevant and an innovative step that supports appropriate decision-making. However, implementing these technologies faces real challenges, including data inaccuracies that can lead to incorrect recommendations, affecting agricultural productivity and sustainability (Carletto, 2021; Khan et al., 2021; Sinha & Dhanalakshmi, 2022). Farmers may also lack access to or the ability to use these systems, creating a technology gap. To overcome these problems, this research will use the Rule Based System method, which will be analyzed and adjusted to the actual conditions of agriculture (Cravero et al., 2022). This method was chosen because of its flexibility in handling various situations and the ease of modifying rules as data changes or needs (Hayes et al., 2022; Ullah et al., 2023). The latest technology, such as remote sensing and geographic information systems, will be utilized to obtain accurate and relevant data (Mashala et al., 2023; Sikakwe, 2023).

This research is essential because by determining the optimal type of crop based on altitude and rainfall, farmers can increase crop yields (Yu et al., 2021), reduce the risk of crop failure, and contribute to the sustainability of the agricultural sector (Benyam et al., 2021). By integrating information technology in agriculture, this research supports precision agriculture and better resource management (DeLay et al., 2022; Erickson & Fausti, 2021; Liu et al., 2021). The integration of technology in Rule-Based Systems can improve the effectiveness and efficiency of such systems. Advanced inference engines, machine learning for rule automation, and Big Data analysis can refine and optimize existing rules. IoT devices provide real-time data for quick decisions, while AI helps identify new patterns and validate rules. This research bridges gaps in agricultural practice by using a Rule-Based System to determine suitable crop types based on altitude and rainfall. It addresses challenges like data inaccuracies and farmers' access to advanced systems by providing precise, location-specific recommendations through accurate geographic and climate data. Additionally, the integration of modern technologies such as remote sensing and geographic information systems enhances the precision and relevance of these recommendations.

The research developed a special algorithm that crunches geographic and climate data, providing recommendations for crops appropriate to local conditions (Maier et al., 2024). The technology is easy to use, even by farmers in remote areas, and incorporates traditional knowledge (Nugroho et al., 2023). Thus, this study aims to provide recommendations for types of crops based on altitude and rainfall data using a Rule-Based System (Musanase et al., 2023). The integration process involves implementing a Rule-Based System algorithm that utilizes fuzzy logic to enhance the accuracy of variable determination and categorization of altitude and rainfall data to recommend suitable crop types. To ensure reliability, the algorithm's parameters will be adjusted based on model optimization results, and its performance will be evaluated through accuracy metrics and error rates. Additionally, the system integrates advanced technologies such as real-time weather prediction, IoT devices, and AI, which provide real-time data and identify new patterns. This integration not only refines and optimizes existing rules but also ensures timely and accurate recommendations, thereby improving the agricultural decision-making process. The results of this study are expected to improve agricultural efficiency, environmental inequality, and adaptation to climate change. It also assists farmers in making more informed decisions when recommending types of crops (Gopi & Karthikeyan, 2024).

Previous research identified that primary (nitrogen, phosphorus, potassium) and secondary (calcium, magnesium) nutrients, as well as micronutrients (zinc, iron) and beneficial nutrients (silicon, selenium), can increase photosynthetic capacity, water use efficiency, cell membrane stability, and enzymatic and antioxidant activity in plants, thereby effectively reducing abiotic stress. Proper nutrient management significantly increases crop resistance to adverse environmental conditions, providing valuable guidance for developing more effective agricultural strategies (Kumari et al., 2022). A study (Bouguettaya & Zarzour, 2022) evaluated using CNN-based deep learning techniques for agricultural crop classification using UAV imagery. Through literature analysis, the study helps researchers and farmers select suitable algorithms and identify potential challenges and solutions in using UAV imagery for precision agriculture. The results showed that combining UAV data and deep learning significantly increased agricultural productivity by providing accurate and real-time information about crop conditions. Subsequent research developed a fuzzy rule-based system for diabetes classification that showed high accuracy in early diagnosis of diabetes. Using public datasets and simple features such as blood glucose levels and BMI, the model achieved an accuracy of 96.47%, higher than previous techniques. This model is not only effective in detecting diabetes but also easy to interpret, so it can provide significant benefits to the health sector in efforts to prevent and manage diabetes (Aamir et al., 2021). Recent research developed a highly explainable rules-based cumulative belief system with effective rule modeling and inference procedures. The proposed CBRBS system significantly improves accuracy, computational efficiency, and explanatory capabilities compared to classical rule-based systems. Through a series of experiments, CBRBS proved effective in various applications, including pipeline leak detection and other classification problems, making it a promising solution for future rule-based applications (Yang et al., 2022).

2. RESEARCH METHOD

2.1 Research Design

This research design combines experimental methods, quantitative analysis, and model validation. The quantitative approach processes and analyzes historical data from the Central Bureau of Statistics and other internet sources covering January 1 to December 31, 2023.

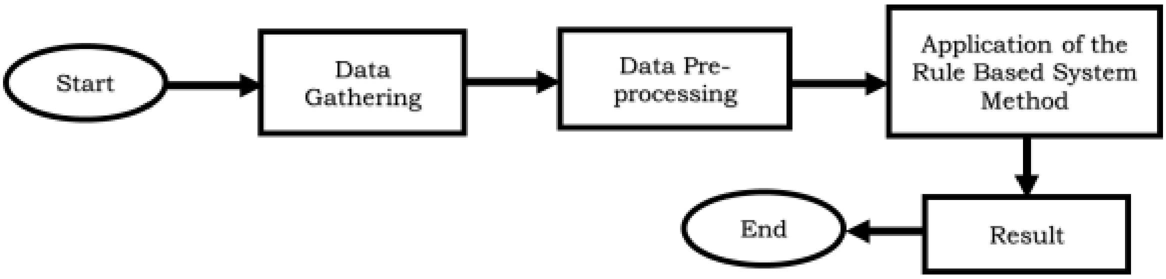

Figure 1. Research Flow

In Figure 1. Explaining the flow of research, this study begins with data collection as the first stage to obtain altitude and rainfall data; after that, data processing is carried out to produce information about environmental conditions in the area; the information includes classification of altitude and rainfall. The next stage is applying the Rule Based System method to determine the type of crops based on altitude and rainfall. The last stage is the results that can later be used if the data is accurate.

2.2 Data Gathering

The data Gathering comes from the Central Bureau of Statistics and other internet sources, including altitude, rainfall, and types of crops that can be grown in an area. Agricultural crop type information consists of 20 crop type data, while rainfall data consists of 12 data covering January 1 to December 31, 2023. The altitude data includes 18 data referring to sub-districts in the Tegal Regency area.

2.3 Pre-processing Data

In the data pre-processing stage, steps, including cleaning, normalization, and data transformation, are implemented to ensure its readiness before further analysis. This process includes tracking and calculating the total rainfall over the past four years and the average value. These steps are crucial to optimize data quality, supporting the accuracy of the resulting analysis results.

2.4 Variable Selection and Model Optimization

This study's main variables were altitude and rainfall, which were analyzed using fuzzy logic. The application of fuzzy logic aims to improve the accuracy of determining relevant variables, which will be categorized into two main functions: input and output. The input variables in this system include altitude and rainfall, while the output variables are determined as the type of agricultural crop. This approach allows for more efficient and effective modeling in recommending optimal plant types based on specific geographical and climatic conditions (Bhat et al., 2023).

2.5 Algorithm Implementation

The Rule Based System algorithm is implemented to classify and recommend types of crops based on altitude and rainfall. The following is the rule base for plant growing requirements for land elevation.

2.6 Algorithm Configuration and Model Evaluation

Algorithm configuration involves setting parameters based on the results of model optimization. The evaluation model is carried out using accuracy and error rates to measure the extent of accuracy in recommending types of crops.

$$\text{Accuracy} = \sum \frac{Correct\ Attempts}{Total\ Attempts}\ x\ 100 \qquad (2)$$

Correct Attempts are the number of attempts in which a user judges a recommendation as accurate. Total Attempts is the total number of attempts made, including precise and inaccurate (Ukwuoma et al., 2023).

$$Error\ Rate = 100 - Accuracy \qquad (3)$$

It calculates the percentage of inaccurate attempts based on the total effort (Senderowicz et al., 2023).

3. RESULTS AND DISCUSSIONS

The research process was carried out by implementing the Rule-based system method to recommend types of crops based on altitude and rainfall. Figure 2 shows rainfall data in the Tegal Regency area. Figure 3 shows altitude data in the Tegal Regency area of various sub-districts. Table 1 shows data on plant growing requirements to determine the type of plant.

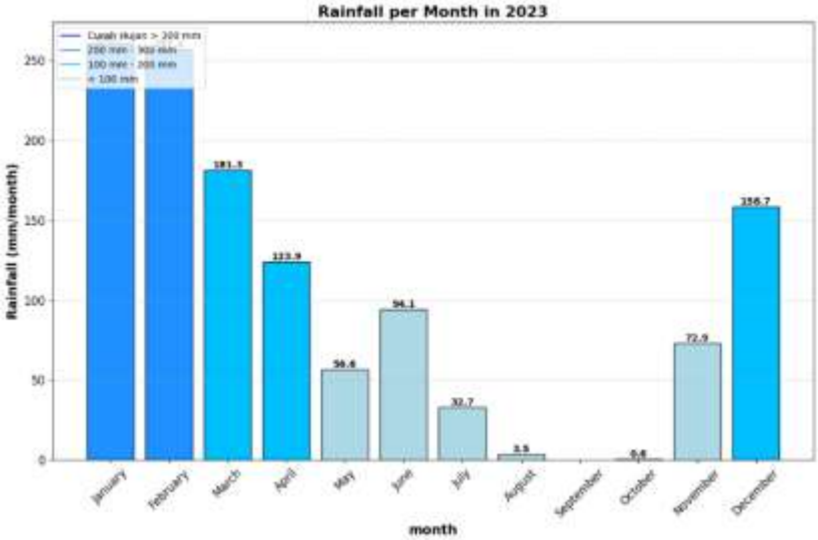

Figure 2. Rainfall Data

Figure 2. Displays rainfall data in Tegal Regency for 2023. The data includes monthly rainfall, January 260 mm, February 250 mm, March 181.3 mm, April 123.9 mm, May 56.6 mm, June 94.1 mm, July 32.7 mm, August 3.5 mm, September 0 mm, October 0.6 mm, November 72.9 mm, and December 158.7 mm.

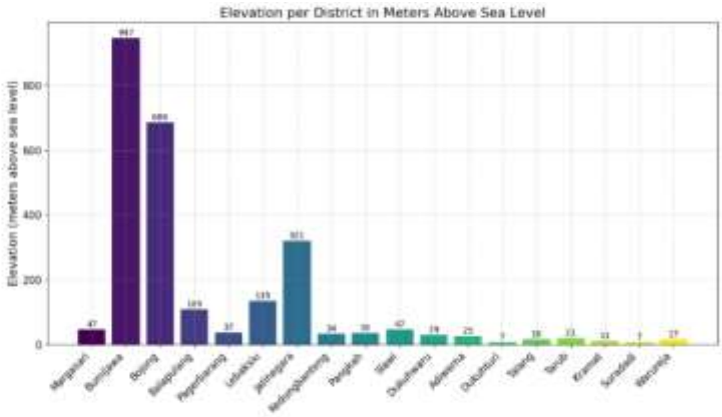

Figure 3. Altitude Data

Figure 3. Displays altitude data in Tegal Regency. This data covers altitudes in various sub-districts such as Margasari District with an altitude of 47 masl, Bumijawa District 947 masl, Bojong District 686 masl, Balapulang District 109 masl, Pagerbarang District 37 masl, Lebaksiu District 135 masl, Jatinegara District 321 masl, Kedungbanteng District 34 masl, Pangkah District 35 masl, Slawi District 47 masl, Dukuhwaru District 29 masl, Adiwerna District 25 masl, Dukuhturi District 7 masl, Talang District 16 masl, Tarub District 21 masl, Kramat District 11 masl, Suradadi District 7 masl, and Warureja District 17 masl.

Table 1. Plant Growing Terms Data

No	Crops	Land Elevation (masl)	Rainfall (mm/year)
1	Paddy	0-1500	1500-2000
2	Corn	0-1500	600-1200
3	Soya bean	0-800	800-1300

4	Red onion	0-900	500-3000
5	Tea	800-2000	2000-3000
6	Chilli	0-1500	600-1250
7	Carrot	1200-1500	1500-2500
8	Tomato	0-1500	750-1250
9	Potato	1000-2000	1000-1500
10	Palm oil	0-500	2000-3000
11	Peanuts	0-500	500-1000
12	Sweet potato	0-1500	750-1500
13	Garlic	600-1500	1000-2000
14	Cucumber	0-800	1500-2000
15	Coffee	400-1500	1500-3000
16	Clove	0-900	1500-2500
17	Nutmeg	0-700	1500-3000
18	Cocoa	300-800	1500-2500
19	Quinine	700-1500	1500-3000
20	Rubber	700-1500	1500-3000

Table 1. Explain the data on plant growing requirements to calculate the Rule Based System algorithm results. Once the data is collected, it is normalized to produce numerical numbers. After normalization, variable selection was carried out using altitude and rainfall variables. This study uses fuzzy logic to determine the input and output to get a rule or rule. The results of implementing fuzzy logic are presented in Table 2.

Table 2. Input Output

Function	Variable	Set Name Variable
INPUT	Height	Lowland (<300 masl)
	Place	Temperate Plains (300 – 500 masl)
		Plateau (>500 masl)
	Rainfall	Light (<1000 mm/year)
		Keep (1000 – 2000 mm/year)
		Heavy (>2000 mm/year)
OUTPUT	Kind	rice, corn, soybeans, onion, tea, chili,
	Plant	carrot, tomato, potato, palm oil, peanut,
	Agriculture	sweet potato, garlic, cucumber, coffee,
		cloves, nutmeg, cocoa, quinine, rubber

Table 2. Describes the results of applying fuzzy logic to apply the rule-based system after this. After getting inputs and outputs using fuzzy logic, the Rule Based System method is applied to determine the results of recommendations for suitable plant types. The results of implementing the Rule-Based System are presented in Table 3.

Table 3. Rule Based System

No	Height	Rainfall	Types of plants
1	Low	Low	Corn, Peanuts
2	Low	Keep	Soybeans, Nutmeg
3	Low	Tall	Shallot, Chili, Palm Oil, Garlic, Rubber
4	Keep	Low	Corn
5	Keep	Keep	Rice, Potato, Sweet Potato, Cucumber, Cocoa
6	Sedang	Tall	Tea
7	Tall	Low	Corn
8	Tall	Keep	Rice, Tomato, Coffee, Clove, Quinine
9	Tall	Tall	Tea, Carrots

After getting the Rule Based on the data above, you get the results described in Table 4.

Table 4. Plant Recommendation Results

No	Subdistrict	Plant yield (recommendation)
1	Margasari	Corn, Peanuts, Soybeans, Nutmeg
2	Bumijawa	Rice, Tomato, Coffee, Clove, Quinine
3	Bojong	Rice, Tomato, Coffee, Clove, Quinine
4	Balapulang	Corn, Peanuts, Soybeans, Nutmeg
5	Pagerbarang	Corn, Peanuts, Corn, Peanuts, Soybeans, Nutmeg
6	Lebaksiu	Corn, Peanuts, Soybeans, Nutmeg
7	Jatinegara	Rice, Potato, Sweet Potato, Cucumber, Cocoa
8	Kedungbanteng	Corn, Peanuts, Soybeans, Nutmeg
9	Pangkah	Corn, Peanuts, Soybeans, Nutmeg
10	Slawi	Corn, Peanuts, Soybeans, Nutmeg
11	Dukuhwaru	Corn, Peanuts, Soybeans, Nutmeg
12	Adiwerna	Corn, Peanuts, Soybeans, Nutmeg
13	Dukuhturi	Corn, Peanuts, Soybeans, Nutmeg
14	Talang	Corn, Peanuts, Soybeans, Nutmeg
15	Tarub	Corn, Peanuts, Soybeans, Nutmeg
16	Kramat	Corn, Peanuts, Soybeans, Nutmeg
17	Suradadi	Corn, Peanuts, Soybeans, Nutmeg
18	Warureja	Corn, Peanuts, Soybeans, Nutmeg

In Table 4, the results of implementing the Rule Based System algorithm are explained by entering altitude values according to the data attached to Figure 4 and entering rainfall data using total rainfall in 2023 to produce recommendations for sub-districts in Tegal Regency. After the results of the plant type recommendation are appropriate, the results of the calculation of the evaluation of the results are depicted in Table 5.

Table 5. Evaluation of Results

No.	Subdistrict	Error rate	Accuracy
1	Margasari	20.00%	80.00%
2	Bumijawa	14.29%	85.71%
3	Bojong	12.50%	87.50%
4	Balapulang	11.11%	88.89%
5	Pagerbarang	10.00%	90.00%
6	Lebaksiu	9.09%	90.91%
7	Jatinegara	8.33%	91.67%
8	Kedungbanteng	7.69%	92.31%
9	Pangkah	7.14%	92.86%
10	Slawi	6.67%	93.33%
11	Dukuhwaru	6.25%	93.75%
12	Adiwerna	2.70%	94.30%
13	Dukuhturi	2.57%	94.43%
14	Talang	2.45%	94.55%
15	Tarub	2.33%	94.67%
16	Kramat	2.23%	94.77%
17	Suradadi	2.13%	94.88%
18	Warureja	2.03%	94.97%
	Average	15.00%	85.00%

Testing to recommend crop types on agricultural land in Tegal Regency, considering geographical location and rainfall using the Rule-Based System method, showed accurate evaluation results. This is evidenced by the recommendation of agricultural crop types per sub-district, which has an average accuracy of 85% and an error value of 15%. These results demonstrate that the method can reliably provide appropriate recommendations for farmers, helping them determine the proper types of crops for their land to optimize yields and reduce the risk of losses due to crop failure. This research contributes significantly to developing data-driven agricultural recommendation systems that can be applied in regions with similar geographical and climatic conditions.

This study examines the use of a rule-based system method to recommend crop types based on altitude and rainfall in Tegal Regency, utilizing data from the Central Bureau of Statistics and various internet sources for the period from January 1 to December 31, 2023, with results showing an average accuracy rate of 85% and an error rate of 15%. The study suggests integrating real-time weather prediction technology and additional environmental variables to enhance recommendation precision. Compared to previous research, which focused on nutrient management and UAV image analysis for crop classification using deep learning (CNN) and fuzzy-based systems, this current research specifically uses geographic and climatic data through methodologies involving data collection, preprocessing, variable selection, and model optimization using fuzzy logic (Aamir et al., 2021; Bouguettaya & Zarzour, 2022; Kumari et al., 2022). The results indicate that the rule-based system is reliable in providing high-accuracy crop type recommendations, filling the gap in previous research that did not comprehensively apply geographic and climatic data for crop recommendations. Integrating altitude and rainfall data allows for more precise and location-specific recommendations, enhancing agricultural efficiency and sustainability, and assisting farmers in making better decisions regarding suitable crop types for their land, thereby reducing the risk of crop failure.

4. CONCLUSION

This study demonstrates that a Rule-Based System recommending crop types based on altitude and rainfall in Tegal Regency achieved an 85% accuracy rate. This system effectively supports sustainable agricultural decisions by enabling farmers to adjust crop choices to specific geographical and climatic conditions, thus minimizing crop failure risks. The research significantly contributes to science by integrating data-driven approaches with practical applications and filling critical gaps in previous studies. Future research should incorporate real-time weather prediction and other environmental variables to enhance recommendation precision and expand the system's applicability to similar regions.

REFERENCES

Aamir, K. M., Sarfraz, L., Ramzan, M., Bilal, M., Shafi, J., & Attique, M. (2021). A fuzzy rule-based system for classification of diabetes. *Sensors*, *21*(23). https://doi.org/10.3390/s21238095

Benyam, A. A., Soma, T., & Fraser, E. (2021). Digital agricultural technologies for food loss and waste prevention and reduction: Global trends, adoption opportunities and barriers. *Journal of Cleaner Production*, *323*, 129099. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.129099

Bhat, S. A., Hussain, I., & Huang, N.-F. (2023). Soil suitability classification for crop selection in precision agriculture using GBRT-based hybrid DNN surrogate models. *Ecological Informatics*, *75*, 102109. https://doi.org/https://doi.org/10.1016/j.ecoinf.2023.102109

Born, L., Prager, S., Ramirez-Villegas, J., & Imbach, P. (2021). A global meta-analysis of climate services and decision-making in agriculture. *Climate Services*, *22*, 100231. https://doi.org/https://doi.org/10.1016/j.cliser.2021.100231

Bouguettaya, A., & Zarzour, H. (2022). Deep learning techniques to classify agricultural crops through UAV imagery : a review. *Neural Computing and Applications*, *34*(12), 9511–9536. https://doi.org/10.1007/s00521-022-07104-9

Carletto, C. (2021). Better data, higher impact: improving agricultural data systems for societal change. *European Review of Agricultural Economics*, *48*(4), 719–740. https://doi.org/https://doi.org/10.1093/erae/jbab030

Castiglione, A. M., Mannino, G., Contartese, V., Bertea, C. M., & Ertani, A. (2021). Microbial biostimulants as response to modern agriculture needs: Composition, role and application of these innovative products. *Plants*, *10*(8), 1533. https://doi.org/https://doi.org/10.3390/plants10081533

Cravero, A., Pardo, S., Sepúlveda, S., & Muñoz, L. (2022). Challenges to use machine learning in

agricultural big data: a systematic literature review. *Agronomy*, *12*(3), 748. https://doi.org/https://doi.org/10.3390/agronomy12030748
DeLay, N. D., Thompson, N. M., & Mintert, J. R. (2022). Precision agriculture technology adoption and technical efficiency. *Journal of Agricultural Economics*, *73*(1), 195–219. https://doi.org/https://doi.org/10.1111/1477-9552.12440
Erickson, B., & Fausti, S. W. (2021). The role of precision agriculture in food security. *Agronomy Journal*, *113*(6), 4455–4462. https://doi.org/https://doi.org/10.1002/agj2.20919
Gopi, P. S. S., & Karthikeyan, M. (2024). Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model. *Multimedia Tools and Applications*, *83*(5), 13159–13179. https://doi.org/https://doi.org/10.1007/s11042-023-16113-2
Hayes, S. C., Ciarrochi, J., Hofmann, S. G., Chin, F., & Sahdra, B. (2022). Evolving an idionomic approach to processes of change: Towards a unified personalized science of human improvement. *Behaviour Research and Therapy*, *156*, 104155. https://doi.org/https://doi.org/10.1016/j.brat.2022.104155
Khan, N., Ray, R. L., Sargani, G. R., Ihtisham, M., Khayyam, M., & Ismail, S. (2021). Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture. *Sustainability*, *13*(9), 4883. https://doi.org/https://doi.org/10.3390/su13094883
Kumari, V. V., Banerjee, P., Verma, V. C., Sukumaran, S., Alickal, M., Chandran, S., Gopinath, K. A., Venkatesh, G., Yadav, S. K., Singh, V. K., & Awasthi, N. K. (2022). *Plant Nutrition : An Effective Way to Alleviate Abiotic Stress in Agricultural Crops*. https://doi.org/10.3390/ijms23158519
Labeyrie, V., Renard, D., Aumeeruddy-Thomas, Y., Benyei, P., Caillon, S., Calvet-Mir, L., Carrière, S. M., Demongeot, M., Descamps, E., & Junqueira, A. B. (2021). The role of crop diversity in climate change adaptation: Insights from local observations to inform decision making in agriculture. *Current Opinion in Environmental Sustainability*, *51*, 15–23. https://doi.org/https://doi.org/10.1016/j.cosust.2021.01.006
Liu, W., Shao, X.-F., Wu, C.-H., & Qiao, P. (2021). A systematic literature review on applications of information and communication technologies and blockchain technologies for precision agriculture development. *Journal of Cleaner Production*, *298*, 126763. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.126763
Maier, G., Albanese, A., Ciavotta, M., Ciulli, N., Giordano, S., Giusti, E., Salvatore, A., & Schembra, G. (2024). WatchEDGE: Smart Networking for Distributed AI-Based Environmental Control. *Computer Networks*, 110248.
Mashala, M. J., Dube, T., Mudereri, B. T., Ayisi, K. K., & Ramudzuli, M. R. (2023). A systematic review on advancements in remote sensing for assessing and monitoring land use and land cover changes impacts on surface water resources in semi-arid tropical environments. *Remote Sensing*, *15*(16), 3926. https://doi.org/https://doi.org/10.3390/rs15163926
Musanase, C., Vodacek, A., Hanyurwimfura, D., Uwitonze, A., & Kabandana, I. (2023). Data-Driven Analysis and Machine Learning-Based Crop and Fertilizer Recommendation System for Revolutionizing Farming Practices. *Agriculture*, *13*(11), 2141.
Nugroho, H. Y. S. H., Sallata, M. K., Allo, M. K., Wahyuningrum, N., Supangat, A. B., Setiawan, O., Njurumana, G. N., Isnan, W., Auliyani, D., & Ansari, F. (2023). Incorporating Traditional Knowledge into Science-Based Sociotechnical Measures in Upper Watershed Management: Theoretical Framework, Existing Practices and the Way Forward. *Sustainability*, *15*(4), 3502.
Rezk, N. G., Hemdan, E. E.-D., Attia, A.-F., El-Sayed, A., & El-Rashidy, M. A. (2021). An efficient IoT based smart farming system using machine learning algorithms. *Multimedia Tools and Applications*, *80*, 773–797. https://doi.org/https://doi.org/10.1007/s11042-020-09740-6
Senderowicz, L., Bullington, B. W., Sawadogo, N., Tumlinson, K., Langer, A., Soura, A., Zabré, P., & Sié, A. (2023). Measuring contraceptive autonomy at two sites in Burkina Faso: a first attempt to measure a novel family planning indicator. *Studies in Family Planning*, *54*(1), 201–230. https://doi.org/https://doi.org/10.1111/sifp.12224
Sikakwe, G. U. (2023). Mineral exploration employing drones, contemporary geological satellite remote sensing and geographical information system (GIS) procedures: A review. *Remote Sensing Applications: Society and Environment*, 100988. https://doi.org/https://doi.org/10.1016/j.rsase.2023.100988
Sinha, B. B., & Dhanalakshmi, R. (2022). Recent advancements and challenges of Internet of Things in smart agriculture: A survey. *Future Generation Computer Systems*, *126*, 169–184. https://doi.org/https://doi.org/10.1016/j.future.2021.08.006
Tian, Z., Wang, J., Li, J., & Han, B. (2021). Designing future crops: challenges and strategies for

sustainable agriculture. *The Plant Journal*, *105*(5), 1165–1178. https://doi.org/https://doi.org/10.1111/tpj.15107

Ukwuoma, C. C., Cai, D., Heyat, M. B. Bin, Bamisile, O., Adun, H., Al-Huda, Z., & Al-Antari, M. A. (2023). Deep learning framework for rapid and accurate respiratory COVID-19 prediction using chest X-ray images. *Journal of King Saud University-Computer and Information Sciences*, *35*(7), 101596. https://doi.org/https://doi.org/10.1016/j.jksuci.2023.101596

Ullah, K., Ullah, Z., Aslam, S., Salam, M. S., Salahuddin, M. A., Umer, M. F., Humayon, M., & Shaheer, H. (2023). Wind farms and flexible loads contribution in automatic generation control: an extensive review and simulation. *Energies*, *16*(14), 5498. https://doi.org/https://doi.org/10.3390/en16145498

Yang, L. H., Liu, J., Ye, F. F., Wang, Y. M., Nugent, C., Wang, H., & Martínez, L. (2022). Highly explainable cumulative belief rule-based system with effective rule-base modeling and inference scheme. *Knowledge-Based Systems*, *240*, 1–26. https://doi.org/10.1016/j.knosys.2021.107805

Yu, S., Khan, S., Mo, F., Ren, A., Lin, W., Feng, Y., Dong, S., Ren, J., Wang, W., & Noor, H. (2021). Determining optimal nitrogen input rate on the base of fallow season precipitation to achieve higher crop water productivity and yield. *Agricultural Water Management*, *246*, 106689. https://doi.org/https://doi.org/10.1016/j.agwat.2020.106689