International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 01 | Jan 2026 www.irjet.net p-ISSN: 2395-0072

A Review on Dharaansh: The Sustainable Farming Advisor using Machine Learning

M. D. CHOUDHARI[1], KHUSHI DHABALE[2], EKTA SATGHARE[3], DIYA TEMBHURNE[4], SAHMITA , NINAVE[5].

[1]Assistant Professor AI & DS Department K. D. K. COLLEGE OF ENGINEERING, Nagpur
[2,3,4,5] K. D. K. COLLEGE OF ENGINEERING, Nagpur

ABSTRACT- *Dharaansh: A Sustainable Farming Advisor based on machine learning can significantly enhance crop productivity and resource use efficiency while providing site-specific data-driven recommendations to the farmer. The system will integrate real-time and historical data on soil pH, soil temperature, and moisture and key climatic variables like ambient temperature, humidity, and rainfall to produce advisory outputs on suitable crops, alternate cropping options, and fertilizer management strategies. This model is trained using supervised learning algorithms on curated agronomic datasets that comprise soil properties, nutrient levels, and weather patterns to predict the most suitable crops and optimal fertilizer regimes for given field conditions, minimizing the risk of crop failure and overuse of inputs. The system also uses rule-based logic and sensor thresholds that raise flags for highly acidic or alkaline soils, suggesting corrective soil amendments like lime or organic matter to restore soil health. The application combines intelligent recommender techniques to make personalized, context-aware recommendations to support precision agriculture and sustainable farming practices. Overall, this Sustainable Farming Advisor seeks to enable efficient fertilizer application, resilient crop planning in response to changing climate conditions, and accessible real-time decision support for farmers.*

Keywords: Machine learning, Sustainable farming advisor, soil Ph, Crop recommendation, Smart farming, Sustainable farming, Fertilizer recommendation.

INTRODUCTION

Farming is the backbone of India's economy, but millions of farmers continue to grapple with unforeseeable weather, lessening soil fertility, pest attacks, and uncertainty due to a lack of dependable information. To empower farmers on such critical issues, an AI-powered agricultural support system by the name Dharaansh has been developed, known as Dharaansh: The Sustainable Farming Advisor.

Dharaansh focuses on accurate crop prediction by analyzing soil properties such as pH and NPK levels along with atmospheric conditions of temperature, humidity, and rainfall to recommend the most suitable crops and reduce the risk of crop failure. It also focuses on soil health and fertility management by providing pH validation, fertility checks, and corrective suggestions that include organic amendments, biofertilizers, and crop rotation.

It gives real-time weather advisory services for guidance on scheduling irrigation, harvest, and multi-cropping activities while safeguarding against adverse weather conditions, enabling sustainable and profitable farming because of predictive pest and disease alerts integrated into the system, besides promotion of eco-friendly farming practices.

With its regional language support, awareness of government schemes and a user-friendly interface presenting visual reports and insights, Dharaansh helps bridge the gap between traditional farming and modern technology, empowering farmers to achieve productivity, profitability, and long-term sustainability.

LITERATURE REVIEW

Most recent work on sustainable crop and fertilizer advisory systems focuses on software-centric, machine-learning models operating on curated datasets rather than live IoT streams. These usually ingest soil test reports of pH, N–P–K, organic carbon, historical weather data, and crop performance records stored in relational databases or CSV files; then apply classification or ensemble algorithms that generate recommendations. Several studies propose web-based or desktop applications where farmers or extension workers would enter soil and climate attributes manually, and the backend ML engine returns

suitable crops and fertilizer plans, thus proving that even offline or low-connectivity settings can benefit from AI-driven decision support.

The classical machine-learning techniques dominate the software-based literature. Many experiments compare the performance of algorithms such as K-Nearest Neighbors, Decision Trees, Naïve Bayes, Support Vector Machines, Logistic Regression, Random Forest, XGBoost, and Gradient Boosting on benchmark crop recommendation datasets, often recording accuracies above 95% for the best models. Some works extend the basic task of crop prediction to recommending fertilizers through learning mappings from soil nutrients and target crop to type and quantity of fertilizer, mostly using multi-output classification or regression frameworks. More recently, works have also focused on explainable AI, where feature-importance scores and interpretation methods help agronomists and farmers understand why a particular crop-fertilizer combination is recommended.

Another important strand of software-based research emphasizes integrated advisory platforms, which integrate crop recommendation, fertilizer optimization, and at times even price or market guidance into one AI-powered portal. These systems provide user-friendly dashboards and form-based input screens, allowing non-technical users access to advanced analytics without having to handle raw code or configurations. Reviews of such platforms argue that pure software solutions, trained on high-quality soil and climate datasets, can significantly improve input-use efficiency and yield outcomes even prior to full IoT integration, especially in regions with developing sensor infrastructure. This literature provides essential grounding for a machine-learning-based, software-driven Sustainable Farming Advisor grounded on soil pH, temperature, humidity, and climatic data in recommending suitable crops, alternates, and fertilizers.

COMPARATIVE ANALYSIS & RESEARCH GAP

Study	Methodology	Key Features	Efficiency Improvement	Research Gaps
Shastri et al., 2025	Gradient Boosting Ensemble Model	Soil nutrients, pH, climatic attributes	Improved general and all-inclusive decision-making rate and dependability using enhanced feature inputs.	The study suffers from limited geographic difference in the dataset, which limits the model's capacity to extrapolate across different agricultural -climatic portions. Also, the absence of temporal or seasonal validation elevates challenges of overfitting, as the model may not alter effectively to yearly climate variations. The lack of transparency further reduces its practical applicability for farmers who need lucid recommendations.
Baishya, 2025 (TinyML)	TinyML and Lightweight Random Forest.	IoT-based real-time sensing, on-device inference	Accomplish faster, low-power forecasts suitable for edge positioning or placement.	In spite of strong TinyML performance, the model has yet to be authenticated under real field conditions where sensor noise, environmental variations, and hardware inconsistencies can affect dependability. Its dataset remains relatively small, restricting model transferability to different soil types. Moreover, long-term aspects such as device ageing, calibration drift, and durability of on-device inference are not examined.
Sam & D'Abreo, 2025	Random Forest, Support Vector Machine and Temporal Evaluation.	Environmental and Economic parameters	Offers more practical performance through time-aware testing and better perceptions for farm plannings.	Dependence on contrast to economic data, it restricts hardiness, and the absence of adaptive learning limitations, the model's ability to respond to changing climatic patterns.
Prity, 2024 (Springer)	Random Forest, Support Vector Machine,	Yield history with farmer preferences	Provides more purified recommendations as	Use of open datasets minimizes local significance, and the lack of transparency

	Artificial Neural Network.		compared to algorithmic systems.	limits acceptance. Field deployment and real-world evaluations are missing.
Kiran, 2024 (MDPI)	End-to-end ML System (Random forest/Gradient Boosting Machine)	Multi-source integration with user interface	Strengthens decision support by combining soil and weather data into a centralized platform	Location bias in data minimizes transferability, and the model lacks clearness. Real-time weather integration is also missing.
Gopi, 2023 (HMFO-ML)	HMFO + Probabilistic Neural Network + Extreme Learning Machine	Merged or Unified crop recommendation with yield forecasting	Enhances system performance through composite optimization and bifunctional -task modeling	High algorithmic complexity limits practical deployment, and the absence of geographic or multi-region testing affects abstraction. Contrasts with newer DL methods or techniques are also missing.

COMPARATIVE SUMMARY

A relative study of DHARAANSH with the seven existing crop recommendation systems indicates that your model is unique for its adaptability, interpretability, and design for field-level deployment. While most related work in recent literature focuses on either algorithmic accuracy or computational enhancements, DHARAANSH focuses on regional scalability, real-time environmental responsiveness, and farmer usability, which have not been well addressed in most current literature. For example, the Gradient Boosting model developed by Shastri et al. (2025) achieves high computational efficiency but relies heavily on a geographically narrow dataset, thereby severely limiting generalization to other agro-climatic zones; DHARAANSH resolves this through facilitating flexibility in dataset expansion and using a feature design considering localized soil variations and various cropping patterns. Similarly, TinyML-based systems such as Baishya (2025) achieve overall low-power, on-device inference but their validity is yet to be determined under real agriculture noise conditions, for example, fluctuating sensor quality, moisture interference, or seasonal drifts. By contrast, DHARAANSH is structured to integrate stable pre-processing and noise-handling mechanisms to give it field robustness.

Combined environmental and economic parameter models, such as Sam & D'Abreo 2025, have wider analytical capabilities but are still prone to possible unreliability in economic data and the absence of adaptiveness in their learning framework. DHARAANSH overcomes such weaknesses by facilitating regular updates of datasets and allowing the models to change with changing climatic or agronomic conditions. The approaches described by Prity 2024 and Kiran 2024 have their focus on user-friendliness with multi-source integration, but they lack testing at the deployment level and do not provide clarity with respect to the uncertainty of the prediction-an extremely important factor in decision-making related to farming. DHARAANSH compensates for this by placing a strong emphasis on interpretability, integrating transparent feature-impact analysis, thereby making the recommendations more understandable and credible for the end users.

The Rao et al. (2024) ensemble frameworks enhance stability and reduce the variance in predictions. However, this is constrained by the geographically biased datasets the assembling relies on. DHARAANSH has been designed to be modular and region-adaptive; it can embed region-specific calibration to avoid these limitations. Likewise, metaheuristic-based models such as Gopi 2023 show strong optimization but are computationally heavy to the extent that most typical rural settings have very limited resources to accommodate them. DHARAANSH avoids such high complexity by employing lightweight yet powerful models with real-world deployment feasibility in mind.

METHODOLOGY

1. Data Acquisition from User

The user inputs necessary information regarding the environment and soil through the system. The collected input parameters are:

- Temperature
- Humidity
- Soil Type
- Soil pH
- Rainfall

- Region
- Season

These inputs act as the foundation for all further predictions and recommendations.

2. Input Processing

The input values are taken by the system and validated. It checks:

- Whether all required fields are filled
- Whether the values fall within acceptable agricultural ranges

The validated data is then passed to two modules:

- Crop Recommendation Engine
- Crop History Check Module

3. Crop Recommendation Engine

The system compares the values of environmental and soil parameters with agricultural datasets. The module highlights:

- Primary Recommended Crop
- Alternative Crop Options

The system further calculates approximate levels of:

- Nitrogen (N) Requirement
- Phosphorus (P) Requirement
- Potassium Requirement

The module also predicts the suitable irrigation method, depending on:

- Rainfall
- Soil moisture capacity
- Crop selection

The outputs of this module are sent for display to the user.

4. Crop History Check Module

The module again receives the same inputs, especially Soil Type, Region, and Season. It retrieves the historical crop pattern of the land. It checks whether the same crop has been grown repeatedly:

- If the same land has been used for the same crop 3 or more times a warning is generated.

Outputs from this module include:

- Repeated-crop warning
- Soil fertility warning
- Suggestions for restoring soil fertility: crop rotation, organic manure, green cover crops, etc.
- The results are passed on to the user interface.

5. Soil pH Monitoring and Alert

System

The system will check whether soil pH < 5.5, indicating acidic soil.

2. If pH is below the threshold:

- A pH warning message is generated.
- Recommendations for improving soil pH are developed (e.g., lime, organic compost, gypsum addition).

6. Output Generation

The system compiles final result from all the modules and delivers:

1. Crop Recommendation

- Recommended Crop
- Alternative Crop

- Required NPK levels
- Irrigation types that are suitable for

2. Warning & Alerts
- Soil fertility warning
- Crop repetition warning
- Soil PH warning if PH< 5.5

3. Improvement Suggestions
Soil restoration methods
- soil PH improvement suggestion

7. System Feedback Loop

Optional Future Enhancement to achieve greater accuracy over time:
- The user feedback regarding crop performance can be stored.
- Refine recommendations by training machine learning models.

.

PROPOSED WORK

1. User Interaction Layer

The system starts by having the user input environmental and soil information like temperature, humidity, pH, rainfall, and type of soil, region, and season of cultivation. This information is gathered through the frontend interface and sent to the backend processing unit. The system checks the input format for correctness and values within their acceptable range.

2. Data Processing Layer

After receiving input, the system pre-processes the data:
- Converts raw values to standardized units
- It classifies soil type and season
- Checks for missing or inconsistent data

The cleaned data is then passed on to its respective modules for analysis.

3. Crop Recommendation Module

The system compares the received parameters with agricultural knowledge datasets.
It finds the best crop suited for the given land based on the matching conditions of temperature, soil type, rainfall, region, and so on. It generates:
- Recommended Crop
- Alternative Crop(s)in case the primary crop is risky

This module also predicts:
- Ideal NPK fertilizer requirements (Nitrogen, Phosphorus, Potassium)
- Suitable irrigation method: drip, sprinkler, flood irrigation

4. Crop History Verification Module

Previous cropping cycles of the same land are checked. It checks if the same crop had been grown more than three consecutive times. When repeated cropping is detected:
- EMS generates a warning about soil fertility.

5. The system also provides:

Crop rotation recommendations. Soil restoration tips: organic manure, green manure, microbial culture, etc.

6. Soil pH Monitoring Module

The module analyzes the soil pH input. If the calculated pH is less than 5.5, the following is automatically initiated:

- A soil acidity warning
- Recommendations on improvement in soil pH (application of lime, compost, ash, etc.)

7. Output Generation Layer

After receiving results from all modules, the system compiles them into a user-friendly output. Final output is:

- Recommended crop
- Alternative crop(s)
- N, P, K fertilizer levels
- Irrigation method
- Soil pH warning
- Soil fertility warning
- Repeated crop warning
- Suggestions
- PH improvement strategies for soil fertility restoration.

8. Decision Feedback (Optional Enhancement)

The end may give feedback after ad herring to suggestions. 2. Future versions should include machine learning models to increase accuracy by using previous outcomes.

PROJECTED OUTCOME AND FUTURE SCOPE

The Dhaaransh system will offer reliable crop suggestions through analysis of soil and environmental factors. In return, it will help farmers in the selection of the right crop while enhancing yield and improving use of resources. The platform will also create awareness for soil health by providing warnings related to pH, fertility alerts, and balanced NPK recommendations. This can reduce soil degradation and enhance long-term land sustainability. By guiding farmers on proper methods of irrigation and fertilizer requirement, the system intends to reduce unnecessary expenditure.

In the future, Dhaaransh can be designed to become a more enhanced smart farming solution. This will be achieved by integrating real-time IoT sensors, machine learning-based prediction models, and weather forecast APIs for better accuracy. Additional features include the prediction of pests and diseases, integration of a soil health card, and farm-to-market price forecasting, which shall further assist farmers.

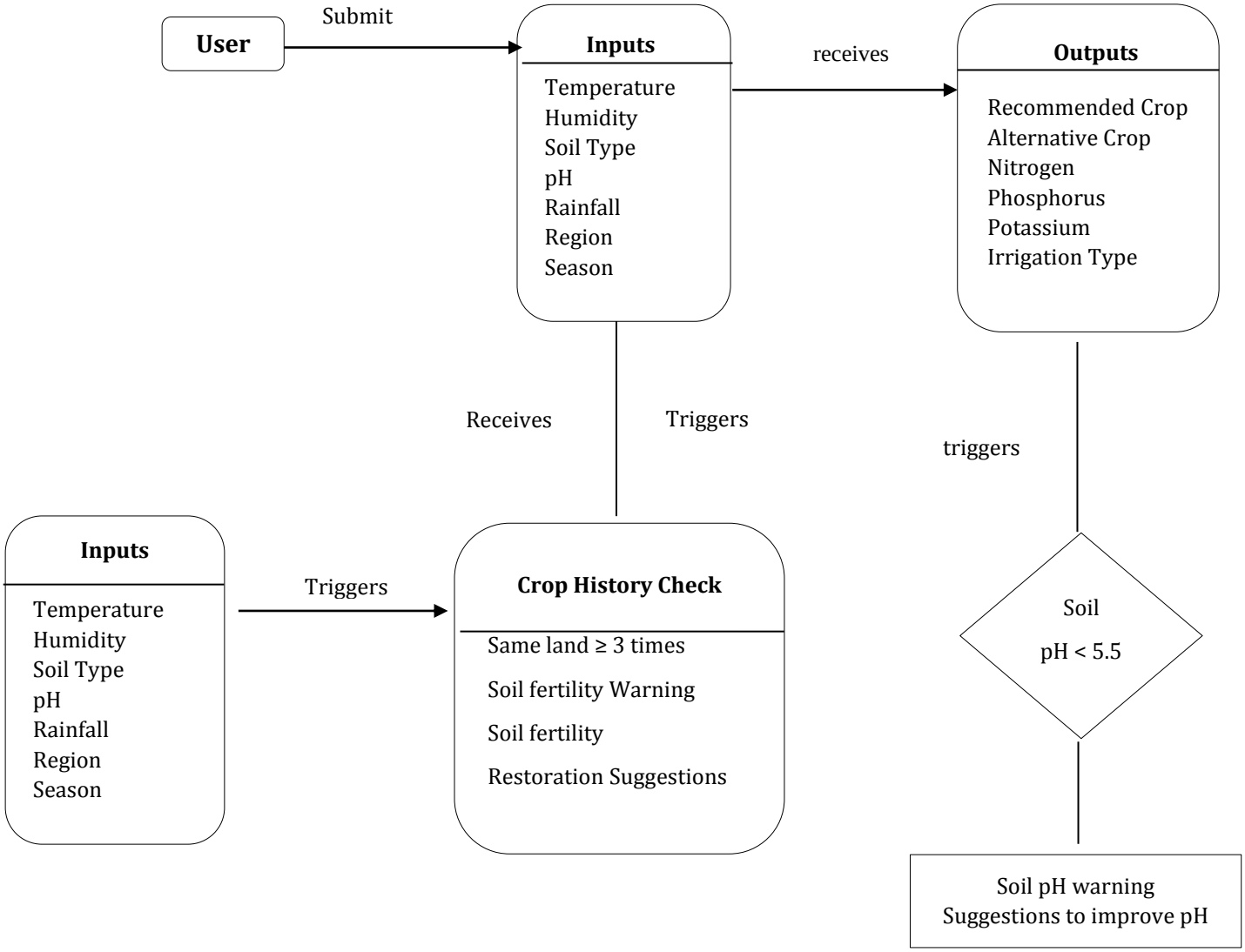

Fig 1. Flowchart

The system shall also transform into a multilingual mobile app by incorporating smart irrigation automation and alerts within the farming community for pest or climate hazards. These changes will make Dhaaransh a full-fledged digital agriculture assistant, promoting sustainable farming and increasing productivity

CONCLUSION

Dharaansh aims to be an integrated AI-enabled agriculture support system that assists farmers with informed decisions for sustainable and profitable farming. Based on soil, weather, pest, and market trend analysis, it undertakes crop recommendations, timely alerts, and expert advice. The potential to redefine traditional farming practices is still quite high though many obstacles lie ahead, from data inaccuracy and connectivity to hurdles in technology adoption. Advanced AI models and market transparency tools can contribute much towards enhancing crop yield, minimizing losses, and promoting sustainable agricul-

ture. Overall, Dharaansh represents a step toward smart farming, empowering farmers with technology to secure better productivity and economic growth.

REFERENCES

[1] Yu, S. & Mu, Y. (2022). Sustainable Agricultural Development Assessment: A Comprehensive Review and Bibliometric Analysis DOI:**https://doi.org/10.3390/su141911824**

[2] Yi Ding, Luo Jun, Gao Haodic, Zhang Xing, Ye Lie, Siti Sarah Maidin, Wan Hussain Wan Ishak, Walton Wider (2024). Transforming Agriculture: An Insight into Decision Support Systems in Precision Farming. Journal of Applied Data Sciences DOI:https://doi.org/10.47738/jads.v5i4.274

[3] Alebachew Chiche (2024). Hybrid Decision Support System Framework for Crop Yield Prediction and Recommendation. International Journal of Computing. DOI:https://doi.org/10.47839/ijc.18.2.1416

[4] T. Jalaja, T. Adilakshmi, Meka Dheeraj Reddy, K. Sai Kamal (2024). Empowering Agriculture: A Machine Learning-Based Decision Support System for Crop Selection and Profitability Analysis. International Journal of Intelligent Systems and Applications in Engineering. DOI:https://ijisae.org/index.php/IJISAE/article/view/5800

[5] Muhammad Indra Gunawan, Joni Wilson Sitopu, Gamar Sechan, Indra Gunawan (year N/A). Optimizing Crop Selection: A Multi-Criteria Decision Support System for Sustainable Agriculture. International Journal of Enterprise Modelling. Link:https://ieia.ristek.or.id/index.php/ieia/article/view/94

[6] Martine J. Barons, Lael E. Walsh, Edward E. Salakpi, Linda Nichols (2024). A Decision Support System for Sustainable Agriculture and Food Loss Reduction under Uncertain Agricultural Policy Frameworks. Agriculture, 14(3), 458. Link:https://doi.org/10.3390/agriculture14030458

[7] Meenakshi Malik, Mukesh Sehgal, A.K. Kanojia, R.V. Singh (2018). A review paper on decision support system/expert system developed on mango. International Journal of Plant Protection, 11(1), 119-123.arXiv: Link:https://doi.org/10.15740/HAS/IJPP/11.1/119-123

[8] Zhai Z., Martínez J.F., Beltrán V., Martínez N.L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. Computers and Electronics in Agriculture, 170, 105256. DOI:https://doi.org/10.1016/j.compag.2020.105256

[9] Iffat Ara, Lydia Turner, Matthew Tom Harrison, Marta Monjardino, Peter de Voil, Daniel Rodriguez (2021). Application, adoption and opportunities for improving decision support systems in irrigated agriculture: A review. Agricultural Water Management, 257, 107271 Link:https://ideas.repec.org/a/eee/agiwat/v257y2021ics0378377421004388.html

[10] S Sridevy, M Nirmala Devi, M Sankar (2023). Decision support systems in agricultural industry perspective. International Journal of Statistical and Applied Mathematics, 8(2S):29-31. DOI:https://doi.org/10.22271/maths.2023.v8.i2Sa.984

[11] Desta Abayechaw (2021). Review on Decision Support System for Agrotechnology Transfer (DSSAT) Model. International Journal of Intelligent Information Systems, 10(6), 117-124. DOI:https://doi.org/10.11648/j.ijiis.20211006.13

[12] John E. Ikerd (1991). A Decision Support System for Sustainable Farming. Northeastern Journal of Agricultural and Resource Economics, 20(1), 109-113 DOI:https://doi.org/10.1017/S0899367X00002919

[13] Luiz Henrique A. Rodrigues, Fabio Zimmermann (2025). Digital Decision Support Systems for Sustainable Organic Farming. Informatics Studies, 12(2). Link:https://informaticsstudies.org/index.php/informatics/article/view/741

[14] Emmanuel Asolo, Ifechukwu Gil-Ozoudeh, Chibundom Ejimuda (2024). AI-Powered Decision Support Systems for Sustainable Agriculture using AI-Chatbot Solution. Journal of Digital Food, Energy & Water Systems, 5(1). DOI:https://journals.uj.ac.za/index.php/DigitalFoodEnergy_WaterSystems/article/view/3260

[15] Banashri Rath, Decision Support System for Drafting of Sustainable Agriculture Production Policy for Odisha. International Journal of Supply Chain Management, 2(2). DOI:https://doi.org/10.59160/ijscm.v2i2.745

[16] Vidya G. Kumbhar, T.P. Singh (2013). A Systematic Study of Application of Spatial Decision Support System in Agriculture. International Journal of Scientific & Engineering Research, 4(12). Link:https://www.ijser.org/researchpaper/A-Systematic-Study-of-Application-of-Spatial-Decision-Support-System-in-Agriculture.pdf

[17] Suman Kumar Das, Pujyasmita Nayak (2024/2025). Integration of IoT-AI powered local weather forecasting: A Game-Changer for Agriculture. arXiv preprint (2024). DOI:https://arxiv.org/abs/2501.14754

[18] Anat Goldstein, Lior Fink, Gilad Ravid (2019). A Framework for Evaluating Agricultural Ontologies. arXiv preprint. arXiv:https://arxiv.org/abs/1906.10450

[19] Suman R. Venu, R. G. Kumar, M. K. Kumar, T. G. Prasad, B. Suresh, P. Neelima (2023). An Intelligent and Service Based Smart Agriculture Recommendation System. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 153-158.. Link:https://ijisae.org/index.php/IJISAE/article/view/4051

[20] Digital agro-advisory tools in the global south: a behavioral analysis of impacts, and future directions. Discover Agriculture, 3, article 40. (2025). LinkI:https://link.springer.com/article/10.1007/s44279-025-00190-y