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Machine Learning-Based Decision Support System for Sustainable Small holder Dairy Farming Using Environmental and Farm Performance Analytics

Meenakshi S[1], Dr Ramakrishna[2]

[1]Nitte (Deemed to be University), Assistant Professor, Department of Commerce and Management, Dr. NSAM First Grade College, Nitte, Udupi, India- 574 110
meenakshi1991s@nitte.edu.in
[2]Professor Department of Humanities NMAM Institute of Technology, Nitte
ramakrishnab@nitte.edu.in

ABSTRACT: There is a need to make decisions that integrate productivity, resource efficiency, animal condition, profitability and environmental pressure for dairy farming by smallholders to be sustainable. In this research, a machine learning-based decision support system is proposed to combine the environmental and the farm performance analytics using Random Forest classifier in Python with Google Colab. Farm level variables include milk yield, herd size, feed efficiency, feed cost, water use, energy use, GHG intensity, manure management, animal-health status, mortality, heat stress and net margin. The model classifies farms according to their sustainability status after preprocessing and ranks influential factors for provide interpretable recommendations. A smallholder farm record simulation was employed for a reproducible demonstration experiment, which resulted in an accuracy of 88.89%, a macro F1 score of 88.88% and a macro one-versus-rest ROC-AUC of 93.63%. It transforms forecasts into management advice relating to feed, water, energy and waste. Results show that the proposed architecture has potential, but must be field validated before deployment in real operations in various smallholder dairy systems.

I. INTRODUCTION

While dairy farming is part of the rural economy, household nutrition, employment and local milk supply are affected by smallholder dairy farms, their sustainability is affected by long-term production inefficiencies, increasing input costs, climate stress, lack of records and environmental factors. Typically the assessment of conventional farms involves an evaluation of their productivity and/or sustainability. A farmer can get more milk at the same time they may be spending more money on feed, water, energy, manure emissions or animal-health risks. Thus, a multi-faceted, analytical approach is needed to sustainably manage dairy production, which can incorporate several interacting factors and translate them into action.

Machine learning provides a helpful foundation for such integration since it can detect nonlinearity and interactions among the various farm variables, especially variables of different types. Random Forest is well suited for smallholder farm analytics due to its ability to work with structured tabular data, its tolerance of complex interactions, multiclass prediction ability and its ability to provide variable importance information that can enhance the transparency of the decision-making process. Most of the current dairy ML applications, however, focus on milk yield or disease detection, behavior, or automated milking, while most of the works on sustainability are based on static indices, life cycle assessment or multi-criteria scoring. The latter are useful pieces of evidence, but few approaches integrate farm performance, environmental indicators, predictive classification and recommendations oriented towards the farmer in the same framework.

This research is then aimed at developing a Machine Learning Based Decision Support System for Sustainable Smallholder Dairy Farming based on Environmental and Farm performance Analytics. The design of the proposed system includes indicators of milk productivity, feed efficiency, farm economics, animal health, water requirements, energy requirements, greenhouse-gas intensity, manure management and heat stress. In this section, a Random Forest classifier was written in Python and run in Google Colab to classify sustainability and generate the variables that most drive the classification of each decision. The proposed contribution is a budget-friendly, easily interpretable, and data-driven framework to assist farmers and extensionists with prioritizing management actions within the limited resources of smallholder farms. The framework also provides the basis for future field scale digital advisory services.

II. RELATED WORK

The research on sustainable dairy management has taken two parallel tracks: assessing the sustainability of the farms and analyzing the livestock using data. Chand et al. [1] identified an integrated sustainability index for small-scale dairy farming in Rajasthan that integrates economic, social and ecological dimensions of dairy farming but was still based on indicators rather than a prediction. Cortez-Arriola et al. [2] conducted a farming-system scenario analysis for smallholder dairy farms in Mexico to identify and analyse key production-environment trade-offs, but lacked a continuously learning decision model. Later, DEXi-Dairy [6] developed a multi-criteria tool to assess the economic, environmental and social sustainability of European dairy systems, which again used structured expert assessment as shown in table 1.

Table 1. Representative related work and the gap addressed by the proposed study.

Study	Primary focus	Method/analytics	Key limitation relative to this study
[1] Chand et al., 2015	Smallholder sustainability index	Economic, social and ecological indicators	Static assessment; no predictive ML or automated recommendations
[2] Cortez-Arriola et al., 2016	Sustainable intensification	Scenario and farming-system optimization	Scenario-based; not continuously data-driven
[3] Cockburn, 2020	ML for dairy management	Review of dairy ML applications	Broad ML focus; no integrated smallholder sustainability DSS
[4] Shine & Murphy, 2022	ML mapping study	129 dairy ML publications	Applications fragmented by task and technology
[5] Ji et al., 2022	Milk performance prediction	Machine learning on robotic milking data	Technology-rich setting; limited environmental integration
[6] Wilfart et al., 2023	Whole-farm sustainability	DEXimulticriteria expert model	Integrated assessment but non-ML and European-focused
[7] Vidal et al., 2023	Animal-health prediction	ML classification from accelerometer data	Single health outcome rather than whole-farm sustainability
[8] Hansen et al., 2025	Environmental prediction	18 ML/statistical models with LCA targets	Environmental outputs separated from farmer-facing decisions
[9] Foschi et al., 2025	Carbon-footprint prediction	ML for data optimization and CO2e prediction	Primarily carbon footprint; limited whole-farm performance
[10] Ndlovu et al., 2025	Environmental optimization	LCA combined with machine learning	Breeding/forage focus; not a smallholder operational DSS

Research work in machine-learning has shown great predictive capability for dairy management. Cockburn [3] reviewed applications in health, production, behavior and management, and Shine and Murphy [4] mapped 129 studies and described a lot of application of tree-based algorithms in dairy decision-support problems. In a robotic dairy system, Ji et al. [5] predicted

milk yield, composition and milking frequency using machine learning and demonstrated high prediction accuracy, however, with the premium of high farm data requirement. The use of a classification algorithms for metritis prediction using accelerometer data was demonstrated by Vidal et al. [7] as a valuable tool for predictive livestock health monitoring.

In recent years, there has been a growing body of research demonstrating the connection between machine learning and environmental assessment. Hansen et al. [8] compared and tested eighteen statistical and machine-learning models aimed at predicting greenhouse-gas, energy and nitrogen intensity. Foschi et al. [9] created a machine learning-based tool to minimise data requirements for dairy carbon-footprint estimation, and Ndlovu et al. [10] used both a life-cycle assessment and machine learning to explore lower impact dairy breeding and forage strategies. Together, these studies show that predictive analytics is valuable but that there is a recurring challenge, namely that few frameworks include an environmental performance dimension, a productivity dimension, a farm economics dimension, an animal condition dimension, an interpretability dimension and an actionable dimension, all within a low cost framework that utilizes variables readily available and recorded on the farm.

III. RESEARCH METHODOLOGY

3.1 Research Design

The research suggested in this work will be based on supervised machine learning research design to determine the sustainability of smallholder dairy farms. The predictor variables used are environmental, production, economic, resource-use and animal-health indicators that are used to classify farms by sustainability into three categories: low, moderate, and high. The entire analytical process comprises five steps, namely: Data Acquisition, Data Preprocessing, Reference Label Construction, Random Forest Modelling and Decision Support Generation[11-26].

The methodology aims to design a practical sustainability assessment system that can be used with data collected at various points on the farm, which can be easily gathered even during a smallholder farming system where the technological infrastructure to collect the data is limited.

3.2 Research Population and Data Collection

The research population will be smallholder dairy farms. Cross sectional data is taken from the participating farms at multiple sources to increase the completeness and reliability of data. Data can be gathered by means of:\

- Structured farmer interviews;
- Farm registers and record of production;
- Medical and animal-health records;
- Extension-service records; and
- Make direct measurements and observations of the farm.

The statistical unit (observational unit) in the dataset is each farm.

Table 2. Core variables for the proposed smallholder dairy decision-support model.

Variable	Analytical dimension	Decision relevance
Herd size (cows)	Farm structure	Scale and management load
Milk yield (L/cow/day)	Productivity	Output efficiency
Feed efficiency (L/kg DM)	Productivity/resource use	Milk output per feed input
Feed cost (INR/cow/day)	Economics	Input-cost pressure
Water use	Environment/resource use	Water

(L/cow/day)		efficiency
Energy use (kWh/cow/day)	Environment/resource use	Energy intensity
GHG intensity (kg CO2e/L milk)	Environment	Climate impact per milk output
Manure management score (0–10)	Environment/management	Waste handling and nutrient recycling
Animal health score (0–10)	Animal performance	Preventive health and welfare proxy
Mortality rate (%)	Animal performance	Loss and welfare risk
Net margin (INR/L milk)	Economics	Farm financial viability
Heat stress days/month	Environment/animal performance	Climate exposure

3.3 Selection of Predictor Variables

Twelve predictor variables are included in the proposed sustainability assessment model. These variables cover the key productive and economic, environmental, resource efficiency and animal health aspects of dairy farming.

The following variables have been chosen:

- Herd size;
- Production rate of milk per cow/day;
- Feed efficiency;
- Feed cost;
- Water use;
- Energy use;
- Greenhouse-gas intensity;
- Manure-management score;
- Animal-health score;
- Mortality rate;
- Net margin (per litre of milk); and
- Number of days per month with heat stress.

The variables are chosen to give a multi-dimensional picture of farm sustainability, but should be ones that could be practically collected from smallholder dairy farms.

3.4 Data Preprocessing

The collected data goes through systematic data quality assessment and pre-processing before going into model development. Records are checked for missing data, duplicate records, impossible values, inconsistent measures and units of measurement[27-35].

Where appropriate, numeric variables with missing observation can be imputed with the median value within appropriate farm groups. Depending on the type of variable, categorical management related variables are encoded by ordinal encoding or one-hot encoding.

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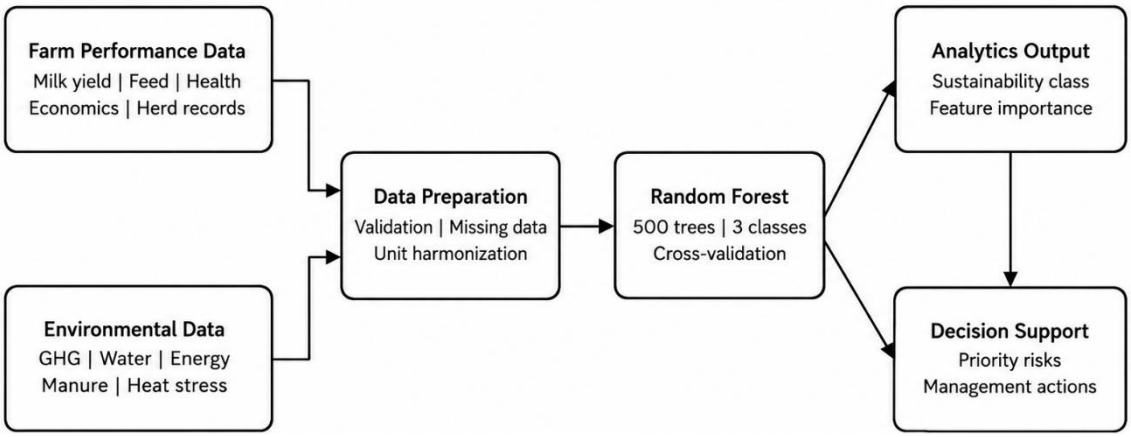


Figure 1. Proposed architecture integrating farm-performance analytics, environmental analytics, Random Forest classification, and farmer-oriented decision support.

All continuous variables are kept as measured variables as the Random Forest algorithm does not involve feature standardization/normalization when training the model.Biologically and economically impossible values and outliers are carefully reviewed and not thrown out in the first place. Where possible, the original farm records or data-collection forms are used to confirm suspicious records.

3.5 Construction of Reference Sustainability Labels

Since machine-learning based supervised models need a set of classes of outcomes, a reference sustainability classification is created prior to model training. The farms are classified as Low, Moderate or High sustainability on the basis of a normalized composite sustainability benchmark.The composite benchmark is a composite of relevant farm-performance, economic, animal-health, resource-use and environmental indicators. The individual indicators are standardized so that they can be compared, even when they are measured in different units and have different scales.

Algorithm 1. Random Forest DSS workflow.

Input: farm and environmental variables X; reference sustainability class y.
1) Validate units, ranges, duplicates, and missing values.
2) Split data using stratified 80:20 training/test partition.
3) Train RandomForestClassifier(n_estimators=500, max_depth=10, min_samples_leaf=2, max_features='sqrt', class_weight='balanced').
4) Predict Low, Moderate, or High sustainability and class probabilities.
5) Evaluate accuracy, macro precision/recall/F1, confusion matrix, and macro ROC-AUC.
6) Rank feature importance and map dominant risk factors to management recommendations.
Output: sustainability class, confidence, ranked drivers, recommended management actions.

The composite sustainability scores are subsequently discussed with experts, dairy specialists or agricultural extension staff to ensure that the categories generated are meaningful agronomically and practically sustainable.Reference labelling process is explained and documented prior to model training. This is needed to reduce the chance of information leakage, and to ensure that sustainability classes were not "just made up" based on patterns identified in the development of the models.

3.6 Dataset Partitioning

After its pre-processing and the creation of the references labels, the entire data is split into training and test sets.

- 80:20 Train/ Test split is used with:
- The 80% of the observations are used for model training; and
- 20% will be dedicated to the independent testing of models.

- In stratification, an approximately equal number of Low, Moderate and High sustainability class are sampled from the training data and the testing data.
- The testing set is not used to develop the model and is only used at the end to assess the model performance.
- The development of a random forest model is performed.Random Forest Model Development is performed.

The main machine-learning algorithm used in the sustainability classification is a Random Forest classifier. Random Forest is chosen as it is well suited to heterogeneous tabular farm level data and can model nonlinear and complex relationships between the predictor variables.

The method is also fairly robust to correlated predictors, noisy observations and can give an estimate of the importance of the predictors which helps in understanding the decision made by the model.

The initial first proposed configuration of the Random Forest model is:

- Maximum depth of the tree: 5;
- Maximum tree depth: 10;
- Minimum leaves: 25; and
- Minimum Leaf Size: one-fourth of the Total Number of Predictors;
- Full-time: 68.4% of the students; and
- Set the seed value randomly (for reproducibility).

The settings include a starting model specification which can then be further refined in a cross validation process.

3.8 Hyperparameter Optimization

Five-fold stratified cross validation is used to optimize model hyper parameters on the training set.The training data set is randomly split into 5 roughly equal-sized subsets (with the same relative proportions of each sustainability class) during cross-validation. The four subsets are used to train the model, with the other subset used to validate the model. This is done until each subset has been used as the validation set.The macro F1-score is considered as the main optimization criteria as it treats the Class Low, Moderate and High equally, without taking into account the frequency of the classes.Only the training data is used to select the hyperparameter values as the test data should not be used to make model-selection decisions.

3.9 Software and Computational Environment

The analytical process is carried out in Python, in the Google Colab computing environment.

Some of the main libraries that are used in Python are:

- pandas for data dataframes organization, cleaning, transformation and manipulation;
- R for data partitioning, modelling using the Random Forest algorithm, cross validation, prediction and performance evaluation;
- matplotlib for plotting results of analysis.
- Use of a fixed random seed to enhance data partitioning and model-development reproducibility, as appropriate.

3.10 Model Performance Evaluation

The last test dataset, which was 20% that has not been used before, is used to test the final Random Forest model. Various classification-performance measures are computed to get a comprehensive sense of how models are performing.

The following are part of the method of evaluating the performance:

- Classification accuracy;
- Macro precision;
- Macro recall;
- Macro F1-score;

The integration of multiple class confusion matrix; andArea under the curve (ROC-AUC) of the macro one-versus-rest receiver operating characteristic (ROC) curve.The macro-averaged measures are particularly highlighted as they provide a performance measurement for each sustainability category separately and then average the results at the end. Thus, during the evaluation process, the three sustainability farms (Low, Moderate and High) will be given equal consideration.The confusion matrix is used to analyze the distribution of correct and incorrect predictions in the three classes of sustainability and to detect particular classes that might be hard for the model to distinguish.

3.11 Feature-Importance Analysis

Once the model has been trained, the feature-importance scores are pulled from the Random Forest model and are used to identify the most significant variables at the farm level that are most influential in the model's classification.The overall significance of the variables, like greenhouse-gas intensity, feed efficiency, animal-health score, water use, energy use, mortality, and economic performance, can then be looked at.Thefeature_importance scores are only used to determine the relative importance of features in predicting the model. They are not intended to be used as indicators of relationships of individual farm variables to sustainability outcomes.

3.12 Decision-Support and Recommendation Generation

A decision-support component then transforms the outputs of the model into recommendations for farm management after the classification for sustainability.

- The recommendation system takes into account both the foreseen sustainability category as well as the major risk factors of the individual farm. Farms identified with Low sustainability are made recommendations focusing on the variables that have the greatest impact on poor sustainability.
- For instance, high GHG emission and low feed efficiency farms might be recommended to use ration balancing, forage quality, more milk from the animal, and better manure management.

Similarly:

- If water use is excessive, it could result in water-use monitoring, leak control, and water-use efficiency recommendations for cleaning or for drinking water systems;
- If significant energy use is detected, recommendations may be made for energy efficient equipment and practices;
- Low animal health ratings can lead to suggestions for preventive animal health such as vaccinations, hygiene and disease surveillance;
- Excessive deaths could lead to suggestions for veterinary care, calf management, housing, nutrition and disease prevention;

If performance is not good, feed-cost management, productivity improvement and resource allocation recommendations may be made.The intention of the decision-support layer is to make the output from the machine-learning layer practically interpretable for farmers, extension specialists and farm advisers.

3.13 Prototype Simulation

The field data set on which the analysis presented here is based is not available, so a simulated set of 540 records of dairy farms is used to the entire analytical process.The underlying sustainability profile is balanced in the simulated data, and has two levels: Low, Moderate and High. A realistic overlap between the farm types is captured within the generated reference labels, and a separation between the categories of sustainability is avoided, since controlled uncertainty is introduced.The proposed model architecture, the analytical process, the evaluation measures, the feature-importance analysis and the recommendation process are only using the simulated data set. Therefore, the results of the performance in the simulations should not be considered as proof of the effectiveness of the models in the real world.

3.14 Field Validation

In the last empirical research, the suggested methodology should be applied to empirical data collected from the actual smallholder dairy farms. All of the classification-performance measurements should then be re-computed with the field data set.External validation should be implemented on farms not used for the model construction and development process, as

well as internal validation through train-test evaluation. External validation is needed to find out if the trained model can perform well on other conditions in farming, other management systems, geographical areas or production environments.The methodological and research integrity of the research is ensured by keeping the difference between simulation-based prototype development and empirical field validation throughout the research.

3.15 Overall Methodological Workflow

The entire research methodology can thus be summarized as under:

Data collection on farms → Data quality control and data preprocessing → Construction of sustainability reference labels → Stratified train-test partitioning → Train with Random Forest → 5-fold cross-validation and hyperparameter optimization → Test with other farms not included in training set → Performance evaluation → Feature-importance analysis → Sustainability classification → Management recommendations on farms → External field validation.

IV. RESULTS

A simulated smallholder dairy-farm demonstration was produced that included 540 dairy-farm registers with the 12 variables outlined in the methodology. The data was split into 432 training records and 108 test records, stratified by the 3 sustainability classes as shown in table 3.

Table 3. Random Forest demonstration performance on the 108-record test set.

Performance metric	Value
Accuracy	88.89%
Macro Precision	88.88%
Macro Recall	88.91%
Macro F1-score	88.88%
Macro ROC-AUC (OvR)	93.63%
High class F1-score	90.14%
Low class F1-score	87.32%
Moderate class F1-score	89.19%

The fitted model (Random Forest) had an overall test accuracy of 88.89%. The overall performance in terms of macro precision, macro recall and macro f1-score were relatively balanced (88.88%, 88.91% and 88.88% respectively) with no class performing exceptionally well. The macro one versus rest ROC-AUC was high (93.63%), indicating good discrimination for each sustainability category. A confusion matrix was used to determine the accuracy of the classification, showing that 32 out of 35 High-sustainability farms, 31 out of 36 Low-sustainability farms and 33 out of 37 Moderate-sustainability farms were correctly classified as shown in figure 2.

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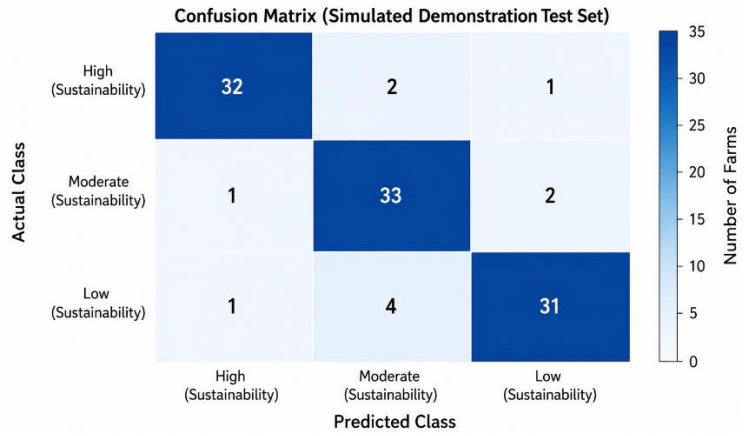


Figure 2. Confusion matrix for the simulated demonstration test set. Diagonal values indicate correct classifications.

Class level results were also pretty consistent. The High class obtained 88.9% precision, 91.4% recall, and a 90.1% F1-score. The precision, recall and F1 score for the Low class were 88.6%, 86.1% and 87.3% respectively, and for the Moderate class, the precision, recall and F1 score were 89.2%, 86.1% and 87.3% respectively. Misclassifications primarily were between neighbouring sustainability profiles and not between very different farm situations. The benefit of this pattern is that it shows the level of model uncertainty is small in the majority of cases, and larger in transition cases where management actions and environmental pressures are likely to both be significant as shown in figure 3.

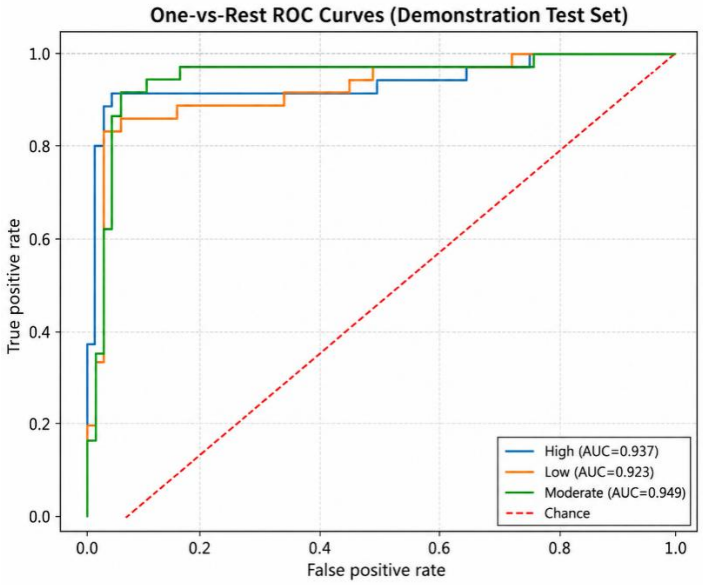


Figure 3. One-vs-rest ROC curves for High, Low, and Moderate sustainability classes in the simulated demonstration.

The most important factors found to influence the score were greenhouse-gas intensity (19.30%), net margin (15.85%), mortality rate (11.95%), manure-management score (11.12%), energy use (8.39%), and animal-health score (7.89%) (Table 3). Milk yield contributed 6.96%, feed efficiency 5.88%, feed cost 4.51%, water use 4.35%, heat stress 2.54%, and herd size 1.26%. The ranking demonstrates the importance of the combination of environmental and farm-performance analyses – sustainability classification was not production-based. A sustainability rating of acceptable milk yield was still given when other indicators such as emissions, mortality, resource use or economic margin were unfavourable.

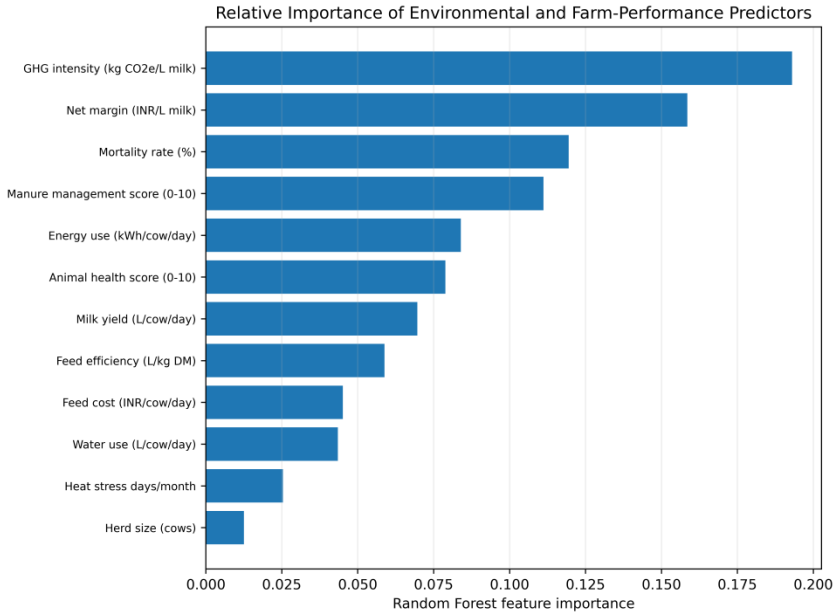


Figure 4. Random Forest feature importance for environmental and farm-performance variables in the simulated demonstration

V. DISCUSSION

These outputs can be translated into priority actions for the operation of DSS. High manure scores, high energy use, high water use, high mortality or poor health scores can signal farms to improve their rations, productivity per animal, manure storage or nutrient recycling, and/or energy or water use efficiency, respectively. These results are numerical only and not field validated and need to be substituted with field results from smallholder farms before any substantive claims about these can be made. There is a need to report five-fold cross-validation when validating a model in the field to quantify stability and minimise the reliance on any single train-test split as shown in table 4.

Table 4. Leading model drivers and example DSS responses.

Predictor	Importance	Example management response if unfavorable
GHG intensity (kg CO2e/L milk)	19.30%	Improve feed digestibility, milk output per animal, and manure handling.
Net margin (INR/L milk)	15.85%	Review feed cost, milk yield, input purchasing, and marketing margin.
Mortality rate (%)	11.95%	Prioritize preventive health, hygiene, vaccination, and early treatment.
Manure management score (0-10)	11.12%	Improve storage, composting/biogas options, and nutrient recycling.
Energy use (kWh/cow/day)	8.39%	Audit pumping, cooling, lighting, and equipment operating time.
Animal health score (0-10)	7.89%	Strengthen disease surveillance, housing hygiene, and veterinary follow-up.
Milk yield (L/cow/day)	6.96%	Improve ration balance, forage quality, heat mitigation, and lactation management.
Feed efficiency (L/kg DM)	5.88%	Optimize ration formulation and reduce feed losses.

The results show that sustainability of a dairy farm is not just about milk production, but is multidimensional. The model placed significant emphasis on environmental, economic, productivity and animal-health parameters, revealing that good

production performance can be achieved at high greenhouse-gas intensity, low profitability, animal death rates, low resource use efficiency, and manure management problems. The most common misclassifications were between adjacent sustainability classes indicating some farms have transitional characteristics between the Low, Moderate, and High classes. This pattern suggests that there is greater uncertainty about what constitutes a sustainable or unsustainable condition on a farm, as the conditions are not clearly either one or the other. The outputs of the model can be useful for decision support, enabling identification of priority management areas. Farms with low feed efficiency results may need to optimize their ration and minimize their feed losses, while farms with poor manure management results could benefit from better storing, composting, using manure for biogas, or using manure as a soil amendment. High energy/water consumptions can lead to efficiency audits; low animal-health scores and high mortality can motivate better efforts with regard to animal health, hygiene, vaccination, veterinary care and monitoring of disease. However, these interpretations are based on simulated farm records, and are merely evidence of technical feasibility. For practical deployment, such data representing a smallholder dairy-farm are needed to validate the field.

VI. CONCLUSION

This research introduces a Random Forest (RF) based Decision Support System (DSS) to combine Environmental and Farm-Performance Analytics in Sustainable Smallholder Dairy Farming. The proposed system integrates production, economic, animal health, resource use and environmental indicators to categorize farms into low, medium and high sustainability levels and translates factors that influence the sustainability to management recommendations. For the reproducible simulated demonstration, the most important variables were greenhouse-gas intensity, net margin, mortality, and manure management, with an 88.89% accuracy, 88.88% macro F1-score, and 93.63% macro ROC-AUC of the classifier. These values are a measure of technical feasibility and not actual field results. The key contribution is the combination of prediction, interpretation and recommendation in the low cost workflow implemented in python in google colab. Representative smallholder farm data could be collected, sustainability labels validated by experts, sustainability performance compared across seasons and regions, and the sustainability recommendations compared to the actual operating conditions of the smallholders and tested over multiple years to see if they increase environmental efficiency, productivity, profitability and farmer decisions making.

VII. FIELD VALIDATION REQUIREMENTS

The numbers used in the present experiment are not empirical values but are merely examples. These data can be more regular than real smallholder farm data as missing records, variability between seasons, between breeds, between market, between regions, differences in feeding and measurement uncertainty can limit model performance. A publishable field study should thus pre-register the sustainability reference-label protocol, include a representative sample of farms throughout the seasons, avoid leakage from training to testing at farm level, perform a sensitivity analysis for missing variables and perform an external validation of the final classifier on an independent farm sample. DSS should also involve dairy extension specialists in making recommendations which must then be evaluated for feasibility, costs and farmer acceptance.

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