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Comparative analysis of optimization algorithms for maxvit-based tomato leaf disease detection in precision agriculture

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A B S T R A C T

The detection methods used to identify crop diseases require both accuracy and speed because they play a vital role in achieving better crop yields and sustainable agricultural practices. This study conducts an extensive assessment of six optimization algorithms, which include AdamW, Adam, Stochastic Gradient Descent (SGD), Adagrad, RMSprop, and SophiaG, to evaluate their performance within the Multi-Axis Vision Transformer framework for classifying tomato leaf diseases. In this study, a subset of the PlantVillage dataset was employed for model training and evaluation. The experiments were conducted in PyTorch on Google Colaboratory with NVIDIA Tesla T4 GPU acceleration. The MaxViT-Tiny model used pretrained ImageNet-1k weights to establish its initial state, which developers used to train the model through different optimizers with fixed hyperparameters. Model performance was evaluated using F1-score, precision, recall, and accuracy metrics calculated with scikit-learn, along with confusion matrix analysis and convergence curve visualization. AdamW achieved the best performance results among all tested optimizers because it reached an F1 Score and Recall combined with an overall accuracy of 99.89%. SophiaG and Adam achieved similar results, while Adagrad showed the least classification success with 98.32% accuracy, which demonstrated how standard adaptive optimizers fail to manage high-dimensional visual tasks in controlled environments. The results demonstrate that advanced optimization techniques enable technological progress in agricultural smart systems and deep learning capabilities used for plant disease research, which depends on transformer models.

Keywords: AdamW, multi-axis vision transformer, optimization algorithms, SophiaG, tomato leaf diseases

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1. INTRODUCTION

Global food security is increasingly threatened by the combined impacts of pollinator decline, changing climatic conditions, and the widespread occurrence of plant diseases (Amin et al., 2022). Plant diseases represent one of the major constraints to agricultural productivity, causing substantial yield losses, economic damage, and disruptions in food supply chains worldwide (Barman et al., 2024; Javidan et al., 2025; Krishna et al., 2025; Lee & Lee, 2025; W. Liu & Zhang, 2025; Upadhyay et al., 2025). Consequently, the development of rapid, accurate, and automated disease detection systems has become a critical component of sustainable agricultural production and precision agriculture.

Tomato (*Solanum lycopersicum* L.), a member of the Solanaceae family, is among the most economically important vegetable crops cultivated worldwide (Collins et al., 2022; Panno et al., 2021). The world recognizes tomatoes as one of the most popular crops because their diverse culinary applications and their high nutritional value make them valuable worldwide as a food source (Agarwal et al., 2020; Sakkarvarthi et al., 2022). However, tomato production is severely affected by numerous fungal, bacterial, viral, and pest-related diseases, resulting in considerable reductions in yield and quality (J. Liu & Wang, 2020; Shanthi et al., 2024). Conventional disease diagnosis methods rely heavily on visual inspection and laboratory-based analyses, which are often labor-intensive, time-consuming, and susceptible to human error (Chitta et al., 2024; Fraiwan et al., 2022; Ghosh et al., 2025; Wang et al., 2025; Zhu et al., 2024).

Recent advances in artificial intelligence (AI) and deep learning (DL) have transformed plant disease diagnosis by enabling automated, rapid, and highly accurate disease detection systems (Colucci et al., 2025; Das et al., 2024; El Sakka et al., 2024; Hamid et al., 2025; Ouamane et al., 2025; Qin et al., 2025; Wang et al., 2025). Early studies predominantly employed convolutional neural networks (CNNs) for plant disease classification. For example, Zhang et al. (2018) evaluated AlexNet, GoogLeNet, and ResNet architectures and reported that ResNet optimized using SGD achieved a classification accuracy of 97.28% for tomato leaf disease identification. Similarly, Liu and Wang (2020) developed a YOLOv3-based framework that improved disease detection accuracy and speed under real-world conditions through optimized feature extraction and multi-scale image analysis.

More recently, transformer-based architectures have demonstrated superior performance in agricultural image classification because of their ability to model both local and global feature relationships. Hossain et al. (2023) compared several transformer architectures, including MaxViT, EANet, CCT, and PVT, and reported that MaxViT achieved the highest classification accuracy when trained with the AdamW optimizer. Likewise, Nishankar et al. (2025) introduced the ViT-RoT benchmarking framework and demonstrated that transformer-based models such as ConvNeXt-Small and Swin-Small exhibited high classification accuracy and robustness using AdamW optimization. Hybrid architectures have also shown promising results. Tiwari et al. (2024) proposed a Vision Transformer–Deep Neural Network framework optimized with Adam and achieved a classification accuracy of 99.74%, while Ghosh et al. (2025) integrated Swin Transformer, ViT, and EfficientNetV2 models and reported approximately 98% classification accuracy under diverse environmental conditions using AdamW.

Despite the rapid advancement of deep learning architectures, model performance depends not only on network design but also on the optimization strategy employed during training. Optimization algorithms directly influence convergence speed, training stability, computational efficiency, and model generalization. Adam Kingma & Ba (2015) has become one of the most widely used optimizers because of its adaptive learning-rate mechanism based on first- and second-order moment estimation. Several studies have reported that Adam frequently outperforms traditional optimization methods such as SGD and RMSprop in terms of convergence speed and training stability (Osmenaj et al., 2025; Thangaraj et al., 2021). AdamW extends Adam by decoupling weight decay from gradient updates, thereby improving regularization and generalization performance, particularly in transformer-based architectures (Ghosh et al., 2025; Hossain et al., 2023; Nishankar et al., 2025; Shen et al., 2025).

Recently, Liu et al. (2024) proposed Sophia, a scalable second-order optimization algorithm that utilizes a stochastic diagonal Hessian approximation and gradient clipping mechanism to accelerate convergence while maintaining computational efficiency. Sophia demonstrated promising results in large-scale deep learning applications by reducing training costs and convergence time. However, despite its potential advantages, its application in agricultural image classification and plant disease detection remains largely unexplored.

Although previous studies have reported promising results using CNN-based, transformer-based, and hybrid architectures, most investigations have primarily focused on model development while employing a single optimization algorithm. Existing studies rarely perform systematic comparisons of multiple optimization strategies under identical experimental conditions. Furthermore, the effectiveness of recently proposed optimizers such as SophiaG within transformer-based plant disease classification frameworks has not been comprehensively investigated. Therefore, a significant research gap remains regarding the comparative impact of different optimization algorithms on the performance and convergence behavior of transformer-based models for agricultural disease detection. To address this gap, the present study systematically evaluates six optimization algorithms, namely Adam, AdamW, SGD, RMSprop, Adagrad, and SophiaG, using the Multi-Axis Vision Transformer (MaxViT) architecture for tomato leaf disease classification. The study investigates their influence on classification accuracy, convergence characteristics, and training efficiency to identify the most effective optimization strategy for AI-driven disease diagnosis in precision agriculture.

2. MATERIALS AND METHODS

2.1. Dataset and Preprocessing

The PlantVillage Tomato Leaf Disease Dataset served as the dataset for this research. Multiple research studies have utilized this dataset to create automated systems that detect crop leaf diseases using deep learning methods (Dai et al., 2023; Mohameth et al., 2020; Mohanty et al., 2016; Too et al., 2019; Ullah et al., 2023). The researchers found that CNN-based and transfer learning models proved effective on this dataset. The dataset contains 22,930 labeled RGB images of tomato leaves, which researchers organized into 10 classes that include healthy leaves and nine different diseases. The dataset was split into two parts that included 18,345 images for training, which represented approximately 80% of the dataset, and 4,585 images for validation, which formed about 20% of the dataset. The original images came from controlled environments that used standard lighting and a consistent background. The images had a standard resolution of 256×256 pixels, which produced minimal background noise and consistent visual conditions (Mohanty et al., 2016). The preprocessing required all images to be resized to 224×224 pixels for use as input to the MaxViT model, as illustrated in Figure 1.

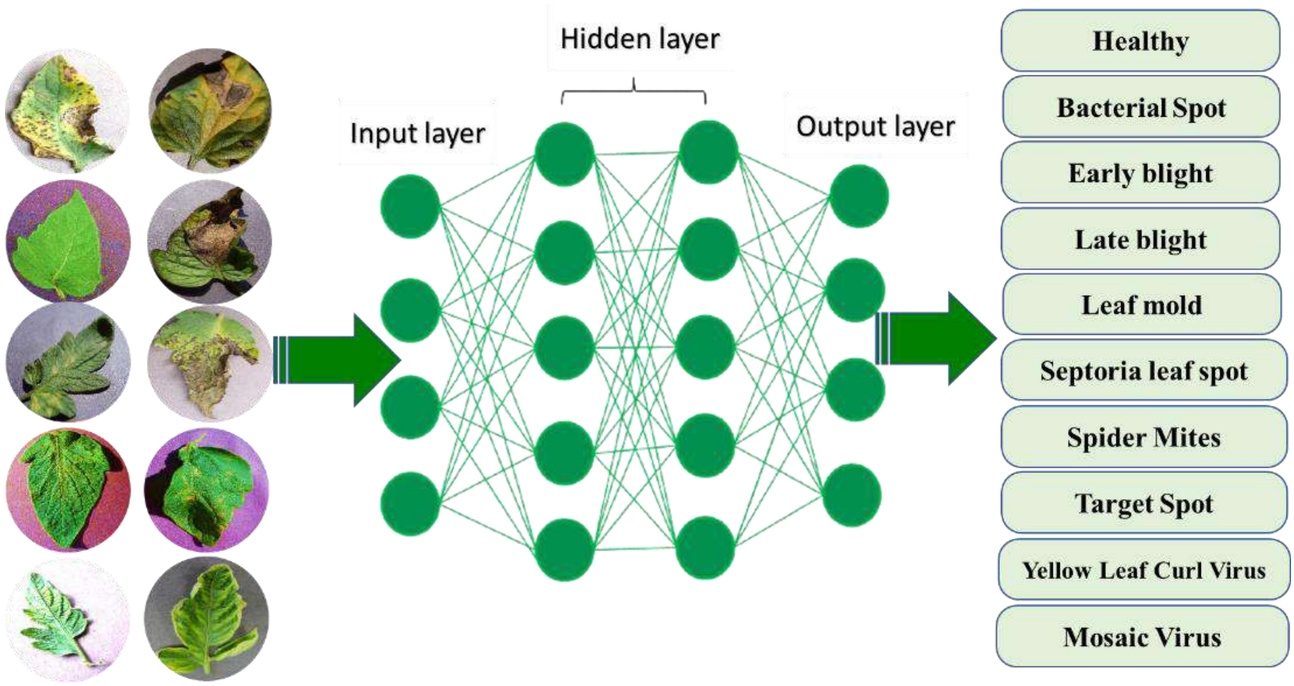


Figure 1. Tomato leaf images are processed through a deep neural network to classify conditions

During training, several preprocessing and data augmentation techniques were applied to improve model generalization and reduce overfitting. Specifically, random horizontal flipping with a probability of 0.5 and random image rotation within ±10° were employed. No augmentation was applied to the validation dataset to ensure unbiased performance evaluation. Subsequently, all images were converted into tensors and normalized using the standard ImageNet normalization statistics with channel-wise mean values of (0.485, 0.456, 0.406) and standard deviation values of (0.229, 0.224, 0.225). These normalization parameters are consistent with the pretrained MaxViT model and facilitate efficient transfer learning by preserving the feature distribution learned from the ImageNet dataset. The processed images were loaded using the PyTorch ImageFolder interface. During training, batches of 32 images were randomly shuffled at each epoch to improve stochastic optimization, whereas the validation dataset was evaluated without shuffling to ensure consistent performance assessment. The methodological workflow of the research is seen in Figure 2.

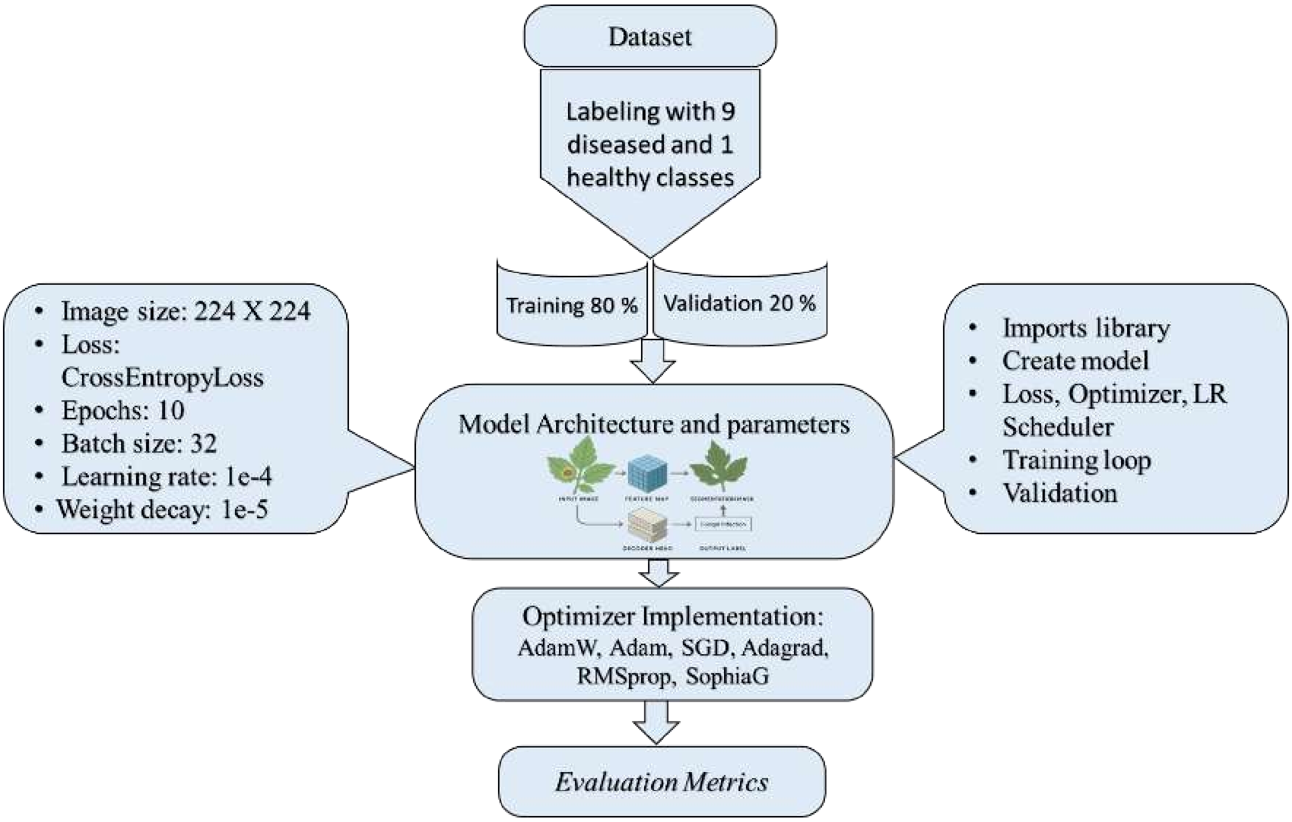


Figure 2. Methodological Framework for Tomato Leaf Disease Classification using MaxViT via various optimizers.

2.2. Model Architecture and Experimental Setup

The MaxViT-Tiny model functions as the base model architecture because it represents a top-level hierarchical vision transformer system which utilizes multiple attention systems. This model combines both local and global attention mechanisms, which enable it to identify plant leaf disease symptoms that appear in different sizes and patterns. The model was initialized with pretrained weights from the ImageNet-1k dataset, which were obtained through the timm library. The model's final classification head was changed when its adaptive average pooling layer was replaced by a fully connected linear classifier. The model was trained for 10 epochs using a batch size of 32 through the CrossEntropyLoss function, which utilized a learning rate of 1e-4 and a weight decay of 1e-5 for regularization purposes. The model was fully fine-tuned, as all 28.5 million parameters were trainable with no frozen layers. The original classification head of the pretrained MaxViT model was replaced with an Adaptive Average Pooling layer followed by a fully connected linear layer containing 10 output neurons corresponding to the ten tomato leaf disease classes. All experiments were implemented using the PyTorch framework on the Google Colaboratory platform, utilizing an NVIDIA Tesla T4 GPU for computational acceleration. The current setup mirrors recent research studies, which include Google Colaboratory and Tesla T4 GPU systems to train deep learning models for plant disease classification and detection (Jain et al., 2022; Jaiswal et al., 2024).

2.3. Optimizer Implementations

The research evaluated optimization strategies by testing six different optimizers, which included AdamW, Adam, SGD, Adagrad, RMSprop, and SophiaG, as summarized in Table 1. The AdamW optimization method functions as an Adam optimizer variant that separates weight decay from gradient updates to enhance its regularization capabilities. The Adaptive Moment Estimation algorithm computes dynamic learning rates that depend on both the first and second gradient moment values to optimize performance across diverse tasks. The oldest optimizer in existence, SGD, uses momentum as a method to speed up the process of reaching convergence. Adagrad uses learning rate adjustment based on how often parameters get updated, while RMSprop uses a moving average of previous gradients to handle problems that change over time. SophiaG functions as a new optimization method that uses second-order optimization through a stochastic Hessian approximation and implements a cosine learning rate schedule.

Table 1 summarizes the hyperparameter settings used to ensure a fair comparison among the evaluated optimizers.

Optimizer	Learning Rate	Weight Decay	Momentum	Rho	LR Scheduler	Other Settings
AdamW	1×10^{-4}	1×10^{-5}	–	–	None	PyTorch default parameters
Adam	1×10^{-4}	1×10^{-5}	–	–	None	PyTorch default parameters
SGD	1×10^{-2}	1×10^{-5}	0.9	–	None	Nesterov=False (default)
RMSprop	1×10^{-4}	1×10^{-5}	default	–	None	Centered=False (default)
Adagrad	1×10^{-2}	1×10^{-5}	–	–	None	Initial accumulator=0
SophiaG	1×10^{-4}	1×10^{-5}	–	0.01	CosineAnnealingLR (Tmax=10)	Hessian update every 50 iterations

The evaluation of each optimizer involved measuring its effects on training dynamics through three specific metrics, which included convergence speed, stability, and final performance metrics, which measured accuracy, precision, recall, and F1 score. Previous work by Thangaraj et al. (2021) successfully applied Adam, SGD, and RMSprop in tomato leaf disease classification using CNNs. We performed additional optimization tests for the MaxViT architecture by assessing both traditional optimization methods and their modern optimization counterparts. The complete implementation of the Multi-Axis Vision Transformer model and the optimizer comparison experiments are publicly available for reproducibility on the GitHub[1] repository.

Prior studies successfully applied Adam, SGD, and RMSprop optimizers in tomato leaf disease classification using CNNs. Inspired by this, we expanded the optimizer comparison within the MaxViT architecture to include both conventional and advanced optimizers. The complete implementation of the Multi-Axis Vision Transformer model and the optimizer comparison experiments are publicly available for reproducibility at the repository.

2.4. Evaluation Metrics

The evaluation of model performance used multiple statistical metrics, which included F1 Score, Precision, Recall, and overall Accuracy, to assess the validation dataset. The scikit-learn library was used to calculate these metrics. The researchers used a normalized confusion matrix to study how different classes were incorrectly identified. Training and validation accuracy curves were generated for all epochs to analyze model convergence behavior. The model achieving the best performance for each optimizer was selected and retained for further comparative analysis. The evaluation system used Precision and Recall together with another measurement index after providing formulas for each measurement requirement, which follows:

(1) Categorical Accuracy = Number of Correct Predictions / Total Number of Predictions
(2) Precision=TP/(TP+FP)
(3) Recall=TP/(TP+FN)
(4) F1-Score= (2 × (Precision × Recall)) / ((Precision + Recall))

TP: True Positives; FP: False Positives; and FN: False Negatives.

[1]- https://github.com/RafiullahRafi/TomatoLeaf_Disease_MultiAxisViT_Optimizers

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Performance evaluation.

The comparative evaluation of various optimization algorithms demonstrates that different algorithms produce distinct results when applied to the Multi-Axis Vision Transformer (MaxViT) deep learning model, which detects tomato leaf diseases. AmadW outperforms all other algorithms by achieving the highest results across every measurement category because it attained an F1 score of 0.9989 and recall and precision scores that matched this achievement, and it showed superior performance during training sessions that lasted for multiple epochs, as demonstrated in Figure 3. The optimizer proved to be the best choice for this field because it showed better generalization, faster convergence, and greater system resilience according to test results, while SophiaG provided similar results through its 0.9982 performance across three essential evaluation standards. Adam successfully maintained a high-performance level with a 0.9970 score while RMSprop achieved a 0.9961 score, yet both these optimizers fell short of reaching the top two performance levels. Traditional optimization methods, such as SGD and Adagrad, display lower performance levels when compared to contemporary optimization techniques. Adagrad records the lowest performance across all evaluation categories as it achieved an F1 score of 0.9832 and reached an overall accuracy of 98%, which represents its best performance.

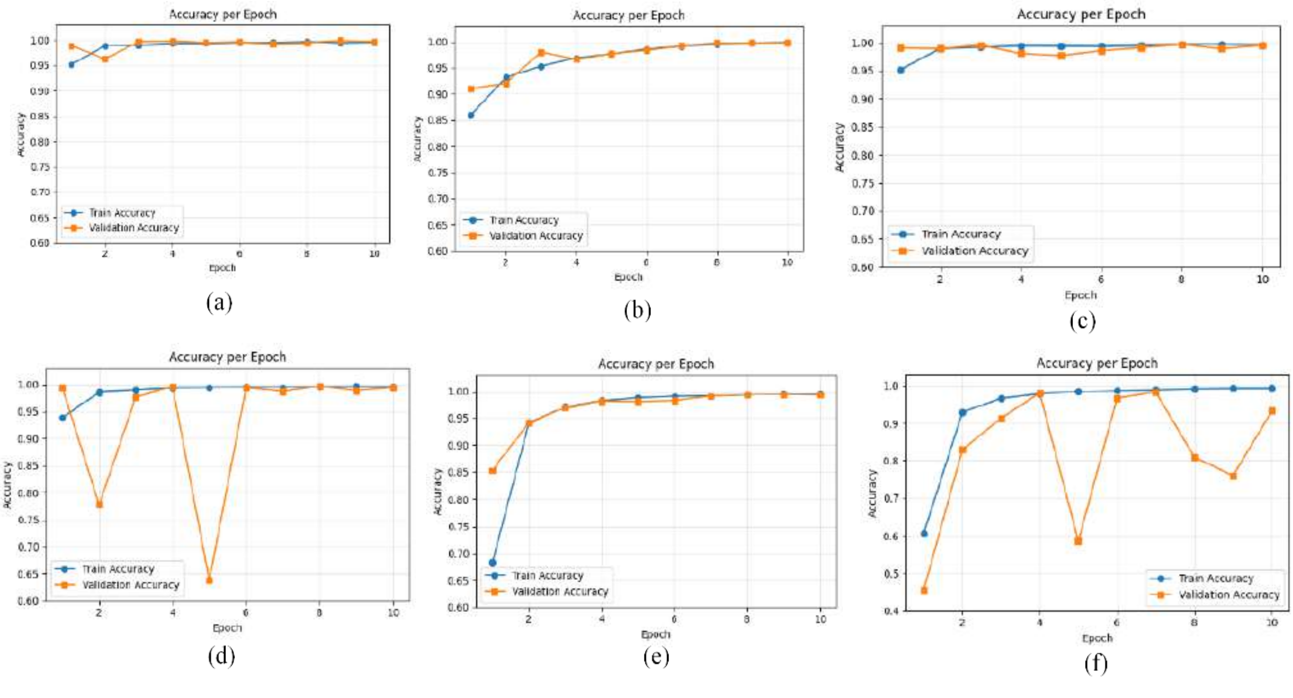


Figure 3. The MaxViT model training and validation accuracy using different optimization algorithms (a) AdamW, (b) SophiaG, (c) Adam, (d) RMSprop, (e) SGD, and (f) Adagrad across training epochs.

The adaptive gradient techniques which developed before modern times become ineffective when they attempt to analyze intricate plant disease detection systems, which require analysis of high-dimensional image data. Modern adaptive optimizers, including AdamW and SophiaG, demonstrate higher performance levels when applied to deep transformer-based models, which include multi-axis vision transformer, because these optimizers deliver better results in high-accuracy requirements of smart agriculture systems, precision agricultural practices, and plant pathology diagnostic processes. Figure 4 illustrates the six different optimizers perform when testing tomato leaf diseases through their metric heatmap assessment, which the MaxViT-Tiny model uses for classification.

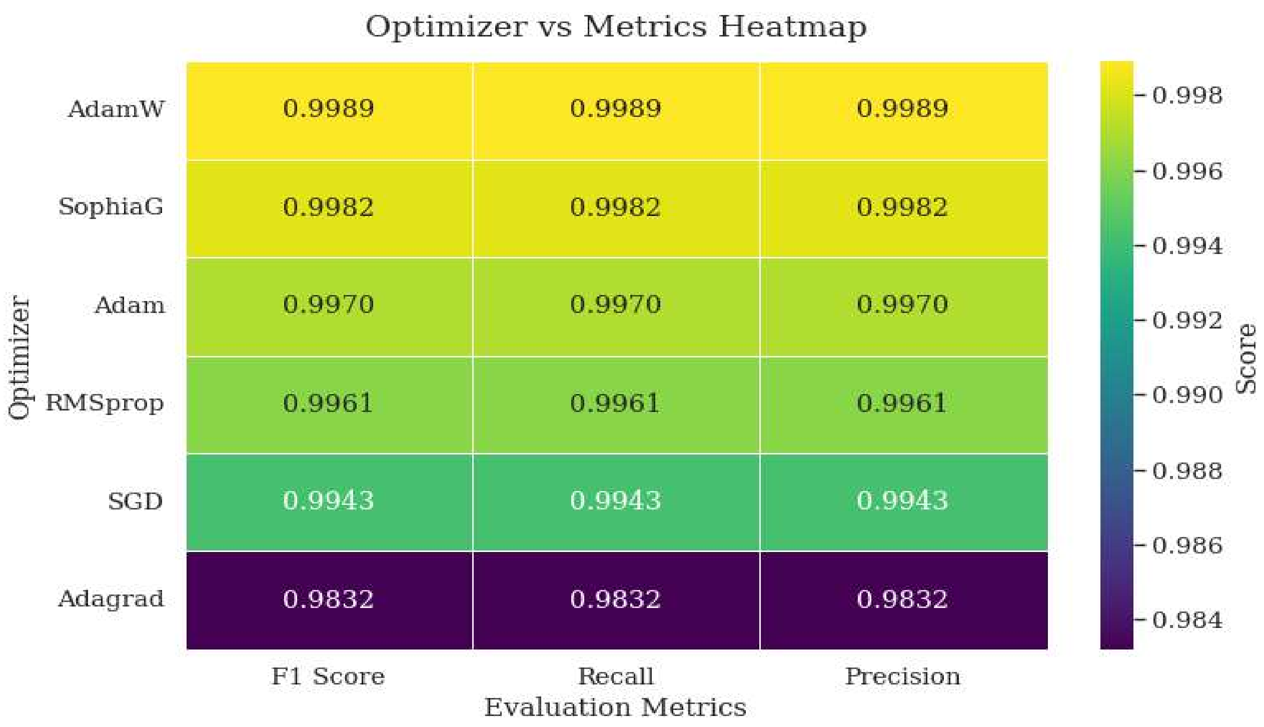
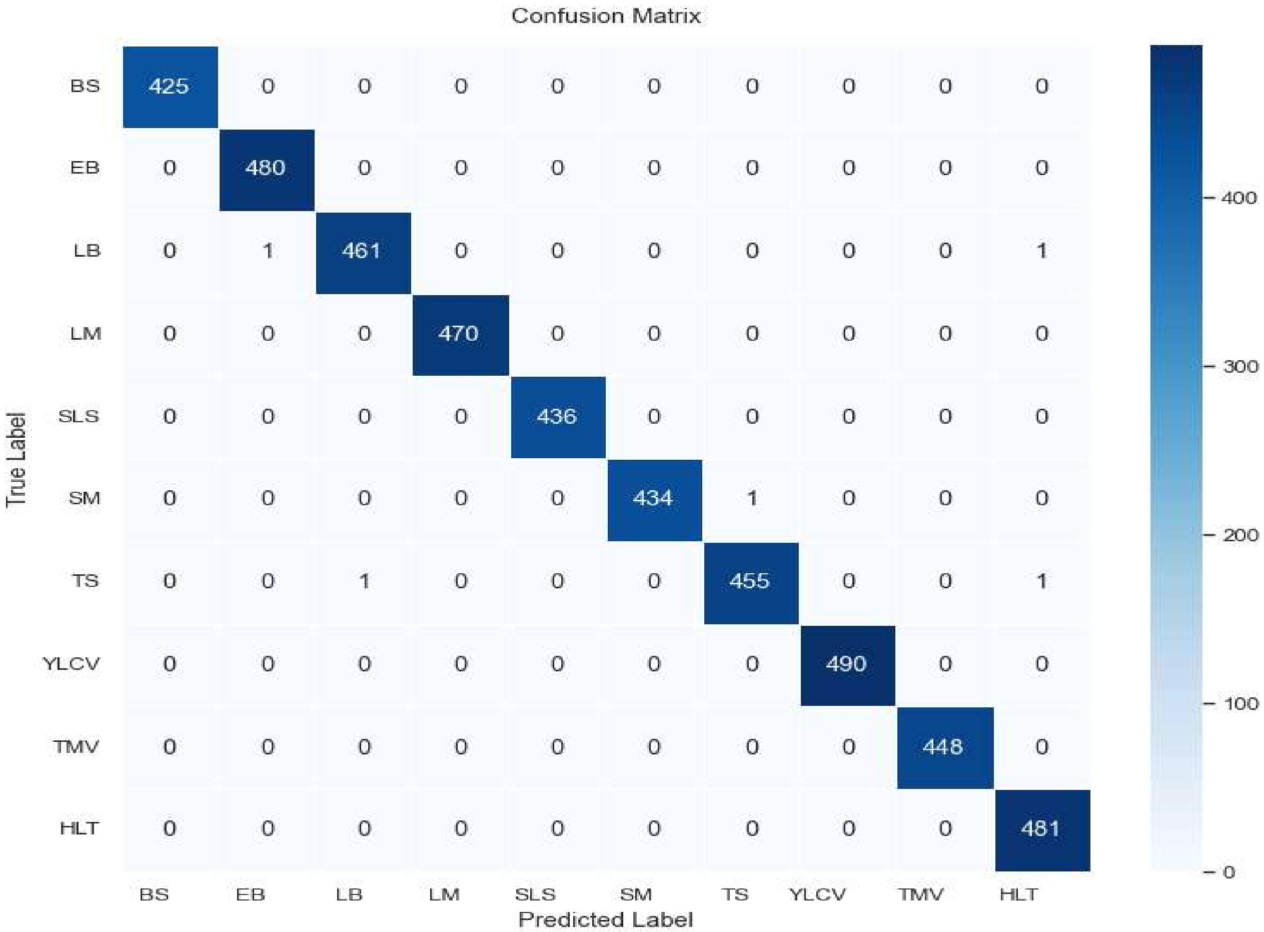


Figure 4. Comparison of various optimizers on tomato leaf disease detection on the MaxViT model.

3.2. Confusion Matrix analysis

Confusion matrix analysis was conducted to assess the classification performance of the MaxViT-Tiny model using different optimization algorithms. The analysis shows how the model predicts every tomato leaf disease category, which demonstrates the strengths and weaknesses of each optimizer to limit classification errors. The AdamW optimizer achieved the lowest number of misclassifications (5), followed closely by SophiaG (8) and Adam (14), indicating superior performance in terms of generalization. The two algorithms, RMSprop and SGD, recorded (18) and (26) misclassifications, while Adagrad showed its highest misclassification count at 77, which indicates that the model struggled with adaptive learning during its training process. The confusion matrix, which Figure 5 displays, shows the classification performance results of the MaxViT-Tiny model, which used the AdamW optimizer for its training. The model demonstrated superior performance compared with the other evaluated optimizers. The AdamW optimizer demonstrates higher correct prediction rates and lower misclassification frequencies, which establish it as the most effective optimization method for this particular situation.

The AdamW optimizer demonstrated superior performance across all metrics, achieving 4580 correct predictions out of 4585 total samples, resulting in only 5 misclassifications, as shown in Figure 5. The system achieved 99.89%accuracy because AdamW effectively reduced loss while maintaining a steady convergence process. The improved performance of the system may be attributed to the efficient second-order gradient approximation method and adaptive learning dynamics, which enhance its capability to handle complex classification tasks.



The abbreviations used in the confusion matrix represent the following full class names: BS – Bacterial Spot, EB – Early Blight, LB – Late Blight, LM – Leaf Mold, SLS – Septoria Leaf Spot, SM – Spider Mites, TS – Target Spot, YLCV – Tomato Yellow Leaf Curl Virus, TMV – Tomato Mosaic Virus, and HLT – Healthy.

Figure 5. Confusion matrix of the MaxViT model for tomato leaf disease classification using the AdamW optimizer, representing the best-performing configuration among all tested optimizers.

The SophiaG optimizer reached 4577 correctly classified samples out of 4585 total samples, with just 8 misclassifications, resulting in an accuracy of 99.82%. The Adam optimizer recorded 4571 correct predictions out of 4585, which resulted in 14 misclassifications and an accuracy of 99.70%. Adam remains an effective optimizer for deep learning workflows because it uses adaptive learning rates together with moment estimation techniques. The RMSprop optimizer produced 4567 correct predictions from 4585 samples, which resulted in 18 misclassifications and achieved an accuracy of 99.61%. The learning rate adjustment mechanism of this optimizer enables efficient handling of non-stationary objectives because it uses recent gradient magnitude data to determine learning rate changes. RMSprop demonstrates strong performance during training because it maintains gradient control even though it falls short of Adam-based optimizers in accuracy.

The SGD optimizer achieved 4559 correct predictions from 4585 total predictions, while making 26 incorrect predictions, which resulted in a 99.43% accuracy rate. Adagrad produced 4508 correct predictions from 4585 total samples while making 77 incorrect predictions, which represents the highest number of incorrect predictions across all tested optimizers, resulting in an accuracy rate of 98.32%. Adagrad applies learning rate adjustments based on how often parameters get updated, but the system experiences excessive learning rate decline throughout the training process, which creates obstacles during the later stages of training. The system shows reduced performance for complex classification tasks, which require handling small differences between classes, because of its high misclassification rate. All optimizers' correct predictions and misclassifications are summarized in Table 2.

Table 2 Performance comparison of optimizers based on accuracy, misclassification, and prediction results.

Optimizer	Total Samples	Correct Predictions	Misclassifications	Accuracy
AdamW	4585	4580	5	99.89%
SophiaG	4585	4577	8	99.82%
Adam	4585	4571	14	99.70%
RMSprop	4585	4567	18	99.61%
SGD	4585	4559	26	99.43%
Adagrad	4585	4508	77	98.32%

3.3 Discussion

This study presented a comparative evaluation of six widely used optimization algorithms—Adam, AdamW, SGD, RMSprop, Adagrad, and SophiaG—within the context of tomato leaf disease classification using the Multi-Axis Vision Transformer (MaxViT) architecture. The study tested multiple optimizers on the PlantVillage dataset because its goal was to find which optimizer achieved the best results for disease detection in precision agriculture. The system achieves its effectiveness because it uses a new stochastic diagonal Hessian approximation method and element-wise gradient clipping system, which leads to rapid learning and effective generalization while using less processing power. AdamW’s minimal misclassification rate (only 5 instances) further reinforces its robustness and reliability for high-stakes agricultural applications.

Recent studies have demonstrated that optimizers play a crucial role in improving the performance and stability of deep learning models for plant disease classification. The CNN-based method achieved its highest identification accuracy of 97.28% for tomato leaf diseases through transfer learning, which utilized AlexNet, GoogLeNet, and ResNet with the SGD optimizer (Zhang et al., 2018). The traditional optimizers SGD and RMSprop provide dependable convergence results; however, they need users to spend time tuning their hyperparameters. The Adam optimizer shows quicker convergence times and improved generalization abilities through its automatic learning rate adjustments, which use first and second moment gradient data (Kingma & Ba, 2015). Multiple studies have demonstrated that Adam performs better than SGD and RMSprop because it produces more accurate results and maintains training stability (Osmenaj et al., 2025; Thangaraj et al., 2021). The AdamW variant enables transformers to achieve better performance through its weight decay decoupling feature, which maintains stable optimization processes during transformer-based architecture operations in MaxViT and ViT-RoT (Hossain et al., 2023; Nishankar et al., 2025). The Sophia optimizer developed by Liu et al. (2024) reached its goal of faster convergence through curved second-order approximation, which reduced the needed computation time. The MaxViT model reached its optimal performance through AdamW optimization, which produced an F1-score of 0.9989 and precision and recall scores of 0.9989. Compared to CNN-based models and transformer-based systems, AdamW enables more precise and dependable classification results for tomato leaf diseases.

The superior performance of AdamW can be attributed to its decoupled weight decay mechanism, which improves regularization while preserving adaptive learning rates, making it particularly suitable for transformer-based architectures such as MaxViT. As shown in Figure. 3(a), AdamW achieved the fastest and most stable convergence, resulting in the highest classification performance. SophiaG produced comparable results because its stochastic second-order Hessian approximation enables efficient optimization and rapid convergence (Figure. 3(b)), although its performance remained slightly below AdamW. In contrast, Adagrad exhibited the weakest performance (Figure. 3(f)) due to its continuously decreasing learning rate, which limited effective parameter updates and caused unstable validation accuracy. Similarly, RMSprop showed noticeable fluctuations during validation (Figure. 3(d)), whereas SGD converged more slowly (Figure. 3(e)) because it relies on a fixed global learning rate despite its stable optimization. These findings indicate that transformer-based models benefit from optimizers that combine adaptive learning rates with effective regularization, explaining the superior performance of AdamW over the other evaluated optimization algorithms.

The findings of this study should be interpreted in light of several limitations. First, the experiments were conducted using the publicly available PlantVillage dataset, which consists of high-quality images captured under controlled lighting conditions with relatively uniform backgrounds. Although these characteristics facilitate consistent model training and fair optimizer comparison, they do not fully represent the variability encountered in real agricultural environments, such as changing illumination, complex backgrounds, occlusions, and varying disease severity. Furthermore, PlantVillage is a curated benchmark dataset and may not adequately capture the diversity of tomato cultivars and field conditions across different geographical regions. Consequently, the generalizability of the proposed MaxViT–AdamW framework may be limited in practical applications. Future research should validate the proposed approach using field-collected datasets acquired under diverse environmental conditions and investigate its robustness across different cultivation systems and geographic locations.

CONCLUSION

This study demonstrates the critical role of optimization algorithms in enhancing the performance, convergence efficiency, and classification accuracy of vision-based deep learning models for agricultural disease detection. The AdamW and SophiaG optimizers prove to be the most effective optimizers for classifying tomato leaf diseases through the MaxViT architecture. The system demonstrates its ability to exceed the performance of both old and new optimization methods, which makes it suitable for use in plant pathology and smart agriculture. The study results provide important knowledge about how artificial intelligence and deep learning technologies link with agricultural diagnostic methods. The research findings lead to better disease detection systems, which help sustainable farming methods to grow and increase agricultural productivity, and improve food security and economic stability. Future research should examine hybrid optimization techniques, validate the proposed approach using field-collected datasets from diverse environmental conditions, and deploy MaxViT-AdamW systems in agricultural field settings to strengthen the connection between precision agriculture research and its practical applications.

CONFLICT OF INTEREST

All authors declare no conflict of interest regarding the publication of this research.

DATA AVAILABILITY

Code used to perform the analyses for this paper is hosted at https://github.com/RafiullahRafi/TomatoLeaf_Disease_MultiAxisViT_Optimizers. All analyses were conducted using Python (v3.x). No additional data have been deposited in a public repository.

AUTHORS CONTRIBUTIONS:

Rafiullah Rafi: Conceptualization, investigation, formal analysis, resources, original draft preparation, review and editing, visualization, supervision, project administration, and funding acquisition. Assistant Professor Alireza Soleimanipour and Associate Professor Abbas Rezaei: Supervision, consultation, review support, academic consultation, and guidance throughout the research. Sarajudin and Sediqullah Hammas: Methodology development and technical assistance.
All authors have read and agreed to the published version of the manuscript.

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AI Statement

Artificial intelligence tools were used only for language improvement and grammatical editing.

REFERENCES

Agarwal, M., Singh, A., Arjaria, S., Sinha, A., & Gupta, S. (2020). ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network. *Procedia Computer Science*, *167*, 293–301. https://doi.org/10.1016/j.procs.2020.03.225

Amin, H., Darwish, A., Hassanien, A. E., & Soliman, M. (2022). End-to-End Deep Learning Model for Corn Leaf Disease Classification. *IEEE Access*, *10*, 31103–31115. https://doi.org/10.1109/ACCESS.2022.3159678

Barman, U., Sarma, P., Rahman, M., Deka, V., Lahkar, S., Sharma, V., & Saikia, M. J. (2024). ViT-SmartAgri: Vision Transformer and Smartphone-Based Plant Disease Detection for Smart Agriculture. *Agronomy*, *14*(2), 327. https://doi.org/10.3390/agronomy14020327

Chitta, S., Yandrapalli, V. K., & Sharma, S. (2024). Deep Learning for Precision Agriculture: Evaluating CNNs and Vision Transformers in Rice Disease Classification. *2024 OPJU International Technology Conference on Smart Computing for Innovation and Advancement in Industry 4.0, OTCON 2024*, 1–6. https://doi.org/10.1109/OTCON60325.2024.10687983

Collins, E. J., Bowyer, C., Tsouza, A., & Chopra, M. (2022). Tomatoes: An Extensive Review of the Associated Health Impacts of Tomatoes and Factors That Can Affect Their Cultivation. *Biology*, *11*(2), 239. https://doi.org/10.3390/biology11020239

Colucci, G. P., Battilani, P., Camardo Leggieri, M., & Trinchero, D. (2025). Algorithms for Plant Monitoring Applications: A Comprehensive Review. In *Algorithms* (Vol. 18, Number 2, pp. 1–47). https://doi.org/10.3390/a18020084

Dai, D., Xia, P., Zhu, Z., & Che, H. (2023). MTDL-EPDCLD: A Multi-Task Deep-Learning-Based System for Enhanced Precision Detection and Diagnosis of Corn Leaf Diseases. *Plants*, *12*(13), 2433. https://doi.org/10.3390/plants12132433

Das, P. K., Rupa, S. S., Pumrin, S., Das, U. C., & Hossen, Md. K. (2024). Deep Learning for Plant Disease Detection and Classification: A Systematic Analysis and Review. *CURRENT APPLIED SCIENCE AND TECHNOLOGY*, e0259016. https://doi.org/10.55003/cast.2024.259016

El Sakka, M., Mothe, J., & Ivanovici, M. (2024). Images and CNN applications in smart agriculture. In *European Journal of Remote Sensing* (Vol. 57, Number 1, pp. 1–30). Taylor & Francis. https://doi.org/10.1080/22797254.2024.2352386

Fraiwan, M., Faouri, E., & Khasawneh, N. (2022). Classification of Corn Diseases from Leaf Images Using Deep Transfer Learning. *Plants*, *11*(20), 1–14. https://doi.org/10.3390/plants11202668

Ghosh, H., Rahat, I. S., Emon, Md. M. R., Mashrafi, Md. J., Al Arafat Tanzin, M. A., Mohanty, S. N., & Kant, S. (2025). Advanced neural network architectures for tomato leaf disease diagnosis in precision agriculture. *Discover Sustainability*, *6*(1), 312. https://doi.org/10.1007/s43621-025-01149-1

Hamid, M. K., Shah, S. K., Husnain, G., Ghadi, Y. Y., Al Maaytah, S. A., & Qahmash, A. (2025). Enhancing Agricultural Disease Detection: A Multi-Model Deep Learning Novel Approach. *Engineering Reports*, *7*(1). https://doi.org/10.1002/eng2.13113

Hossain, S., Tanzim Reza, M., Chakrabarty, A., & Jung, Y. J. (2023). Aggregating Different Scales of Attention on Feature Variants for Tomato Leaf Disease Diagnosis from Image Data: A Transformer Driven Study. *Sensors*, *23*(7), 3751. https://doi.org/10.3390/s23073751

Jain, S., Sahni, R., Khargonkar, T., Gupta, H., Verma, O. P., Sharma, T. K., Bhardwaj, T., Agarwal, S., & Kim, H. (2022). Automatic Rice Disease Detection and Assistance Framework Using Deep Learning and a Chatbot. *Electronics (Switzerland)*, *11*(14), 2110. https://doi.org/10.3390/electronics11142110

Jaiswal, M., Nagwanshi, K. K., Kumar, R., Gaurav, S., & Watti, Y. (2024). Classification of Plant Disease using a State-of-the Art Deep learning Algorithm on a Tesla GPU. *International Journal of Computing*, 240–246. https://doi.org/10.47839/ijc.23.2.3542

Javidan, S. M., Ampatzidis, Y., Banakar, A., Asefpour Vakilian, K., & Rahnama, K. (2025). An Intelligent Group Learning Framework for Detecting Common Tomato Diseases Using Simple and Weighted Majority Voting with Deep Learning Models. *AgriEngineering*, *7*(2), 31. https://doi.org/10.3390/agriengineering7020031

Kingma, D. P., & Ba, J. L. (2015, December 22). Adam: A method for stochastic optimization. *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*.

Krishna, M. S., Machado, P., Otuka, R. I., Yahaya, S. W., Neves dos Santos, F., & Ihianle, I. K. (2025). Plant Leaf Disease Detection Using Deep Learning: A Multi-Dataset Approach. *J*, *8*(1), 4. https://doi.org/10.3390/j8010004

Lee, S., & Lee, S. (2025). Efficient Data Augmentation Methods for Crop Disease Recognition in Sustainable Environmental Systems. *Big Data and Cognitive Computing*, *9*(1), 1–19. https://doi.org/10.3390/bdcc9010008

Liu, H., Li, Z., Hall, D., Liang, P., & Ma, T. (2024, May 23). SOPHIA: A SCALABLE STOCHASTIC SECOND-ORDER OPTIMIZER FOR LANGUAGE MODEL PRE-TRAINING. *12th International Conference on Learning Representations, ICLR 2024*.

Liu, J., & Wang, X. (2020). Tomato Diseases and Pests Detection Based on Improved Yolo V3 Convolutional Neural Network. *Frontiers in Plant Science*, *11*. https://doi.org/10.3389/fpls.2020.00898

Liu, W., & Zhang, A. (2025). Plant Disease Detection Algorithm Based on Efficient Swin Transformer. *Computers, Materials and Continua*, *82*(2), 3045–3068. https://doi.org/10.32604/cmc.2024.058640

Mohameth, F., Bingcai, C., & Sada, K. A. (2020). Plant Disease Detection with Deep Learning and Feature Extraction Using Plant Village. *Journal of Computer and Communications*, *08*(06), 10–22. https://doi.org/10.4236/jcc.2020.86002

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using Deep Learning for Image-Based Plant Disease Detection. *Frontiers in Plant Science*, *7*(September). https://doi.org/10.3389/fpls.2016.01419

Nishankar, S., Pavindran, V., Mithuran, T., Nimishan, S., Thuseethan, S., & Sebastian, Y. (2025). ViT-RoT: Vision Transformer-Based Robust Framework for Tomato Leaf Disease Recognition. *AgriEngineering*, *7*(6), 185. https://doi.org/10.3390/agriengineering7060185

Osmenaj, Z., Tseliki, E.-M., Kapellaki, S. H., Tselikis, G., & Tselikas, N. D. (2025). From Pixels to Diagnosis: Implementing and Evaluating a CNN Model for Tomato Leaf Disease Detection. *Information*, *16*(3), 231. https://doi.org/10.3390/info16030231

Ouamane, A., Chouchane, A., Himeur, Y., Miniaoui, S., Atalla, S., Mansoor, W., & Al-Ahmad, H. (2025). Optimized Vision Transformers for Superior Plant Disease Detection. *IEEE Access*, *13*, 48552–48570. https://doi.org/10.1109/ACCESS.2025.3547416

Panno, S., Davino, S., Caruso, A. G., Bertacca, S., Crnogorac, A., Mandić, A., Noris, E., & Matić, S. (2021). A Review of the Most Common and Economically Important Diseases That Undermine the Cultivation of Tomato Crop in the Mediterranean Basin. *Agronomy*, *11*(11), 2188. https://doi.org/10.3390/agronomy11112188

Qin, Y. M., Tu, Y. H., Li, T., Ni, Y., Wang, R. F., & Wang, H. (2025). Deep Learning for Sustainable Agriculture: A Systematic Review on Applications in Lettuce Cultivation. In *Sustainability (Switzerland)* (Vol. 17, Number 7, p. 3190). https://doi.org/10.3390/su17073190

Sakkarvarthi, G., Sathianesan, G. W., Murugan, V. S., Reddy, A. J., Jayagopal, P., & Elsisi, M. (2022). Detection and Classification of Tomato Crop Disease Using Convolutional Neural Network. *Electronics*, *11*(21), 3618. https://doi.org/10.3390/electronics11213618

Shanthi, D. L., Vinutha, K., Ashwini, N., & Vashistha, S. (2024). Tomato Leaf Disease Detection Using CNN. *Procedia Computer Science*, *235*, 2975–2984. https://doi.org/10.1016/j.procs.2024.04.281

Shen, Y., Yang, Z., Khan, Z., Liu, H., Chen, W., & Duan, S. (2025). Optimization of Improved YOLOv8 for Precision Tomato Leaf Disease Detection in Sustainable Agriculture. *Sensors*, *25*(5), 1398. https://doi.org/10.3390/s25051398

Thangaraj, R., Anandamurugan, S., & Kaliappan, V. K. (2021). Automated tomato leaf disease classification using transfer learning-based deep convolution neural network. *Journal of Plant Diseases and Protection*, *128*(1), 73–86. https://doi.org/10.1007/s41348-020-00403-0

Tiwari, M., Kumar, H., Prakash, N., Kumar, S., Neware, R., Tripathi, S., & Agarwal, R. (2024). Tomato Disease Detection Using Vision Transformer with Residual L1-Norm Attention and Deep Neural Networks. *International Journal of Intelligent Engineering and Systems*, *17*(1), 679–688. https://doi.org/10.22266/ijies2024.0229.57

Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, *161*, 272–279. https://doi.org/10.1016/j.compag.2018.03.032

Ullah, Z., Alsubaie, N., Jamjoom, M., Alajmani, S. H., & Saleem, F. (2023). EffiMob-Net: A Deep Learning-Based Hybrid Model for Detection and Identification of Tomato Diseases Using Leaf Images. *Agriculture*, *13*(3), 737. https://doi.org/10.3390/agriculture13030737

Upadhyay, A., Chandel, N. S., Singh, K. P., Chakraborty, S. K., Nandede, B. M., Kumar, M., Subeesh, A., Upendar, K., Salem, A., & Elbeltagi, A. (2025). Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artificial Intelligence Review*, *58*(3), 1–64. https://doi.org/10.1007/s10462-024-11100-x

Wang, S., Xu, D., Liang, H., Bai, Y., Li, X., Zhou, J., Su, C., & Wei, W. (2025). Advances in Deep Learning Applications for Plant Disease and Pest Detection: A Review. In *Remote Sensing* (Vol. 17, Number 4, pp. 1–31). https://doi.org/10.3390/rs17040698

Zhang, K., Wu, Q., Liu, A., & Meng, X. (2018). Can Deep Learning Identify Tomato Leaf Disease? *Advances in Multimedia*, *2018*, 1–10. https://doi.org/10.1155/2018/6710865

Zhu, T., Yan, F., Lv, X., Zhao, H., Wang, Z., Dong, K., Fu, Z., Jia, R., & Lv, C. (2024). A Deep Learning Model for Accurate Maize Disease Detection Based on State-Space Attention and Feature Fusion. *Plants*, *13*(22), 1–24. https://doi.org/10.3390/plants13223151

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Analysis of international trade patterns of wood-based panels in 15 eastern European and central Asian countries

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A B S T R A C T

Wood-based panels are increasingly important in construction, furniture, interior design, and packaging, yet the drivers of Wood-Based Panel (WBP) trade in Eastern Europe and Central Asia remain insufficiently quantified at the country-panel level. This study provides a focused regional assessment of the determinants of WBP export and import values for 15 Eastern European and Central Asian countries from 2005 to 2020. Pooled ordinary least squares, fixed-effects, and random-effects panel regressions were estimated using GDP per capita, forest coverage, exchange rate, trade policy, and population as explanatory variables. Model selection was guided by Hausman specification tests and overall F-tests. For exports, pooled OLS explains 63.06% of the variation in log export value, while the random-effects model explains 55.97%. GDP per capita and forest coverage are consistently positive and statistically significant export determinants, while the exchange rate has a significant negative coefficient in the pooled and fixed-effects models. For imports, GDP per capita is the most robust determinant, with a positive and highly significant coefficient in all specifications, whereas forest coverage, exchange rate, and population are generally insignificant. Hausman tests favor fixed-effects estimation for both export and import models, confirming that country-specific unobserved heterogeneity is correlated with the regressors. The study contributes by separating export- and import-side determinants for a strategically important but under-studied regional WBP market. The findings suggest that export policies should combine sustainable forest management, stable macroeconomic conditions, and improved processing capacity, whereas import-related policies should focus on domestic demand management, industrial upgrading, and efficient trade facilitation.

Keywords: central Asia, eastern Europe, fixed effects, international trade, panel data, wood-based panels

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1. Introduction

Wood-based panels (WBPs), including plywood, particleboard, medium-density fiberboard (MDF), high-density fiberboard (HDF), and oriented strand board (OSB), are essential inputs for construction, furniture manufacturing, packaging, flooring, and interior applications. Their importance is linked to affordability, structural versatility, and the possibility of using wood residues, recycled fibers, and lower-grade logs in higher-value products (Dukarska, 2023; Gonçalves et al., 2025). Because these products depend simultaneously on forest-resource endowment, processing capacity, market demand, and trade regulation, WBP trade provides a useful empirical setting for examining how natural resources and macroeconomic conditions interact in regional markets.

The global WBP sector has expanded alongside rising demand for engineered wood products, low-carbon building materials, and improved utilization of forest biomass. Countries with abundant forest resources and developed processing industries, such as Russia and several European economies, have increased production and export capacity, whereas economies with growing construction and furniture markets often rely on imports to satisfy domestic demand (Sujová et al., 2016; Zhang et al., 2022; Ivanov et al., 2023). Eastern Europe and Central Asia are therefore particularly relevant because the region contains both forest-rich exporters and smaller economies with different levels of industrial capacity, infrastructure, exchange-rate exposure, and policy openness.

Previous studies have examined forest-products trade, wood-market competitiveness, exchange-rate behavior, and environmental regulations in trade (Buongiorno, 2016; Morland et al., 2018; Saraswati et al., 2023; Sauvage, 2014; Wang et al., 2017). A subset of this literature uses cross-country panel data to model forest-product trade and demand relationships, including comparative-advantage and forest-endowment frameworks (Uusivuori, 2002) and estimates of the income and price elasticities of import demand (Simangunsong & Buongiorno, 2001; Turner & Buongiorno, 2004). However, much of this literature either analyzes aggregate forest-product categories, focuses on large global markets, or relies on gravity-type trade frameworks that do not fully isolate country-specific unobserved characteristics. Existing findings also differ: some studies emphasize income and market size, others stress forest-resource supply, and others identify exchange-rate and policy conditions as key determinants. This variation shows the need for a more focused empirical analysis of WBPs in Eastern Europe and Central Asia.

This study addresses three specific gaps. First, it focuses directly on wood-based panels rather than broad forest-product aggregates. Second, it examines 15 Eastern European and Central Asian countries that share historical trade linkages but differ substantially in forest coverage, industrial structure, exchange-rate conditions, and market size. Third, it compares pooled OLS, fixed-effects, and random-effects models to account for unobserved country characteristics such as logistics systems, institutional quality, industrial history, production technology, and historical trade relationships. By doing so, the study provides a more consistent assessment of how macroeconomic, resource, demographic, and policy factors shape WBP export and import performance.

To address these gaps, this study investigates the determinants of wood-based panel (WBP) trade in 15 Eastern European and Central Asian countries using panel data and comparing pooled ordinary least squares (OLS), fixed-effects, and random-effects models to account for unobserved country-specific characteristics. The analysis focuses on the effects of GDP per capita, exchange rate, trade policy, forest coverage, and population on WBP exports and imports. These variables were selected based on international trade theory and forest-sector literature, where GDP per capita reflects purchasing power, industrial capacity, and investment potential; forest coverage represents raw-material availability and production potential; exchange rate captures changes in international price competitiveness and import costs; trade policy reflects market access through tariffs, non-tariff measures, customs procedures, and trade facilitation; and population represents domestic demand and labor-market scale. Specifically, the study investigates the effects of GDP per capita and exchange rate on WBP export and import performance, examines how trade policy is associated with WBP trade flows, and evaluates the influence of forest coverage and population on export capacity and import demand. Accordingly, the study addresses three research questions: (i) how do GDP per capita and exchange rate influence WBP exports and imports, (ii) how is trade policy associated with WBP trade flows, and (iii) how do forest coverage and population affect export capacity and import demand? It is hypothesized that GDP per capita positively influences both exports and imports, forest coverage has a stronger positive effect on exports than imports, exchange-rate movements significantly affect export competitiveness, and trade policy has a measurable but context-dependent association with WBP trade. By focusing specifically on WBPs rather than aggregated forest products and by estimating separate export and import models, this study provides a more comprehensive understanding of the macroeconomic, resource, demographic, and policy factors shaping regional WBP trade.

The conceptual framework of this study is grounded in international trade theory and forest-sector economics, which emphasize that macroeconomic conditions, resource availability, and policy environment jointly determine trade flows. In this framework, GDP per capita and exchange rate represent demand capacity and international price competitiveness, respectively, influencing both exports and imports. Forest coverage is expected to mainly support export capacity through raw-material availability, while population reflects domestic demand that may increase import dependence. Trade policy influences trade flows by shaping market access through tariffs, non-tariff measures, and trade facilitation. These relationships form the basis for the empirical export and import models estimated in this study.

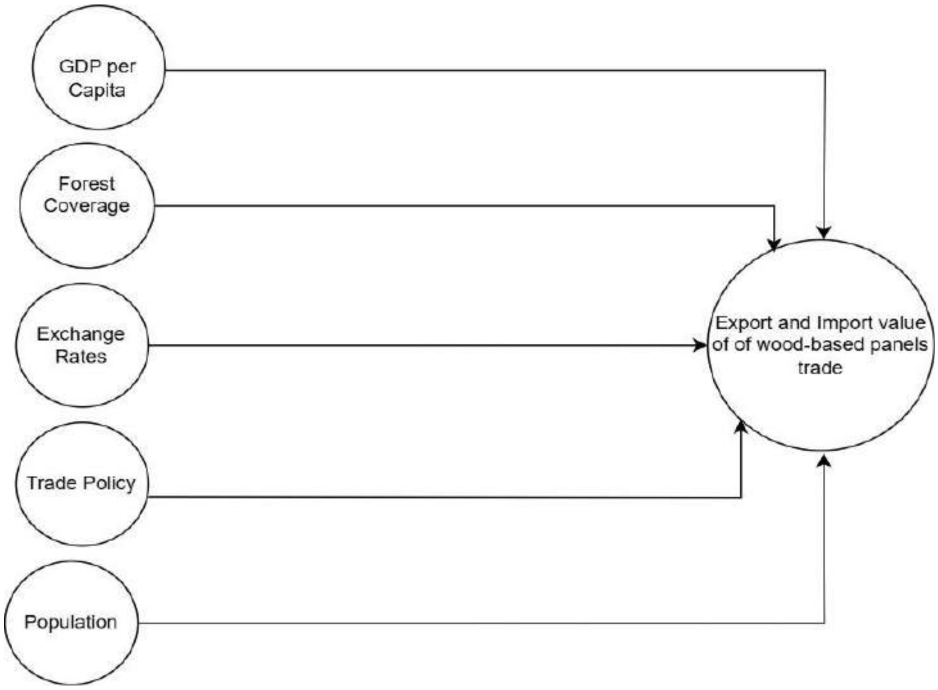

Figure 1. Conceptual framework of the study.

2. Materials and Methods

2.1 Study area and data sources

The analysis covers 15 countries in Eastern Europe and Central Asia: Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, the Republic of Moldova, the Russian Federation, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan. These countries were selected because they form a geographically connected regional market with shared post-socialist trade legacies, strong differences in forest-resource endowment, and varying degrees of industrial development and trade openness. The study period, 2005-2020, was selected according to consistent data availability for WBP trade and macroeconomic indicators across the sample. The endpoint also avoids severe incompleteness in the most recent years and reduces the influence of post-2020 disruptions on the baseline model. Trade and forest variables were compiled mainly from FAO/FAOSTAT, while macroeconomic indicators were obtained from the World Bank, IMF, WTO, and UNCTAD databases.

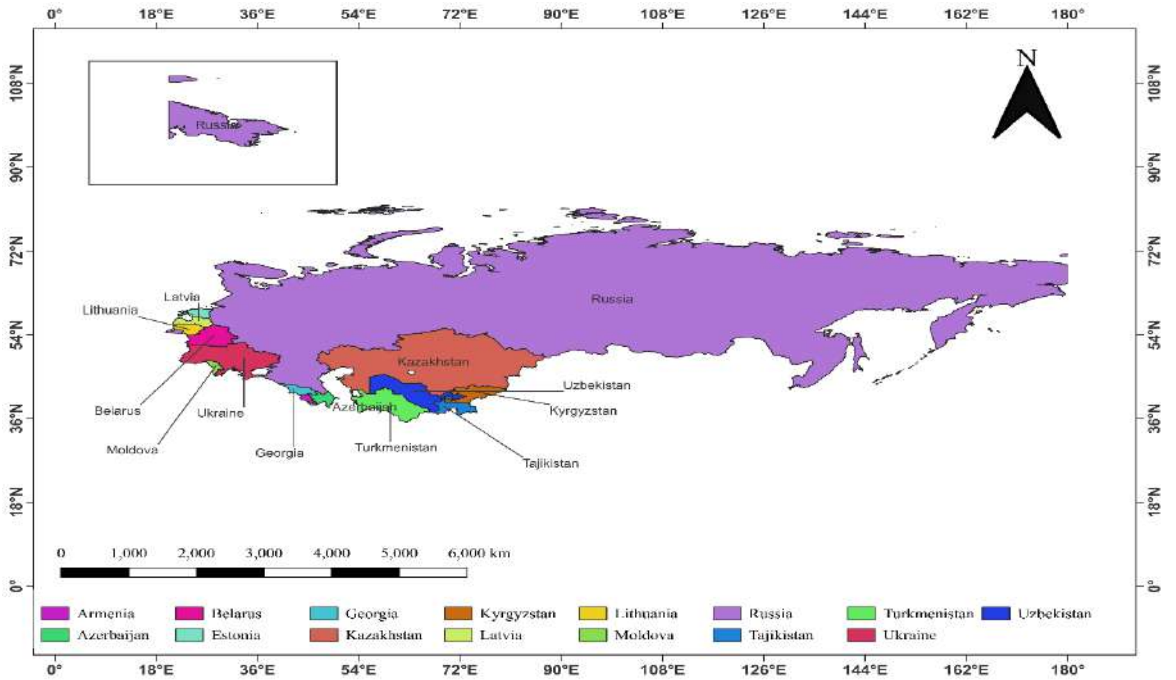

Figure 2. Geographical location of the study countries.

Table 1 Forest and woodland area by country

Country	Forest area (1000 ha)	Forest land (%)
Armenia	328.26	11.53
Azerbaijan	1143.30	13.83
Belarus	8782.10	43.27
Estonia	2438.40	57.04
Georgia	2822.00	40.62
Kazakhstan	3483.92	1.29
Kyrgyzstan	1333.62	6.95
Latvia	3414.66	54.87

Lithuania	2202.67	35.18
Republic of Moldova	386.50	11.72
Russian Federation	815311.60	49.78
Tajikistan	424.80	3.06
Turkmenistan	4127.00	8.78
Ukraine	9696.00	16.73
Uzbekistan	3715.50	8.43

Source: Compiled by the authors from FAOSTAT.

2.2 Variable definitions

The study uses two dependent variables: export value of wood-based panels (EVWBP) and import value of wood-based panels (IVWBP). All variables are transformed into natural logarithms to reduce skewness and allow elasticity-based interpretation of coefficients. Independent variables include GDP per capita (GDP), forest coverage (FC), exchange rate (EXR), trade policy (TP), and population (P). The trade-policy variable is treated as a proxy for the openness or restrictiveness of the policy environment affecting market access, tariff and non-tariff barriers, customs procedures, and trade regulation. Because trade policy is multidimensional, the results for this variable are interpreted cautiously and as associations rather than as the isolated effect of a single policy instrument.

Table 2 Variable definitions and data sources

Variable	**Abbreviation**	**Description**	**Data source**
Export value of wood-based panels	EVWBP	Dependent variable	FAO/FAOSTAT
Import value of wood-based panels	IVWBP	Dependent variable	FAO/FAOSTAT
Gross domestic product per capita	GDP	Economic capacity and income level	World Bank/OECD National Accounts
Forest coverage	FC	Forest-resource availability	FAO/FAOSTAT
Exchange rate	EXR	Currency competitiveness and import-cost channel	World Bank/IMF
Trade policy	TP	Trade openness/restriction and regulatory environment	WTO/UNCTAD
Population	P	Domestic demand and labor-market scale	World Bank

All variables were converted into logarithmic form for regression analysis.

2.3 Econometric model

The empirical analysis estimates separate export and import equations because the determinants of selling panels abroad may differ from those of purchasing panels from foreign suppliers. Export performance is expected to depend more strongly on resource endowment, processing capacity, and price competitiveness, whereas import demand is expected to depend mainly on income, domestic demand, and policy openness. The general panel specification is written as:

$$lnY\_it = \alpha\_i + \beta 1lnP\_it + \beta 2lnGDP\_it + \beta 3lnFC\_it + \beta 4lnEXR\_it + \beta 5lnTP\_it + \varepsilon\_it$$

where Y represents either EVWBP or IVWBP for country i in year t, α_i captures country-specific effects, β denotes the estimated coefficients, and ε_it is the idiosyncratic error term. Pooled OLS assumes common intercepts and homogeneous cross-sectional units. The fixed-effects model allows the intercept to vary by country and therefore controls for time-invariant unobserved heterogeneity, whereas the random-effects model treats country-specific heterogeneity as random and assumes that it is uncorrelated with the regressors (Baltagi, 2005). The Hausman test is therefore central for selecting between fixed and random effects (Hausman, 1978).

2.4 Model selection and estimation strategy

The analysis proceeds in five steps. First, descriptive statistics are reported to summarize the distribution of the variables. Second, pooled OLS is estimated as a baseline specification. Third, fixed-effects and random-effects models are estimated to account for panel structure. Fourth, Hausman specification tests are used to determine whether fixed effects or random effects are more appropriate. Fifth, diagnostic and robustness checks are considered, including multicollinearity assessment through variance inflation factors, tests for heteroskedasticity and serial correlation, and comparison of coefficient signs across pooled, fixed-effects, and random-effects specifications. If diagnostic tests indicate heteroskedasticity or serial correlation, robust or cluster-robust standard errors should be reported.

2.5 Diagnostic checks and robustness considerations

To strengthen the methodological reliability of the analysis, the diagnostic and robustness assessment was revised using the available Stata outputs reported in the thesis appendices and empirical results. The checks focus on model adequacy, coefficient stability, and model-selection diagnostics across pooled OLS, fixed-effects, and random-effects specifications. The available thesis results report the core panel diagnostics needed for specification choice, including F/Wald significance tests, R-squared values, Hausman tests, observation numbers, and the consistency of coefficient signs and significance across model specifications.

Table 3 Diagnostic and robustness checks considered in the panel regression analysis

Diagnostic / robustness check	Reported thesis-based results	Interpretation
Pooled OLS overall fit	Export: N = 212; F(5,206) = 70.33; Prob > F = 0.0000; R-squared = 0.6306; adjusted R-squared = 0.6216. Import: N = 230; F(5,224) = 29.22; Prob > F = 0.0000; R-squared = 0.3948; adjusted R-squared = 0.3813.	Both baseline models are statistically significant, but the import model has lower explanatory power than the export model.
Fixed-effects within fit	Export: N = 212; countries = 15; within R-squared = 0.2398. Import: N = 238; countries = 15; within R-squared = 0.2570.	The within R-squared values show moderate within-country explanatory power, suggesting that additional time-varying factors may also influence trade.
Random-effects overall fit	Export: N = 212; Wald chi2(5) = 62.24; Prob > chi2 = 0.0000; overall R-squared = 0.5597; rho = 0.7221. Import: N = 230; Wald chi2(5) =	The random-effects models are jointly significant, but the rho values indicate important country-level heterogeneity.

	54.92; Prob > chi2 = 0.0000; overall R-squared = 0.3790; rho = 0.4212.	
Hausman specification test	Export: chi-square = 63.05; p-value = 0.0000. Import: chi-square = 11.58; p-value = 0.0410.	The null hypothesis of random-effects consistency is rejected for both models; fixed effects are preferred.
Coefficient-stability check	Export: GDP and forest coverage are positive in the main specifications; exchange rate is negative in pooled OLS and fixed effects; trade policy changes sign across specifications. Import: GDP remains positive and highly significant across pooled OLS, fixed-effects, and random-effects models.	The substantive conclusions are robust for GDP-driven imports and resource/economic export determinants, while trade-policy effects should be interpreted cautiously.

Overall, the diagnostic evidence supports the use of fixed-effects estimation as the preferred specification. The Hausman tests reject the random-effects assumption for both export and import equations, while the significant F/Wald statistics confirm that the explanatory variables jointly improve model fit. The robustness comparison also shows that GDP is the most stable determinant of imports, whereas GDP and forest coverage are the most consistent export-side determinants. Because the thesis output does not report separate VIF, Wooldridge serial-correlation, or modified Wald heteroskedasticity statistics, the robustness discussion is based on the reported model-comparison diagnostics and coefficient stability across specifications.

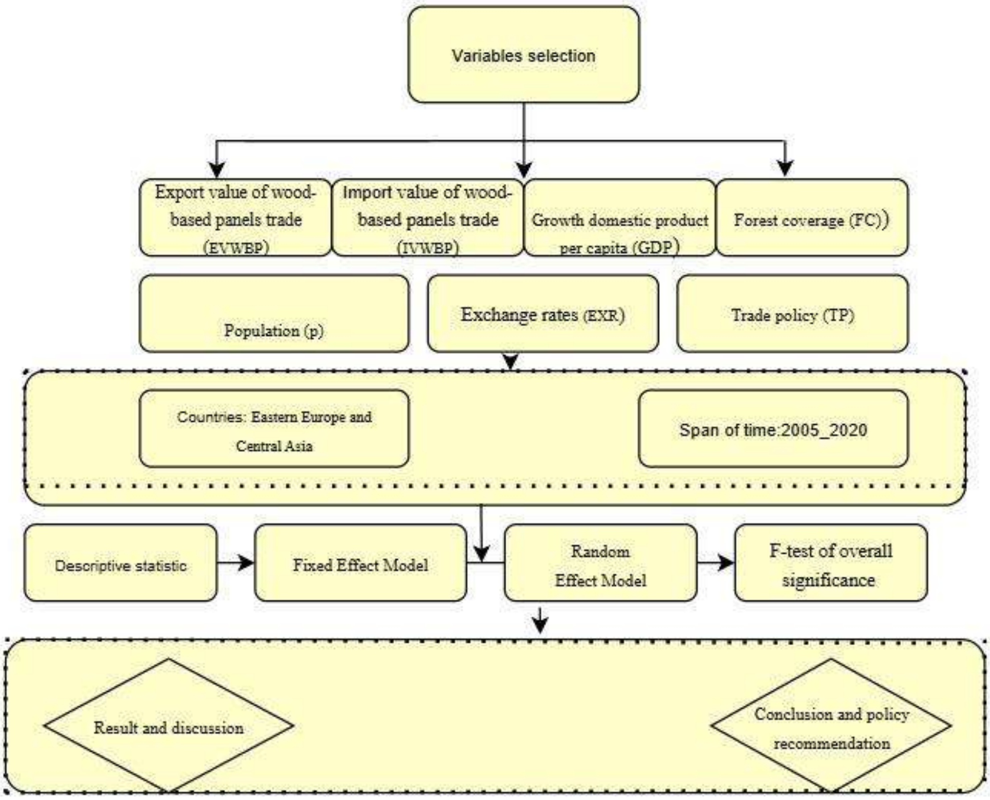

Figure 3. Analytical roadmap of the study.

3. Empirical results

3.1 Descriptive statistics

Table 4 Summary of descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min.	Max.
log_EVWBP	216	15.4365	3.8238	6.9078	21.4495
log_IVWBP	234	17.9147	1.6620	9.9988	20.5543
log_P	240	15.8111	1.4007	7.9643	18.7974
log_GDP	240	24.2814	1.3976	22.1671	28.0105
log_FC	240	2.7026	1.1026	0.1310	4.0438
log_EXR	240	2.7910	2.6844	-1.2112	9.3445
log_TP	236	1.2301	1.2249	-1.2040	2.8034

Source: Computed by the authors using Stata. EVWBP = export value; IVWBP = import value.

The descriptive statistics show that export values vary more widely than import values. The standard deviation of log_EVWBP is 3.8238, compared with 1.6620 for log_IVWBP, indicating stronger cross-country and temporal heterogeneity in exports. This pattern is consistent with the uneven distribution of forest resources and processing capacity across the sample. GDP, forest coverage, exchange rate, and trade-policy variables also show notable variation, supporting the use of panel techniques that account for country-specific differences rather than relying only on pooled cross-sectional variation.

3.2 Pooled OLS results

Table 5 Pooled OLS export regression results (dependent variable: log_EVWBP)

Variable	Coefficient	Std. err.	t	p-value	95% confidence interval
log_P	-0.1981	0.1712	-1.16	0.249	-0.5355 to 0.1394
log_GDP	1.6223***	0.1788	9.07	0.000	1.2697 to 1.9748
log_FC	1.4794***	0.1787	8.28	0.000	1.1271 to 1.8317
log_EXR	-0.2403**	0.0755	-3.18	0.002	-0.3891 to -0.0914
log_TP	-0.3131*	0.1524	-2.05	0.041	-0.6135 to -0.0127
Constant	-23.9976***	2.9881	-8.03	0.000	-29.8888 to -18.1065

Number of observations = 212; F(5,206) = 70.33; Prob > F = 0.0000; R-squared = 0.6306; adjusted R-squared = 0.6216. Significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 6 Pooled OLS import regression results (dependent variable: log_IVWBP)

Variable	Coefficient	Std. err.	t	p-value	95% confidence interval
log_P	-0.0763	0.0940	-0.81	0.418	-0.2617 to 0.1090
log_GDP	0.8728***	0.0969	9.01	0.000	0.6818 to 1.0638
log_FC	-0.0521	0.0972	-0.54	0.592	-0.2438 to 0.1395
log_EXR	-0.0148	0.0381	-0.39	0.697	-0.0899 to 0.0602
log_TP	-0.2761***	0.0828	-3.33	0.001	-0.4393 to -0.1128
Constant	-1.6008	1.6255	-0.98	0.326	-4.8041 to 1.6025

Number of observations = 230; F(5,224) = 29.22; Prob > F = 0.0000; R-squared = 0.3948; adjusted R-squared = 0.3813. Significance: * p<0.05, ** p<0.01, *** p<0.001.

The pooled OLS export model indicates that a 1% increase in GDP per capita is associated with an estimated 1.62% increase in export value, while a 1% increase in forest coverage is associated with an estimated 1.48% increase in export value, holding other variables constant. The negative exchange-rate coefficient suggests that currency movements affect export competitiveness through price channels. For imports, the GDP coefficient indicates that a 1% increase in GDP per capita is associated with an estimated 0.87% increase in import value. These baseline elasticities show that the statistically significant variables also have meaningful economic importance.

3.3 Fixed-effects results

Table 7 Fixed-effects export regression results (dependent variable: log_EVWBP)

Variable	Coefficient	p-value	Interpretation
log_P	0.1178	0.437	Not significant
log_GDP	1.3804*	0.050	Positive and marginally significant
log_FC	19.9522***	0.001	Positive and highly significant
log_EXR	-0.1539*	0.048	Negative and significant
log_TP	0.4096*	0.018	Positive and significant
Constant	-75.4040***	0.000	Significant

Number of observations = 212; number of countries = 15; within R-squared = 0.2398. Significance: * p<=0.05, ** p<0.01, *** p<0.001.

Table 8 Fixed-effects import regression results (dependent variable: log_IVWBP)

Variable	Coefficient	p-value	Interpretation
log_P	-0.0787	0.473	Not significant
log_GDP	2.4777***	0.000	Positive and highly significant
log_FC	4.2805	0.302	Not significant
log_EXR	-0.0401	0.393	Not significant
log_TP	0.1371	0.247	Not significant
Constant	-52.5600***	0.000	Significant

Number of observations = 238; number of countries = 15; within R-squared = 0.2570. Significance: * p<=0.05, ** p<0.01, *** p<0.001.

After controlling for country-specific time-invariant heterogeneity, forest coverage remains a strong positive determinant of exports, while exchange rate remains negative and significant. GDP is marginally significant in the export model, suggesting that within-country changes in economic capacity may support exports but that much of the GDP-export relationship is also captured by persistent country characteristics. The relatively large fixed-effects coefficient for forest coverage should be interpreted cautiously because forest coverage changes slowly over time; in a fixed-effects model, limited within-country variation can magnify coefficient size. Therefore, the coefficient indicates the direction and importance of forest-resource availability, but it should not be interpreted as a simple short-run causal elasticity. In the import model, GDP is the only robust significant determinant, indicating that import demand is mainly income-driven once country-specific factors are controlled.

3.4 Random-effects results

Table 9 Random-effects export regression results (dependent variable: log_EVWBP)

Variable	Coefficient	Std. err.	z	p-value	95% confidence interval
log_P	0.0538	0.1510	0.36	0.722	-0.2421 to 0.3496
log_GDP	1.8642***	0.3550	5.25	0.000	1.1685 to 2.5599
log_FC	2.0112***	0.5733	3.51	0.000	0.8875 to 3.1348
log_EXR	-0.1194	0.0736	-1.62	0.105	-0.2636 to 0.0249
log_TP	0.3439*	0.1710	2.01	0.044	0.0088 to 0.6790
Constant	-36.4676***	8.4534	-4.31	0.000	-53.0360 to -19.8992

Number of observations = 212; number of countries = 15; Wald chi2(5) = 62.24; Prob > chi2 = 0.0000; within R-squared = 0.2022; between R-squared = 0.6309; overall R-squared = 0.5597; rho = 0.7221. Significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 10 Random-effects import regression results (dependent variable: log_IVWBP)

Variable	Coefficient	Std. err.	z	p-value	95% confidence interval
log_P	-0.1822	0.1067	-1.71	0.088	-0.3913 to 0.0269
log_GDP	1.2634***	0.1797	7.03	0.000	0.9112 to 1.6157
log_FC	-0.1245	0.2390	-0.52	0.602	-0.5929 to 0.3439
log_EXR	-0.0694	0.0433	-1.60	0.109	-0.1544 to 0.0155
log_TP	-0.1284	0.1132	-1.13	0.257	-0.3502 to 0.0935
Constant	-9.2296*	4.0548	-2.28	0.023	-17.1769 to -1.2823

Number of observations = 230; number of countries = 15; Wald chi2(5) = 54.92; Prob > chi2 = 0.0000; within R-squared = 0.2108; between R-squared = 0.5900; overall R-squared = 0.3790; rho = 0.4212. Significance: * p<0.05, ** p<0.01, *** p<0.001.

The random-effects results are broadly consistent with the pooled OLS export model for GDP and forest coverage. GDP and forest coverage remain positive and highly significant for exports, while trade policy is positive and significant. In the import model, GDP remains positive and highly significant, but other variables are not statistically significant. The difference between fixed- and random-effects estimates suggests that unobserved country characteristics are important and should not be ignored; this is later confirmed by the Hausman tests.

3.5 Model selection and overall significance

Table 11 Hausman specification test results

Model	Chi-square	p-value	Decision
Export model	63.05	0.0000	Reject random-effects consistency; fixed effects preferred
Import model	11.58	0.0410	Reject random-effects consistency; fixed effects preferred

The null hypothesis is that the difference in coefficients is not systematic. Because both p-values are below 0.05, fixed-effects estimation is preferred for both export and import equations.

Table 12 Overall model significance tests

Model	F-statistic	Prob > F	R-squared	Decision
Export full model	70.33	0.0000	0.6306	Overall model is statistically significant
Import full model	29.22	0.0000	0.3948	Overall model is statistically significant

The F-tests confirm that the explanatory variables jointly improve model fit. R-squared values should be interpreted as explanatory power rather than causal completeness.

The Hausman tests favor fixed effects for both export and import models. This means that unobserved country-specific factors are systematically correlated with the regressors, making the fixed-effects estimator more appropriate than the random-effects estimator. The significant F-tests confirm that the full models are statistically meaningful. However, the lower within R-squared values in fixed-effects models indicate that some time-varying determinants of trade are not captured in the current specification. These may include logistics costs, institutional quality, production technology, trade agreements, geopolitical shocks, energy costs, sanctions, and changes in global demand. Therefore, the results should be interpreted as robust associations within the available specification, not as complete causal explanations.

3.6 Robustness interpretation

The robustness assessment compares the pooled OLS, fixed-effects, and random-effects specifications. For exports, the pooled OLS model explains 63.06% of the variation in log export value, while the random-effects model explains 55.97%; both are jointly significant. For imports, the pooled OLS and random-effects models explain 39.48% and 37.90% of the variation, respectively. The fixed-effects within R-squared values are lower, 0.2398 for exports and 0.2570 for imports, which is expected because the fixed-effects estimator uses only within-country variation after controlling for time-invariant country characteristics. The Hausman tests support fixed effects for both export and import equations, confirming that unobserved country-specific factors are correlated with the regressors and should be controlled.

Across specifications, GDP remains the most reliable import determinant, with positive and highly significant coefficients in pooled OLS, fixed-effects, and random-effects models. On the export side, GDP and forest coverage remain positive in the main specifications, indicating that economic capacity and resource availability are central to export performance. Exchange rate is negative in the pooled OLS and fixed-effects export models, while trade policy changes sign across specifications; therefore, the trade-policy coefficient should be interpreted as context-dependent rather than as a uniform causal effect.

4. Discussion

4.1 Export determinants

The export results show that WBP export performance is mainly determined by economic scale, forest-resource availability, and exchange-rate conditions. GDP is positive and significant in the pooled OLS and random-effects models and marginally significant in the fixed-effects model. This implies that economically stronger countries are better positioned to produce and export WBPs because they can support industrial investment, processing capacity, transport infrastructure, and export-oriented firms. This finding is consistent with Buongiorno (2016) and Morland et al. (2018), who emphasize the role of income, market scale, and competitiveness in forest-product trade. The slightly weaker GDP effect under fixed effects suggests that part of the GDP-export relationship reflects persistent national characteristics rather than only year-to-year changes.

Forest coverage is the most consistent export-side resource variable. Its positive and significant coefficient across export models indicates that countries with larger forest endowments have stronger raw-material availability and therefore greater potential for WBP production and export. This finding agrees with studies showing that forest-resource supply supports forest-product competitiveness (Saraswati et al., 2023; Coelho Junior et al., 2023) and with panel evidence that forest endowment is a significant determinant of net forest-product trade (Uusivuori, 2002). However, forest coverage alone is not sufficient. Resource-rich countries can convert forests into export value only when harvesting, processing, logistics, certification, and sustainability standards are effectively managed. This is why country-specific effects are important in the present study.

Exchange rate has a significant negative coefficient in the pooled OLS and fixed-effects export models. This suggests that exchange-rate movements affect export competitiveness through price channels. Depending on the definition of the exchange-rate variable, a negative coefficient may indicate that currency appreciation reduces export competitiveness or that depreciation improves foreign-market affordability. This result is consistent with Wang et al. (2017), who reported that exchange-rate fluctuations influence pricing behavior among wood-based panel exporters. The finding also implies that exporters in the region are sensitive to macroeconomic instability and currency volatility.

Trade policy shows mixed signs across models, which indicates that its effect is context-dependent. In the pooled model, the coefficient is negative, while in the fixed- and random-effects export models it is positive. This difference may reflect the broad nature of the trade-policy proxy. Trade policy can include both restrictive elements, such as tariffs and non-tariff barriers, and facilitative elements, such as preferential agreements, customs simplification, export promotion, or regulatory harmonization. Therefore, the results should be interpreted cautiously and should motivate future research using more disaggregated policy indicators.

4.2 Import determinants

GDP is the most robust determinant of WBP imports. It is positive and highly significant in pooled OLS, fixed-effects, and random-effects models. This indicates that as countries become economically stronger, their demand for imported panels increases. Higher GDP can stimulate construction, housing, furniture production, renovation activities, and downstream manufacturing, all of which increase demand for WBPs. Unlike exports, imports are less dependent on domestic forest-resource availability because they are driven primarily by purchasing power and domestic demand. This result is consistent with demand-side interpretations in forest-products trade models (Morland et al., 2018; Nepal et al., 2021) and with panel-data evidence that import demand for forest products, including wood-based panels, is elastic with respect to income (Turner & Buongiorno, 2004).

Trade policy is negative and significant only in the pooled OLS import model. This suggests that restrictive trade policies may reduce import values when cross-country differences are not fully controlled. However, the coefficient becomes insignificant in fixed- and random-effects models, indicating that policy effects may be absorbed by country-specific characteristics or may not vary enough over time to be strongly identified within countries. This result also highlights the limitation of using a broad trade-policy proxy rather than precise measures such as tariff rates, non-tariff measures, customs delays, trade-agreement participation, or regulatory quality.

Forest coverage, exchange rate, and population do not show robust statistical significance in the import equations. The insignificant forest-coverage coefficient may indicate that domestic forest resources do not directly determine import demand once GDP and country effects are controlled. Some forest-rich countries may still import specialized panels due to quality, design, or industrial requirements, while forest-poor countries may rely on substitutes or domestic processing based on imported raw materials. Population is also insignificant, suggesting that import demand is more strongly related to income and industrial activity than to demographic size alone.

4.3 Model limitations and robustness

The Hausman tests clearly support fixed effects, confirming that unobserved country-specific characteristics matter. Nevertheless, the modest within R-squared values show that the models do not capture all time-varying drivers of WBP trade. Important omitted factors may include infrastructure quality, transport costs, energy prices, domestic production capacity, firm-level competitiveness, institutional quality, sanctions, regional conflicts, global price shocks, and changes in environmental standards. Diagnostic tests for multicollinearity, heteroskedasticity, and serial correlation should therefore be reported with the final estimation output, and robust or cluster-robust standard errors should be used when required.

Another limitation concerns the trade-policy variable. Because trade policy is multidimensional, a single proxy may not fully capture tariffs, quotas, non-tariff barriers, customs procedures, export incentives, trade agreements, and regulatory quality. Future studies should use disaggregated policy measures and product-level trade data. In addition, the period 2005-2020 includes major economic and geopolitical changes; future research could use dynamic panel models, structural-break tests, or interaction terms to examine whether determinants differ before and after major regional shocks. Robustness checks using alternative policy indicators, lagged explanatory variables, or exclusion of influential countries such as the Russian Federation would further strengthen the reliability of the results.

5. Conclusion and policy implications

This study examined the determinants of wood-based panel export and import values in 15 Eastern European and Central Asian countries from 2005 to 2020. The main contribution of the study is its focused treatment of WBPs as a distinct forest-product category and its comparison of export and import determinants using panel-data models that account for country-specific heterogeneity. The first objective was to evaluate economic factors. The results show that GDP is a key determinant of both exports and imports, while exchange rate significantly affects export performance in the pooled and fixed-effects models. The second objective was to assess trade policy. Trade policy has a significant association with exports and imports in some specifications, but its sign and significance vary across models, indicating that policy effects are complex and context-specific. The third objective was to examine resource and demographic factors. Forest coverage strongly supports exports, whereas population is not a robust determinant of either exports or imports.

The Hausman tests support the use of fixed-effects models for both export and import equations. This confirms that country-specific unobserved heterogeneity is important and that ignoring it may lead to biased results. Overall, exports are shaped by economic capacity, forest-resource availability, and exchange-rate competitiveness, while imports are mainly driven by GDP and domestic demand conditions. These conclusions are directly based on the empirical findings and should be interpreted within the limitations of the available variables and time period.

5.1 Policy implications

First, sustainable forest management should be treated as a trade-development strategy. Since forest coverage positively affects exports, governments should strengthen reforestation, responsible harvesting, certification systems, legality verification, and forest monitoring. These actions can improve raw-material security while maintaining environmental sustainability and access to environmentally sensitive export markets.

Second, macroeconomic stability is important for export competitiveness. The significant exchange-rate effect shows that currency volatility can influence WBP export performance. Policymakers should support stable macroeconomic conditions, reduce transaction costs for exporters, improve access to trade finance, and provide information services that help firms manage exchange-rate risk.

Third, trade policies should be simplified and targeted. Customs procedures, excessive tariffs, non-tariff barriers, and regulatory uncertainty can reduce trade efficiency. Governments should improve trade facilitation, harmonize standards, negotiate market-access arrangements, and distinguish between policies that restrict inefficient trade and policies that support sustainable export growth.

Fourth, countries should strengthen domestic processing capacity. GDP-driven import demand suggests that economic growth increases demand for WBPs. Investments in domestic manufacturing, technology upgrading, energy efficiency, quality certification, and workforce development can reduce excessive import dependence while improving export potential. Industry stakeholders should also focus on higher-value panels, improved design standards, and reliable supply-chain management.

Future research should use more disaggregated product-level data, dynamic panel models, and detailed trade-policy indicators. Incorporating variables such as logistics performance, institutional quality, energy costs, sanctions, trade agreements, industrial capacity, exchange-rate volatility, and global price indices could improve explanatory power. Firm-level or regional-level data would also help identify how microeconomic competitiveness translates into national trade performance. Additional robustness checks, including alternative time periods, exclusion of dominant exporters, and lagged-variable specifications, are recommended to test the stability of the findings.

Author Contributions

Conceptualization, S.A.H.; methodology, S.A.H.; software, S.A.H. and S.M.K.M.; validation, S.M.K.M., and A.R.B.; formal analysis, S.A.H.; investigation, S.A.H. and A.R.B.; resources, S.A.H. and S.M.K.M.; data curation, S.M.K.M., A.R.B., and S.A.H.; writing—original draft preparation, S.A.H.; writing—review and editing, S.M.K.M., A.R.B., and S.A.H.; visualization, A.R.B. and A.R.; supervision, S.A.H.; project administration, S.A.H. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare no conflict of interest.

Artificial Intelligence (AI) Use Statement

The authors declare that no artificial intelligence tools were used in the research, analysis, writing, or preparation of this manuscript.

REFERENCES

Baltagi, B. H. (2005). Econometric analysis of panel data (3rd ed.). John Wiley & Sons.

Buongiorno, J. (2016). Gravity models of forest products trade: Applications to forecasting and policy analysis. Forestry, 89(2), 117-126.

Coelho Junior, L. M., Santos, H. F., Soares, N. S., Martins, J. M., & Silva, M. L. (2023). International competitiveness of exports of forest products. Ciência Rural, 53, e20220137.

Dukarska, D. (2023). Wood-based materials in building. Materials, 16(8), 2987. https://doi.org/10.3390/ma16082987

Gonçalves, F. D., Carvalho, L. H., Rodrigues, J. A., & Ramos, R. M. (2025). Wood-based panels and volatile organic compounds (VOCs): An overview on production, emission sources and analysis. Molecules, 30(15), 1-30. https://doi.org/10.3390/molecules30153195

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica, 46(6), 1251-1271.

Ivanov, et al. (2023). Wood-based panel production and export trends in Russia. Gravity models of forest products trade: Applications to forecasting and policy analysis. Forestry, 89(2), 117-126.

Morland, C., Schier, F., Janzen, N., & Weimar, H. (2018). Supply and demand functions for global wood markets: Specification and plausibility testing of econometric models within the global forest sector. Forest Policy and Economics, 92, 92-105.

Nepal, P., Johnston, C. M., & Ganguly, I. (2021). Effects on global forests and wood product markets of increased demand for mass timber. Sustainability, 13(24), 13943.

Saraswati, R. I., Harianto, H., & Rifin, A. (2023). Factors affecting forest product exports. Jurnal Manajemen & Agribisnis, 20(1), 22.

Sauvage, J. (2014). The stringency of environmental regulations and trade in environmental goods (OECD Trade and Environment Working Papers No. 2014/03). OECD Publishing. https://doi.org/10.1787/5jxrjn7xsnmq-en

Simangunsong, B. C. H., & Buongiorno, J. (2001). International demand equations for forest products: A comparison of methods. Scandinavian Journal of Forest Research, 16(2), 155-172.

Sujová, A., et al. (2016). International trade in wood products and its determinants. [Incomplete reference — please supply the full author list, publication outlet (journal/publisher), volume/issue, and page numbers.]

Turner, J. A., & Buongiorno, J. (2004). Estimating price and income elasticities of demand for imports of forest products from panel data. Scandinavian Journal of Forest Research, 19(4), 358-373.

Uusivuori, J. (2002). Comparative advantage and forest endowment in forest products trade: Evidence from panel data of OECD-countries. Journal of Forest Economics, 8(1), 53-75.

Wang, F., Yin, Z., & Gan, J. (2017). Exchange-rate fluctuation and pricing behavior in China's wood-based panel exporters: Evidence from panel data. Canadian Journal of Forest Research, 47(10), 1392-1404.

Zhang, et al. (2022). Production and trade development of wood-based panels. (2017). Canadian Journal of Forest Research, 47(10), 1392-1404.

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A field-based assessment of maize leaf diseases in four districts of Kandahar Province, Afghanistan

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A B S T R A C T

Maize (*Zea mays* L.) is the second most important crop in Afghanistan's cereal production system, enhancing food security, animal production, and the sustainability of rural livelihoods. Maize productivity in Afghanistan is low due to various biotic stresses, including leaf diseases. The dataset report of the detection of maize leaf diseases was conducted during the 2025 growing season of maize in the top maize-producing districts of Kandahar province, Afghanistan. Under natural growing conditions, high-quality images of maize leaves were taken, including geo-referenced information about the occurrence of maize leaf diseases in the fields. A total of 1,027 images of maize leaves were taken, classified into three different classes: healthy leaves, leaf spot-infected leaves, and leaf blight-infected leaves. Leaf blight and leaf spot diseases were detected in maize fields throughout the selected districts of Kandahar Province, Afghanistan. Leaf blight and leaf spot diseases were more frequently observed in maize fields with high plant density and poor crop management practices. The dataset can serve as a valuable resource for plant disease detection, agricultural research, and the development of machine learning and deep learning models for maize disease identification. Foliar diseases of maize, including leaf blight and leaf spot, are one of the major constraints of maize cultivation in the province. This study provides a geo-referenced maize leaf disease dataset that can support disease monitoring, early detection, spatial analysis of disease occurrence, and the development of machine learning-based decision-support tools for integrated disease management in Afghanistan.

Keywords: maize, leaf diseases, field-based assessment, Kandahar province

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1. INTRODUCTION

Agriculture serves as a critical pillar of global food security, employment generation, and economic development. Nevertheless, accelerating population growth and increasing food demand have intensified the need for sustainable agricultural intensification to ensure long-term productivity and resource conservation (Eli-Chukwu, 2019; S. Sharma et al., 2023). With numerous uses in food, feed, and as an industrial raw material, maize is among the most significant staple crops in the world (Entuni & Zulcaffle, 2022; Idress et al., 2024; Mohanty et al., 2023). Plant illnesses and pest infestations are significant obstacles to agricultural productivity, frequently resulting in reduced yields and substantial economic losses (Barman et al., 2024; Krishna et al., 2025; Upadhyay et al., 2025).

In Afghanistan, maize is the most important cereal crop after wheat (Elham et al., 2020; Habibi et al., 2025; R. Sharma et al., 2018). Aside from human consumption, the crop plays an important role in the production of feed for poultry, biofuel, animal feed, and other uses (Elham et al., 2023). In this country, maize is cultivated for both grain and fodder purposes, playing an important role in human nutrition as well as livestock and poultry feeding. The total area under maize cultivation is approximately 92,144 hectares, yielding about 180,000 tons of grain annually. However, the national average yield remains relatively low at around 1.95 t ha^{-1}, highlighting the need for improved production practices and effective crop management strategies (Ahmadi et al., 2024), and multiple factors, including low access to improved varieties, poor-quality seeds, low-fertility soil, and inadequate use of fertilizers, limit maize yields in this country. In addition, maize productivity is adversely affected by suboptimal agronomic practices, water scarcity, traditional irrigation methods, and biotic stresses, including diseases, insect pests, and weeds (Mozafari et al., 2020).

The cultivation of maize in Kandahar province is extensive, covering several districts due to the short growth period, water stress resistance, and the crop's multifunctional uses. The cultivation of maize contributes to the livelihood of the people, as the yield increases the availability of food and income for the smallholder farmers. However, the yield of maize in Kandahar is much lower compared to the global standard, mainly due to the limited access to improved technology, improper management, and the effects of crop diseases, pests, and weeds (Mozafari et al., 2020). Among the biotic factors affecting the yield of the crop, leaf disease is considered the most devastating. Among the major biotic constraints affecting maize production, foliar diseases such as leaf blight and leaf spot are particularly important. Maydis leaf blight is recognized as one of the most destructive foliar diseases of maize worldwide and, under favorable environmental conditions, may cause grain yield losses exceeding 40% (Kumar et al., 2022).

Despite the importance of maize production in Kandahar Province, Afghanistan, there is limited field-based information on the occurrence and distribution of maize leaf diseases under natural growing conditions. Most previous studies have relied on experimental datasets or generalized regional information, which may not accurately reflect disease occurrence under actual field conditions. High-resolution field image assessments provide valuable opportunities for documenting disease symptoms and their spatial distribution, thereby supporting disease surveillance and management. Therefore, this study aimed to assess the prevalence and distribution of maize leaf diseases across four major maize-growing districts of Kandahar Province and to provide baseline data for future disease monitoring and management programs.

2. MATERIALS AND METHODS

2.1 STUDY AREA

Study was conducted through four selected districts of southern Afghanistan's Kandahar province during the 2025 maize-growing season. The area which appears in Figure 1 as a separate zone between Uruzgan to the north, Zabul to the east, and Helmand to the west. The territory, which extends over 54000 square kilometers, contains extensive areas of dry terrain. The region experiences high temperature conditions throughout most of the year because precipitation occurs infrequently and humidity dissipates quickly under intense sunlight. The agricultural system depends predominantly on controlled irrigation systems because natural rainfall occurs only during brief moments when rain falls from the clouds. The primary agricultural product of this region consists of maize, which farmers cultivate through controlled irrigation systems that supply their fields with water. The region depends on agriculture as its main economic activity, which requires water resources from the Arghandab River and the flow management systems of the Dahla Dam. The primary agricultural products for the region include wheat and maize, together with assorted fruits and multiple vegetable types. The crop faces multiple threats, which originate from biological organisms and environmental factors that include drought conditions and diminished soil quality, and the emergence of foliar diseases, which cause leaf blight and leaf spot. The study was conducted in four districts of Kandahar Province (Dand, Panjwayi, Arghandab, and Zhari), which were selected for the field assessment of maize leaf diseases.

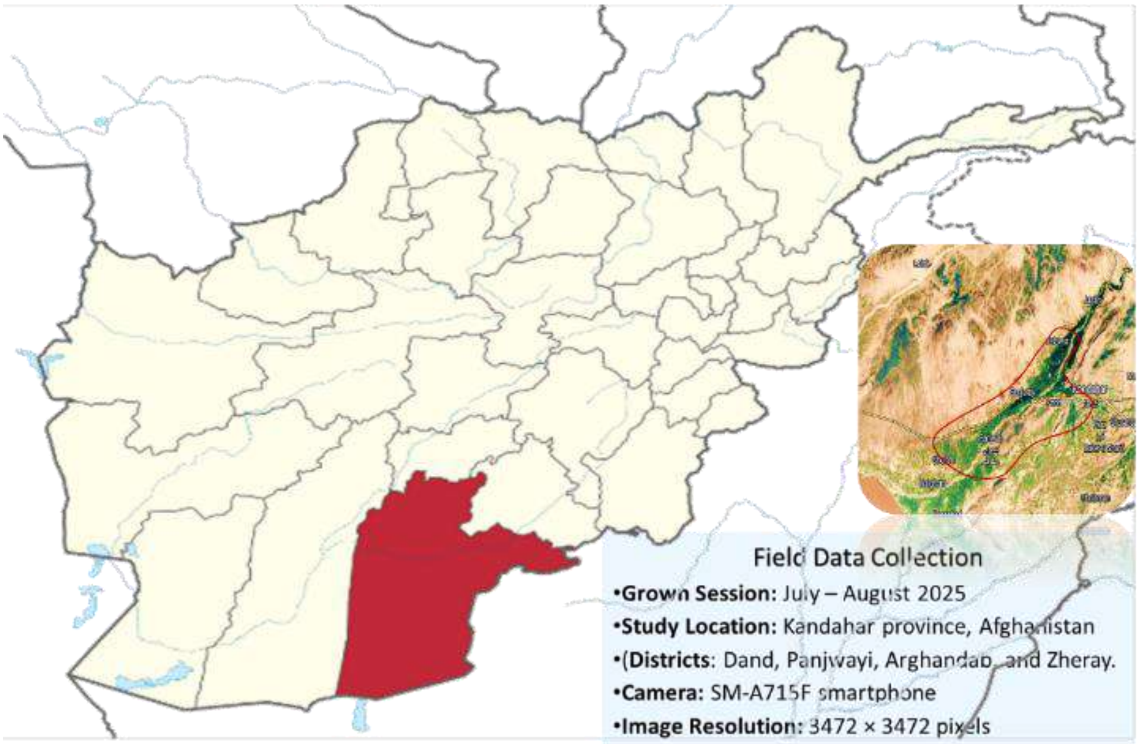

Figure 1. Study area map of Kandahar province, Afghanistan.

2.2 Field-Based Data Collection

Field observations were conducted during the 2025 maize growing season to document the occurrence of maize leaf diseases under natural farming conditions in Kandahar Province, Afghanistan. Maize fields were selected from four major maize-producing districts, and field visits were carried out during critical crop growth stages to identify and record disease symptoms. Visual assessments were performed to identify symptomatic and healthy maize leaves, and representative samples were documented through high-resolution digital imaging under natural field conditions. Only actively growing maize plants were considered to ensure an accurate representation of disease occurrence in fields. All images were captured in situ and stored in JPEG format with corresponding geographic coordinates (GPS) to accurately record sampling locations. Data collection was conducted in four major maize-producing districts of Kandahar Province: Dand (31.570559°N, 65.686175°E), Panjwayi (31.5104304°N, 65.4143471°E), Arghandab (31.659291°N, 65.642287°E), and Zhari (31.625849°N, 65.543815°E). These districts represent diverse agricultural environments and management practices, providing variability in agro-climatic conditions and disease occurrence.

The dataset comprises three statuses of maize leaves: healthy leaves, leaf spot-infected leaves, and leaf blight-infected leaves. All images were acquired using a Samsung SM-A715F smartphone equipped with a 12-megapixel camera, producing images with a resolution of 3472 × 3472 pixels. Image acquisition was performed during July and August 2025, when disease symptoms were clearly visible and distinguishable. Image acquisition was performed during both morning and afternoon periods under different natural lighting and field conditions to ensure a diverse and representative dataset. The resulting geo-referenced image dataset was organized and made publicly available through the Mendeley Data repository (Rafi, 2026), providing a valuable resource for maize disease detection, computer vision research, and the development of artificial intelligence-based decision-support systems for crop health monitoring.

Figure 2. Representative field images of maize cultivation in Kandahar province, Afghanistan

2.3 Disease Identification and Assessment

Maize leaf diseases were identified through visual assessment of characteristic disease symptoms, including lesion shape, color, size, and distribution patterns on leaf surfaces. Based on symptom characteristics, two major disease categories were recorded: leaf blight and leaf spot. Disease incidence was determined by counting infected plants in each field, whereas disease severity was assessed based on infected leaf area. Field assessments were conducted across all study sites to ensure consistency and enable comparisons among districts.

2.4 Data Analysis

Collected field data were organized and summarized to identify which maize leaf diseases existed in the study areas, how common they were, and where they occurred. The researchers used descriptive statistical methods to study how diseases spread and progressed in different districts. The researchers used tables and figures to display their results, which showed how disease pressure and distribution patterns changed. The study used observational field research to examine general patterns and differences between locations instead of testing specific treatment methods.

3. RESULTS

The field survey conducted across multiple villages within the four districts of Kandahar Province revealed a high prevalence of maize leaf diseases during the 2025 growing season. The observed maize fields showed two main leaf diseases, which included leaf blight and leaf spot, according to field studies and image documentation. Healthy maize leaves were present in all locations, but their distribution showed significant differences across different areas. The research team used GPS coordinates to create precise collection site maps for each image. A total of 1,027 maize field images were acquired from four districts of Kandahar Province (Dand, Panjwayi, Arghandab, and Zhari), including adjacent urban villages, to establish an initial dataset for maize leaf disease detection.

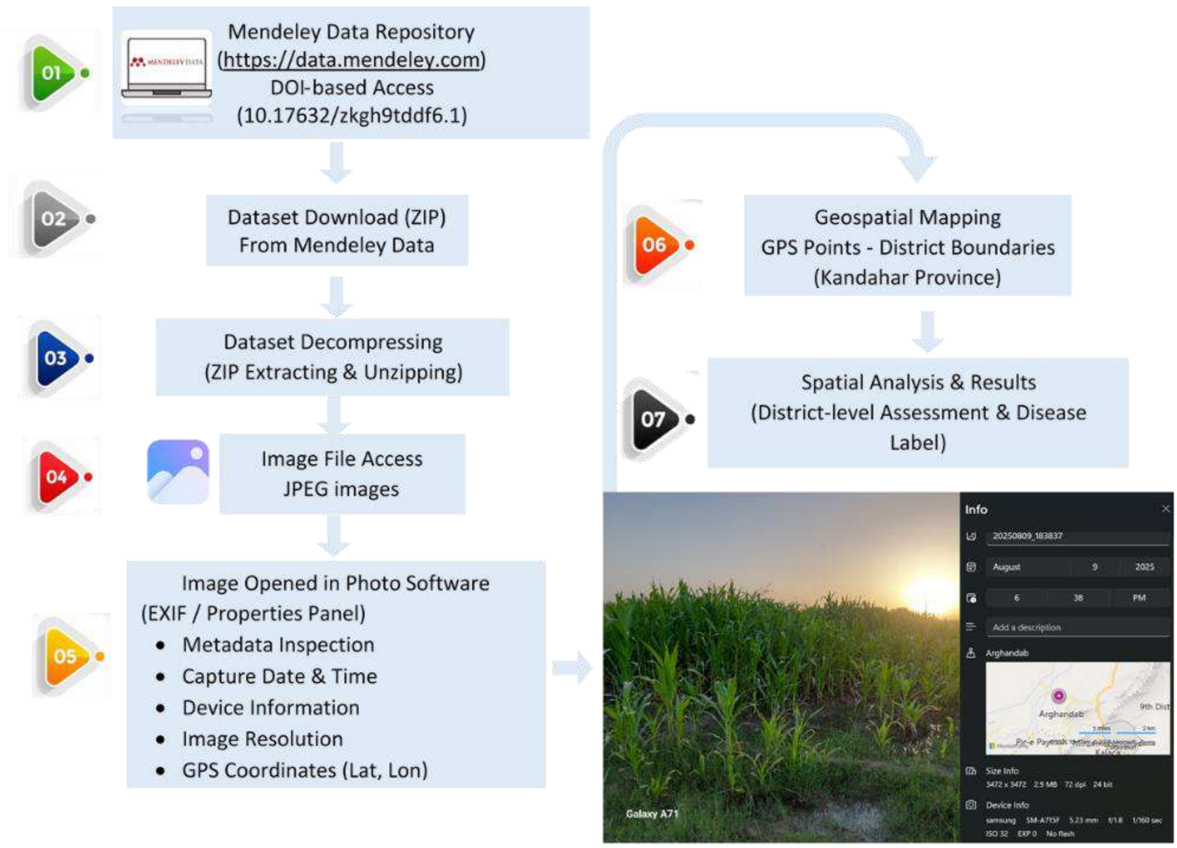

Figure 3. Workflow for accessing the maize leaf disease dataset from Mendeley Data, extracting image metadata, and identifying GPS-based district locations in Kandahar province, Afghanistan.

The workflow shown in Figure 3 shows how users access the maize leaf disease image dataset, which exists in Mendeley Data. The process starts with downloading the dataset, which users need to decompress. Users can open single images through their photo software to check the EXIF metadata that exists in each image. The researchers extracted key image attributes, which included capture date, device information, and GPS coordinates, to identify the corresponding districts within Kandahar Province for geospatial analysis. Table 1 summarizes the number of images collected per district, city, and village, along with GPS coordinates (latitude and longitude) for each collection site

Table 1 Number of collected images from districts and city villages of Kandahar province with their classification status (spot, blight, and healthy)

Province	District	Total images	Status
Kandahar	Dand	185	Spot, Blight, and healthy
	Panjwayi	216	Spot, Blight, and healthy
	Arghandab	286	Spot, Blight, and healthy
	Zhari	151	Spot, Blight, and healthy
	Villages of the City	189	Spot, Blight, and healthy

The complete dataset has three distinct status categories, which include healthy leaves, leaves infected with leaf spot disease, and leaves infected with leaf blight, as shown in Figure 4. The distribution of both leaf spot and leaf blight diseases extended through all areas where maize was cultivated, which demonstrated that these diseases have become established permanent problems within the region. The agricultural diseases that farmers experienced throughout the growing season showed different symptoms at various plant development stages. The spatial analysis of disease spread patterns revealed that different villages and fields experienced different rates of disease transmission. Areas with dense plant populations and insufficient crop management practices experienced higher disease intensity in maize fields. Disease symptoms were observed in maize fields across the study sites; however, further efforts are required to improve knowledge of disease identification, causes, and management practices. The restricted knowledge of farmers about leaf disease identification and control methods resulted in widespread leaf disease distribution throughout the study area.

a b c

Figure 4. Representative maize leaf images illustrating three classes used in the results: **(a)** blight-infected leaf, **(b)** spot-infected leaf, and **(c)** healthy (normal) leaf.

4. Discussion

The research findings show that the combination of maize leaf blight and leaf spot diseases functions as the most common foliar disease that affects maize cultivation throughout the Kandahar Province study area. The diseases that spread naturally throughout field environments serve as primary biotic factors that limit maize farming in the area. The research results from southwestern Ethiopia show that leaf blight and leaf spot diseases serve as major yield-limiting factors because these diseases reduce photosynthetic capacity and grain yield (Abera et al., 2025). The restricted availability of agricultural extension services throughout Kandahar Province creates additional obstacles for farmers who need to develop effective disease control procedures.

The combination of environmental factors, variety resistance, farming practice decisions, crop management methods, and irrigation systems determines the level of disease outbreaks in agricultural fields. The findings of this study revealed that fields with limited crop management practices, inadequate crop protection measures, and the absence of disease control strategies exhibited higher disease incidence. (Nsibo et al., 2024) reported similar findings about maize foliar fungal pathogens, which persist in sub-Saharan Africa due to poor disease management practices and faulty farming methods that lead to leaf blight and leaf spot disease outbreaks. This study demonstrates that insufficient disease control methods increase disease outbreaks that occur in agricultural fields. Agricultural drought has emerged as the primary danger that affects rain-fed maize systems because its effects differ between various growth periods and different geographic areas. A dynamic drought risk assessment study conducted in Jilin Province, China, demonstrated that drought risk changes significantly during maize development stages and is strongly influenced by climatic variability and regional characteristics (Zhang et al., 2019).

The present study, supported by previous research, emphasizes the importance of considering growth stages and geographic variability for improving drought resilience and drought management in maize. The study found that farmers had minimal understanding of maize leaf diseases, which represents a critical finding. The farmers detected abnormal leaf symptoms, but they could not identify specific disease types or predict how these diseases would affect their crop production. The agricultural systems of developing countries show knowledge deficiencies that require extension programs that can teach farmers about disease identification and prevention, and integrated management methods. The exclusion of maize rust from the dataset demonstrates that the agro-climatic conditions of Kandahar Province, which include high temperatures, low rainfall, and low relative humidity, match the area's natural environment. The environmental conditions create a situation that prevents rust development, thus demonstrating the need for actual field studies to determine disease presence. Proposed study results demonstrate that field-based image data collections or datasets provide accurate disease information, which helps farmers make scientifically supported agricultural choices.

This study provides valuable insights into the occurrence of maize leaf diseases in Kandahar Province; however, several limitations should be acknowledged. First, data collection was conducted during a single growing season (2025), which limits the ability to evaluate temporal variations in disease occurrence across multiple years. Future studies incorporating multi-seasonal and multi-year datasets would provide a more comprehensive understanding of disease prevalence and distribution patterns. Second, disease identification was based primarily on visual symptom assessment under field conditions. Although this approach reflects practical field scouting procedures, it may introduce uncertainty when differentiating diseases with similar symptom characteristics. Future research should incorporate laboratory-based pathogen confirmation techniques, including microscopic examination and other diagnostic methods, to improve diagnostic accuracy. Third, the dataset was collected from selected maize-producing districts of Kandahar Province and may not fully represent the diversity of agro-ecological conditions across Afghanistan. Expanding data collection to additional regions with varying climatic conditions, cropping systems, and management practices would improve the representativeness and generalizability of the dataset.

Finally, while the dataset provides high-quality geo-referenced field images of maize leaf diseases, it does not include the development or validation of automated disease classification models. Future studies should utilize this dataset to develop and evaluate machine learning and deep learning approaches for disease detection, early warning systems, and decision-support tools for maize disease management. Continued research in this area will contribute to more effective disease monitoring and sustainable maize production in Afghanistan.

5. CONCLUSION

This study presents a geo-referenced field image dataset of maize leaf diseases collected from four major maize-producing districts of Kandahar Province, Afghanistan. Field observations confirmed the occurrence of two major foliar diseases, namely leaf blight and leaf spot, together with healthy maize leaves across the study area. The dataset was developed under natural field conditions and includes high-resolution images with corresponding geographic coordinates, providing valuable information on disease occurrence in maize-growing regions. The dataset contributes to addressing the limited availability of publicly accessible maize disease data from Afghanistan and supports future research in plant disease detection, computer vision, and artificial intelligence applications in agriculture. Furthermore, the geo-referenced nature of the dataset enables spatial analysis of disease occurrence and may support the development of decision-support tools for crop health monitoring and disease management. Overall, this dataset establishes a foundation for future studies aimed at improving maize disease surveillance, developing automated disease detection systems, and enhancing sustainable maize production in Afghanistan.

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Data Availability Statement

The data that support the findings of this study are openly accessible. The dataset created and examined throughout the current research is stored in the Mendeley Data archive and may be reached via the DOI: https://doi.org/10.17632/zkgh9tddf6.1.

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AI Statement

Artificial intelligence tools were used only for language improvement and grammatical editing.

REFERENCES

Abera, A., Mendesil, E., Temesgen, J., & Bayissa, W. (2025). Foliar disease-causing fungal isolates associated with maize: pathogen variability and species attributes in Southwestern Ethiopia. *Discover Agriculture*, *3*(1), 154. https://doi.org/10.1007/s44279-025-00275-8

Ahmadi, A., Nazir, R., Ebrahimi, H., & Khaleeq, K. (2024). Optimization of Phosphorus Application Rate on Maize Under Agro-ecological Condition of Urozgan. *Journal for Research in Applied Sciences and Biotechnology*, *3*(1), 264–267. https://doi.org/10.55544/jrasb.3.1.42

Barman, U., Sarma, P., Rahman, M., Deka, V., Lahkar, S., Sharma, V., & Saikia, M. J. (2024). ViT-SmartAgri: Vision Transformer and Smartphone-Based Plant Disease Detection for Smart Agriculture. *Agronomy*, *14*(2), 327. https://doi.org/10.3390/agronomy14020327

Elham, H., Ahmad, A., Saeedi, S. A. W., & Safari, Z. S. (2023). The Nature and Extent of Technical Efficiency of Maize Production for Smallholder Farmers in Conflict-Prone Areas. *AgroTech Food Science, Technology and Environment*, *2*(1), 1–14. https://doi.org/10.53797/agrotech.v2i1.1.2023

Elham, H., Zhou, J., Diallo, M. F., Ahmad, S., & Zhou, D. (2020). Economic Analysis of Smallholder Maize Producers: Empirical Evidence From Helmand, Afghanistan. *Journal of Agricultural Science*, *12*(3), 153. https://doi.org/10.5539/jas.v12n3p153

Eli-Chukwu, N. C. (2019). Applications of Artificial Intelligence in Agriculture: A Review. *Engineering, Technology & Applied Science Research*, *9*(4), 4377–4383. https://doi.org/10.48084/etasr.2756

Entuni, C. J., & Zulcaffle, T. M. A. (2022). Identification of Corn Leaf Diseases Comprising of Blight, Grey Spot and Rust Using DenseNet-201. *Borneo Journal of Resource Science and Technology*, *12*(1), 125–134. https://doi.org/10.33736/bjrst.4224.2022

Habibi, N., Sharaf, Z., Fakoor, M. Y., Aryan, S., Mahmoodzada, A. B., Fakhri, A., & Faqiri, S. M. (2025). Nitrogen Matters: Assessing the Effects of Nitrogen Fertilization on Maize Growth and Grain Productivity. *Nitrogen*, *6*(4), 115. https://doi.org/10.3390/nitrogen6040115

Idress, K. A. D., Gadalla, O. A. A., Öztekin, Y. B., & Baitu, G. P. (2024). Machine Learning-based for Automatic Detection of Corn-Plant Diseases Using Image Processing. *Tarım Bilimleri Dergisi*, *30*(3), 464–476. https://doi.org/10.15832/ankutbd.1288298

Krishna, M. S., Machado, P., Otuka, R. I., Yahaya, S. W., Neves dos Santos, F., & Ihianle, I. K. (2025). Plant Leaf Disease Detection Using Deep Learning: A Multi-Dataset Approach. *J*, *8*(1), 4. https://doi.org/10.3390/j8010004

Kumar, B., Choudhary, M., Kumar, K., Kumar, P., Kumar, S., Bagaria, P. K., Sharma, M., Lahkar, C., Singh, B. K., Pradhan, H., Jha, A. K., Kumar, S., & Rakshit, S. (2022). Maydis leaf blight of maize: Update on status, sustainable management and genetic architecture of its resistance. *Physiological and Molecular Plant Pathology*, *121*, 101889. https://doi.org/10.1016/J.PMPP.2022.101889

Mohanty, S. N., Ghosh, H., Rahat, I. S., & Reddy, C. V. R. (2023). Advanced Deep Learning Models for Corn Leaf Disease Classification: A Field Study in Bangladesh. *RAiSE-2023*, *59*(1), 69. https://doi.org/10.3390/engproc2023059069

MOZAFARI, S. H., DASS, A., CHOUDHARY, A. K., RAIHAN, O., & RAJANNA, G. A. (2020). Effect of moisture conservation and integrated nutrient management on summer maize (Zea mays) in Kandahar, Afghanistan. *The Indian Journal of Agricultural Sciences*, *90*(1), 236–239. https://doi.org/10.56093/ijas.v90i1.98693

Nsibo, D. L., Barnes, I., & Berger, D. K. (2024). Recent advances in the population biology and management of maize foliar fungal pathogens Exserohilum turcicum, Cercospora zeina and Bipolaris maydis in Africa. *Frontiers in Plant Science*, *15*. https://doi.org/10.3389/fpls.2024.1404483

Rafi, Rafiullah (2026), "Maize Leaf Disease Image Dataset from Kandahar Province, Afghanistan (2025) ", *Mendeley Data*, V1, doi: 10.17632/zkgh9tddf6.1

Sharma, R., Soofizada, Q., Azmatyar, M. H., & Mohmand, E. (2018). Three New Maize Hybrids for Afghanistan. *Journal of Agricultural Science*, *10*(6), 349. https://doi.org/10.5539/jas.v10n6p349

Sharma, S., Verma, K., & Hardaha, P. (2023). Implementation of Artificial Intelligence in Agriculture. *Journal of Computational and Cognitive Engineering*, *2*(2), 155–162. https://doi.org/10.47852/bonviewJCCE2202174

Upadhyay, A., Chandel, N. S., Singh, K. P., Chakraborty, S. K., Nandede, B. M., Kumar, M., Subeesh, A., Upendar, K., Salem, A., & Elbeltagi, A. (2025). Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artificial Intelligence Review*, *58*(3), 1–64. https://doi.org/10.1007/s10462-024-11100-x

Zhang, F., Chen, Y., Zhang, J., Guo, E., Wang, R., & Li, D. (2019). Dynamic drought risk assessment for maize based on crop simulation model and multi-source drought indices. *Journal of Cleaner Production, 233*, 100–114. https://doi.org/10.1016/j.jclepro.2019.06.051

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Comparative analysis of yield, agro-climatic conditions, and economic feasibility of mung bean in Logar, Afghanistan

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A B S T R A C T

Mung bean is an important legume crop with significant nutritional and economic value in semi-arid agricultural systems. This study was conducted to evaluate the yield performance, agro-climatic conditions, production practices, and economic feasibility of mung bean cultivation in Logar, Afghanistan. Primary data were collected from 190 randomly selected farmers using a structured questionnaire, while secondary information was obtained from scientific literature and climatic databases. The data were analyzed using descriptive statistical methods, including frequencies, percentages, means, and comparative analyses. The results indicated that mung bean cultivation in Logar covers approximately 100 ha, with an average yield of 0.53 t ha^{-1} and an estimated total production of 104.9 t. Comparative analysis showed that the productivity of mung bean in Logar is lower than that reported for other major mung bean-producing regions within Afghanistan and several producing countries. Although temperature conditions are generally suitable for mung bean cultivation, water scarcity, limited irrigation facilities, low adoption of improved seed varieties, and inadequate agronomic management practices were identified as major constraints affecting productivity. Economic analysis revealed a positive benefit-cost ratio (B:C) of approximately 1.3, indicating that mung bean cultivation is economically feasible despite relatively low profitability. The study concludes that improving irrigation management, promoting improved seed varieties, and strengthening agronomic practices could enhance mung bean productivity and economic returns in Logar under semi-arid conditions.

Keywords: agricultural productivity, climate variability, economic analysis, irrigation constraints, Logar, sustainable agriculture

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1. INTRODUCTION

Mung bean (*Vigna radiata L.)* is an important legume crop widely cultivated in tropical and subtropical regions of the world, particularly in South and Southeast Asia. It plays a significant role in human nutrition and food security because its seeds contain approximately 20.97–31.32% protein, 42.62–61.22% carbohydrates, 3.59–5.09% crude fiber, 0.80–2.00% fat, and 3.46 – 4.85% ash, along with considerable amounts of vitamins and essential minerals (Hou et al., 2019). Moreover, mung bean enhances the sustainability of agricultural systems through biological nitrogen fixation, which improves soil fertility and reduces dependence on inorganic fertilizers (Nair et al., 2018).

Global mung bean production is estimated at approximately 7.2 million metric tons annually, with more than 90% of total production concentrated in South and East Asia (Silva Volpato et al., 2025). India, China, and Myanmar are among the leading producing countries, where favorable climatic conditions and improved crop management practices contribute to higher productivity and sustainable production systems (Schreinemachers et al., 2019). Due to its short growth duration and relatively low water requirement, mung bean is well adapted to semi-arid environments and is frequently cultivated as a rotational crop following cereals (Nair et al., 2018).

In Afghanistan, mung bean has become an increasingly important crop, particularly in the provinces of Farah, Kandahar, Kunduz, Nangarhar, Baghlan, and Laghman (Noorzai et al., 2017). Previous studies have reported that, under favorable climatic conditions and improved crop management practices, mung bean yield may reach 1.0 – 2.2 t ha^{-1} (Pajhwok, 2024; Rashidi et al., 2025). Despite this potential, productivity remains below international standards in many parts of Afghanistan due to limited adoption of improved technologies, inadequate irrigation facilities, poor-quality seed, and insufficient access to modern agronomic practices.

Logar is characterized by a semi-arid climate with hot summers, cold winters_ where the average annual rainfall of approximately 300 mm, and an elevation of about 1,922 m above sea level (Climate-Data.org, 2024). These conditions generally provide a suitable thermal environment for mung bean cultivation. However, water scarcity, limited irrigation infrastructure, low soil fertility, and the limited use of improved production practices remain major constraints affecting crop productivity in the province.

Legume crops play an important role in improving food security, nutritional quality, and soil fertility in Afghanistan. Among these crops, mung bean is valued for its high protein content, short growth duration, and ability to fix atmospheric nitrogen, making it suitable for sustainable agricultural systems (Hou et al., 2019). Despite its agronomic and nutritional importance, mung bean productivity in Afghanistan remains relatively low due to traditional production practices, limited access to improved technologies, and inadequate irrigation and crop management systems.

Although mung bean cultivation has expanded in recent years in Logar, limited information is available regarding its productivity, agro-climatic suitability, and economic performance under local farming conditions. Furthermore, no comprehensive study has been conducted to compare mung bean production in Logar with other mung bean-producing regions of Afghanistan and major producing countries worldwide. This knowledge gap limits the development of evidence-based recommendations for improving productivity and profitability under semi-arid conditions.

Therefore, the present study was conducted to evaluate the current status of mung bean production in Logar, Afghanistan. Specifically, the study aimed to assess yield performance, analyze agro-climatic conditions, evaluate economic feasibility, and compare the productivity of mung bean in Logar with that reported from other producing regions. The findings of this study provide scientific information that may support future research, agricultural planning, and improved production strategies for mung bean cultivation in semi-arid environments.

It was hypothesized that the average yield of mung bean in Logar is lower than the yields reported for other major mung bean-producing regions of Afghanistan and selected producing countries worldwide.

2. MATERIALS AND METHODS

2.1 STUDY AREA

The study was conducted in Logar, eastern Afghanistan, located at an elevation of approximately 1,922 m above sea level. The province is characterized by a semi-arid climate with hot summers, cold winters, an average annual temperature of approximately 11°C, and annual precipitation of about 300 mm (Climate-Data.org, 2024). These climatic conditions generally provide a suitable environment for mung bean cultivation; however, limited water availability remains a major constraint affecting crop productivity.

2.2 Research Design

The study employed a descriptive survey design combined with a comparative analysis of secondary data. Primary data were collected from mung bean farmers in Logar, while published information from other Afghan provinces and major mung bean-producing countries was used for comparative assessment.

2.3 Sampling Procedure and Sample Size Determination

Primary data were collected using a random sampling technique. The sample size was determined using Cochran's formula (Cochran, 1977), following established principles of sample size determination in survey research (Ahmed, 2024):

$$n = z^2pq/e^2$$

where n is the required sample size, z is the standard normal deviate corresponding to a 95% confidence level (1.96), p is the estimated proportion of the target population (0.7), q is the complementary proportion ($1 - p = 0.3$), and e is the acceptable margin of error (0.06).

A total of 190 questionnaires were distributed among mung bean farmers across different districts of Logar and were used for data collection and analysis.

2.4 Data Collection

Primary data were collected through a prepared questionnaire administered to mung bean farmers in Logar. Information was obtained on cultivated area, yield, seed sources, irrigation practices, soil fertility management, and major production constraints affecting mung bean production. Field observations were also conducted to verify and supplement information obtained through farmer interviews.

Secondary data were collected from published scientific literature, institutional reports, meteorological databases, and other relevant academic sources. Climatic information was obtained from Climate-Data.org and related databases to support the agro-climatic assessment of the study area.

2.5 Data Analysis

The collected data were coded, organized, and analyzed using Microsoft Excel. Descriptive statistical methods, including frequencies, percentages, means, and comparative tabular analyses, were used to summarize production practices, yield performance, agro-climatic characteristics, and economic indicators of mung bean production in Logar. Comparative assessments were conducted using published data from other Afghan provinces and major mung bean-producing countries.

Economic feasibility was evaluated using the Benefit-Cost Ratio (B:C), which was calculated as the ratio of gross income to total production cost. Tables and figures were prepared using Microsoft Excel to facilitate the presentation and interpretation of the results.

3. RESULTS

3.1 Yield Analysis of Mung Bean in Logar

Based on a survey of 190 mung bean farmers, approximately 100 ha of land were cultivated with mung bean in Logar, Afghanistan. The average yield was estimated at 0.53 t ha^{-1}, resulting in a total production of approximately 104.9 t (Table 1). These findings provide an overview of the current status of mung bean production in the study area.

As presented in Table 1, mung bean yield varied among districts, ranging from 0.49 to 0.55 t ha^{-1}. Mohammad Agha, Pul-e Alam, and Baraki Barak districts represented approximately 70% of the total cultivated area, suggesting that mung bean production in Logar is concentrated in a few major production districts.

Table 1 Mung bean production indicators by district in Logar

District	Number of Farmers	Cultivated Area per Farmer (ha)	Total Cultivated Area (ha)	Yield (t ha^{-1})	Total Production (t)
Mohammad Agha	52	0.57	29.6	0.526	30.6
Pul-e Alam	45	0.56	25.2	0.52	26.0
Baraki Barak	31	0.49	15.2	0.55	16.5
Khoshi	21	0.48	10.1	0.54	10.8
Charkh	21	0.48	10.1	0.51	10.2
Kharwar	10	0.50	5.0	0.50	5.0
Azra	10	0.50	5.0	0.49	4.9
Total	190	—	100	0.53	104.9

3.3 Comparative Yield Data

Table 2 compares the average yield of mung bean in Logar with yields reported from selected Afghan provinces and major mung bean-producing countries. As shown in Table 2, the average mung bean yield in Logar (0.53 t ha^{-1}) was lower than the yields reported for the selected Afghan provinces and major mung bean-producing countries included in the comparison.

Table 2 Comparison of mung bean yield in Logar, selected Afghan provinces, and major mung bean-producing countries

Region / Country	Yield (t ha^{-1})	Source
Logar (Afghanistan)	0.53	Present study
Farah (Afghanistan)	2.00	Pajhwok (2024)
Kandahar (Afghanistan)	1.50–1.82	Noorzai & Choudhary (2017); Fazil et al. (2024)
Kunduz (Afghanistan)	1.22	Khaleeq (2024)
Kabul (Afghanistan)	1.21	Rashidi et al. (2025)
Baghlan (Afghanistan)	1.24	Singh et al. (2018)
India	1.21	Chaudhary et al. (2023)
Pakistan (Punjab)	0.90	Government of Pakistan (2022)
Myanmar	1.30	Schreinemachers et al. (2019)
China	1.00	Industry Research (2024)

3. 2 Agro-Climatic Analysis

Comparative agro-climatic data presented in Table 3 show differences in elevation, temperature, and annual precipitation among the selected Afghan provinces and mung bean-producing countries. Logar had an average annual temperature of 11 °C and annual precipitation of 306 mm. Farah and Kandahar received lower annual precipitation than Logar, whereas Kunduz and Baghlan showed relatively similar precipitation levels. The selected mung bean-producing countries generally exhibited higher average temperatures and wider ranges of annual precipitation compared with Logar.

Table 3 Comparative agro-climatic characteristics of Logar, selected Afghan provinces, and major mung bean-producing countries

Region / Country	Elevation (m)	Average Annual Temperature (°C)	Annual Precipitation (mm)	Source
Logar (Pul-e Alam)	~1,922	11.0	306	
Farah	~750	20.7	100–150	
Kunduz	~351	16.9	300–400	Climate-Dat.org (2024)
Kandahar	~1,010	20.0	~200	
Baghlan	~510	18.5	284	
India	—	20–30	600–1000	Nair et al. (2018)
Pakistan (Punjab)	—	25–35	300–800	Pakistan (2022)
Myanmar	—	25–30	1000–2000	Schreinemachers et al. (2019)
China	—	25–30	500–1000	Industry Research (2024)

3.3 Economic Analysis of mung Bean Cultivation

The economic analysis indicated that the average cost of mung bean production in Logar was approximately 28,000 AFN ha⁻¹, whereas the average gross income was about 37,000 AFN ha⁻¹. Consequently, the average net income was approximately 9,000 AFN ha⁻¹. The Benefit Cost ratio (B:C) for mung bean production in Logar was 1.3 (Table 4).

Table 4 Comparison of economic indicators of mung bean cultivation in Logar and selected regions

Province	Yield (kg ha-¹)	Market Price (AFN kg-¹)	Gross Income (AFN ha-¹)	Total Cost (AFN ha⁻¹)	Net Income (AFN ha-¹)	B:C	Citation
Logar	500–600	70	37,000	28,000	9,000	1.3	Field estimate
Nangarhar	650–750	65–70	42,000–50,000	28,000–30,000	14,000–20,000	1.4–1.7	MAIL (2021)
Helmand	700–800	65–68	45,000–53,000	28,000–32,000	15,000–22,000	1.5–1.8	Hamim & Choudhary (2019)
Kandahar	800–900	65–70	49,000–63,000	30,000–33,000	19,000–30,000	1.6–1.9	MAIL (2021)
India	900–1,200	75–85	67,500–102,000	38,000–48,000	30,000–54,000	1.8–2.2	Islam et al. (2011)
Bangladesh	1,000–1,400	70–80	70,000–112,000	35,000–46,000	35,000–66,000	2.0–2.4	Islam et al. (2011)

3.4 Comparative Economic Data

Data on the economics of some of the other provinces of Afghanistan and from other countries were obtained through other published sources (Table 4) and analyzed for comparison purposes (MAIL, 2021; Hamim & Choudhary, 2019; Islam et al., 2011). The data presented in Table 4, indicate differences in economic returns across regions.

3. 5. Production Management Practices

The frequency analysis of farm management practices shows that 87.9% of farmers engaged in pest and disease management, compared to 86.8% for weed management; however, only 77.4% followed crop rotation as a management practice and 76.3% adhered to proper timing of planting.

On the contrary, implementation of improved seeds was completed by only 29.5% of farmers and only 25.3% of farmers followed the recommendations for fertilization. The use of appropriate methods for planting was carried out by only 19.5% of farmers. Among the surveyed farmers, 91.1% reported experiencing water scarcity or inadequate irrigation facilities, indicating that water availability is a major production constraint in the study area. The data in Table 5, summarize the level of adoption of different agronomic practices among farmers.

Table 5 Frequency analysis of production practices affecting mung bean cultivation

No.	Production Factor	Response	Frequency (n)	Percentage (%)
1	Use of improved seed varieties	Yes	56	29.5
		No	134	70.5
2	Standard application of organic and chemical fertilizers for soil fertility	Yes	48	25.3
		No	142	74.7
3	Planting carried out at the appropriate time	Yes	145	76.3
		No	45	23.7
4	Observance of crop rotation	Yes	147	77.4
		No	43	22.6
5	Weed control practices implemented	Yes	165	86.8
		No	25	13.2
6	Pest and disease control conducted	Yes	167	87.9
		No	23	12.1
7	Appropriate planting method used	Yes	37	19.5
		No	153	80.5
8	Farmers possessed adequate skills and experience	Yes	62	32.6
		No	128	67.4
9	Presence of water scarcity or a weak irrigation system	Yes	173	91.1
		No	17	8.9

4. Discussion

The findings of this study indicate that mung bean productivity in Logar was lower than that reported for other mung bean-producing provinces of Afghanistan and several major producing countries (Figure. 1). Similar studies conducted in Farah, Kandahar, Kunduz, Kabul, and Baghlan reported higher yields than those observed in the present study (Baghlani et al., 2024; Khaleeq et al., 2025; Noorzai et al., 2017). Likewise, average mung bean yields reported from India, Myanmar, China, and Pakistan were higher than those recorded in Logar (Mitra & Kumar, 2024; Schreinemachers et al., 2019; Pakistan, 2022). The comparatively low yield observed in Logar may be attributed to several production constraints identified through the questionnaire survey. Water scarcity and weak irrigation systems were reported as the most important limitations affecting production. In addition, low adoption of improved seed varieties, inadequate fertilizer application, and limited implementation of recommended agronomic practices may have contributed to reduced productivity. Similar constraints have been identified as major factors limiting mung bean production in semi-arid environments (Islam et al., 2011; Singh et al., 2021). Consequently, low productivity may reduce farmer income, limit production efficiency, and decrease the contribution of mung bean to household food security.

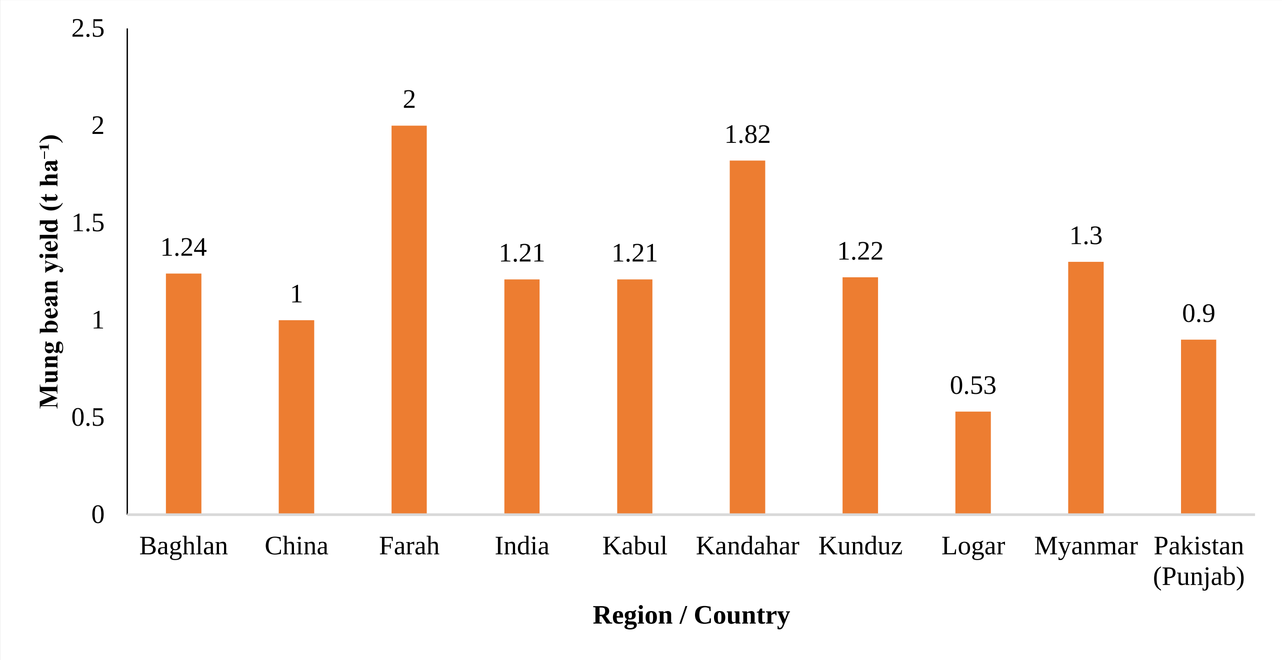

Figure 1. Comparison of average mung bean yield among Logar, selected Afghan provinces, and major mung bean-producing countries (t ha-¹).

The agro-climatic analysis suggests that temperature conditions in Logar are generally suitable for mung bean cultivation. However, annual precipitation is relatively low and occurs mainly during winter and spring, whereas mung bean is cultivated during the summer growing season. Therefore, water availability during flowering and grain-filling stages may be insufficient to support optimum crop growth and yield development. Previous studies have shown that adequate soil moisture during critical growth stages is essential for achieving satisfactory mung bean yields (AVRDC – World Vegetable Center, 2012). The perceptions of farmers obtained through the survey were consistent with the climatic conditions of the region, where water scarcity was identified as the principal environmental constraint. Although provinces such as Farah and Kandahar experience relatively drier conditions, higher yields have been reported where irrigation facilities and water resources are more accessible (Noorzai & Choudhary, 2017). Similarly, major mung bean-producing countries such as India and China achieve higher productivity through favorable moisture availability and improved crop management practices (Schreinemachers et al., 2019).

The economic analysis indicated that mung bean cultivation in Logar remains economically feasible, as reflected by a Benefit Cost ratio (B:C) greater than one. However, relatively low productivity limits overall profitability when compared with other provinces and countries. Previous studies have reported that improved varieties, efficient irrigation management, and better agronomic practices contribute to higher yields and improved economic returns from mung bean cultivation (Islam et al., 2011; MAIL, 2021). Therefore, enhancing irrigation infrastructure, improving access to quality seed, and promoting recommended production practices may increase both productivity and economic benefits for farmers. These findings further suggest that improving production efficiency is essential for strengthening the economic sustainability of mung bean cultivation in Logar.

5. CONCLUSION

This study evaluated the productivity, agro-climatic suitability, production practices, and economic feasibility of mung bean cultivation in Logar, Afghanistan. The results showed that the average mung bean yield was 0.53 t ha^{-1}, which was considerably lower than the yields reported for other major mung bean-producing regions of Afghanistan and selected producing countries. The survey findings indicated that water scarcity and weak irrigation systems were the most important production constraints, reported by 91.1% of farmers. In addition, the adoption of improved seed varieties (29.5%) and recommended fertilizer practices (25.3%) was relatively low, which may have contributed to reduced productivity. Although the agro-climatic assessment showed that temperature conditions are generally suitable for mung bean cultivation, limited water availability during the growing season remains a major challenge. Economic analysis revealed a positive Benefit-Cost Ratio (B:C) of 1.3, indicating that mung bean cultivation is economically feasible despite relatively low profitability. Based on these findings, improving irrigation infrastructure, increasing access to improved seed varieties, and promoting recommended agronomic practices are essential to enhance productivity and economic returns. Further field-based research is recommended to evaluate improved varieties, irrigation strategies, and nutrient management practices under the agro-climatic conditions of Logar.

Author Contributions

Fazal Hanan Safi conceived and designed the study, conducted data collection, performed data analysis, and prepared the original manuscript draft. Saleman Sultani contributed to the study design, literature review, and manuscript editing. Sediqullah Hammas contributed to data interpretation, economic analysis, and critical revision of the manuscript. Abdullah Zaland assisted with methodology development, validation of the results, and manuscript review. Said Hafizullah Hayat supervised the research, provided academic guidance, and critically reviewed and approved the final version of the manuscript. All authors have read and approved the published version of the manuscript.

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Data Availability Statement

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare no conflict of interest.

Artificial Intelligence (AI) Use Statement

Artificial intelligence tools were used only to improve the language and readability of the manuscript. The authors take full responsibility for the scientific content, data analysis, interpretation of results, and conclusions presented in this manuscript

REFERENCES

Ahmed, S. K. (2024). How to choose a sampling technique and determine sample size for research: A simplified guide for researchers. *Oral Oncology Reports, 12*, Article 100662. https://doi.org/10.1016/j.oor.2024.100662

AVRDC – World Vegetable Center. (2012). *Mungbean seed production in South Asia*. World Vegetable Center. https://avrdc.org

Chaudhary, K., Macwan, S., Dhruv, J., Ghadiali, J., & Shruti, S. (2023). Impact of plant growth regulators and chemicals on growth and quality in green gram (*Vigna radiata* L.) cv. GAM-5. *The Pharma Innovation Journal, 12*, 1938–1941.

Climate-Data.org. (2024). *Pul-i-Alam climate: Weather by month*. https://en.climate-data.org/asia/afghanistan/logar/pul-i-alam-764571/

Cochran, W. G. (1977). *Sampling techniques*. John Wiley & sons.

Fazil, K., Hayat, S., Obaid, H., Ashna, A., & Nimgarri, H. (2024). Effect of nitrogen and phosphorus on growth and yield of mungbean. *Journal of Agriculture and Ecology, 18*, 44–47.

Hamim, H., & Choudhary, A. K. (2019). Influence of varying potassium levels on yield, water productivity, profitability, and resource-use efficiency in kharif mungbean (*Vigna radiata*) under semi-arid conditions of Afghanistan. *Indian Journal of Agricultural Sciences, 89*(3), 551–555.

Hou, D., Yousaf, L., Xue, Y., Hu, J., Wu, J., Hu, X., Feng, N., & Shen, Q. (2019). Mung bean (*Vigna radiata* L.): Bioactive polyphenols, polysaccharides,

peptides, and health benefits. *Nutrients*, *11*(6), Article 1238. https://doi.org/10.3390/nu11061238
Industry Research. (2024). *Mung bean market size, share & report*. https://www.industryresearch.biz/market-reports/mung-bean-market-106065
Islam, Q. S., Rahman, M., Hossain, M., & Hossain, M. (2011). Economic analysis of mungbean (*Vigna radiata*) cultivation in some coastal areas of Bangladesh. *Bangladesh Journal of Agricultural Research*, *36*(1), 29–40.
Khaleeq, K. (2024). Optimization of phosphorus fertilizer doses on growth and yield of mung bean (*Vigna radiata*) in northeast agro-ecology of Afghanistan. *International Journal of Multidisciplinary Approach Research and Science*, *2*(2), 719–725.
Khaleeq, K., Ashraf, M. A., & Samim, M. (2025). Response of mung bean (*Vigna radiata* L.) to phosphorus fertilizer levels in northeast agro-ecology of Afghanistan. *International Journal of Scientific Multidisciplinary Research*, *3*(3), 385–392.
MAIL. (2021). *Afghanistan agricultural statistics yearbook*. Ministry of Agriculture, Irrigation and Livestock.
Mitra, R., & Kumar, P. (2024). Physiological and yield response of mung bean (*Vigna radiata* L.) to exogenous application of bioregulatory molecules. *Plant Physiology Reports*, *29*(2), 343–355.
Nair, R. M., Pandey, V. N., Ramasamy, S., Ali, M., Ali, A., & Douglas, C. (2018). *Mungbean seed production training manual: South Asia*. World Vegetable Center. https://avrdc.org/download/publications/manuals/Mungbean-seed-production_South-Asia.pdf
Noorzai, A. U., & Choudhary, A. K. (2017). Influence of summer mungbean genotypes on grain yield and resource-use efficiency in Kandahar province of Afghanistan. *Annals of Agricultural Research*, *38*(2).
Noorzai, A. U., Choudhary, A. K., Parsad, R., & Bana, R. (2017). Growth behaviour, productivity, and profitability of promising mungbean varieties in a semi-arid region of Afghanistan. *Annals of Agricultural Research*, *38*(1).
Pajhwok. (2024, November 14). Farah's mung bean harvest records significant surge. https://pajhwok.com/2024/11/14/farahs-mung-bean-harvest-records-significant-surge/
Pakistan, Government of. (2022). *Economic survey of Pakistan 2021–22*. https://www.finance.gov.pk/survey_2022.html
Rashidi, M. K., Sarhadi, W. A., Salari, H., & Rashid, M. Z. (2025). Comparison of the effects of different types of soil amendments on mung bean yield and yield components. *Acta Fytotechnica et Zootechnica*, *28*(2).
Schreinemachers, P., Sequeros, T., Rani, S., Rashid, M. A., Gowdru, N. V., Rahman, M. S., Ahmed, M. R., & Nair, R. M. (2019). Counting the beans: Quantifying the adoption of improved mungbean varieties in South Asia and Myanmar. *Food Security*, *11*(3), 623–634. https://doi.org/10.1007/s12571-019-00932-9
Silva Volpato, N., Gomez, F. M., Giménez, V. D., & Ciampitti, I. A. (2025). A global dataset on mungbean for managing seed yield and quality. *Scientific Data*, *12*(1), Article 658. https://doi.org/10.1038/s41597-025-02658-0
Singh, C. M., Singh, P., Tiwari, C., Purwar, S., Kumar, M., Pratap, A., Singh, S., Chugh, V., & Mishra, A. K. (2021). Improving drought tolerance in mungbean (*Vigna radiata* L. Wilczek): Morpho-physiological, biochemical, and molecular perspectives. *Agronomy*, *11*(8), Article 1534. https://doi.org/10.3390/agronomy11081534
Singh, M., Tavva, S., Saharawat, Y. S., & Rizvi, J. (2018). A Bayesian assessment of productivity and risks to achieve target yields from improved chickpea and mung bean varieties using on-farm trials in Afghanistan. *Experimental Agriculture*, *54*(3), 470–481. https://doi.org/10.1017/S0014479717000210

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Formulating development strategies for the agriculture sector in Farah, Afghanistan

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A B S T R A C T

Agriculture is considered the backbone of Afghanistan's economy, as the country possesses vast potential in natural resources, horticulture, livestock, and seasonal production. A large proportion of Afghanistan's population is engaged in agriculture, and the agricultural sector plays a key role in household income generation, food security, export development, and regional economic stability. Agriculture is a key pillar of the national economy, and Farah Province, due to its fertile lands, suitable climate, and experienced farmers, has significant growth potential. The aim of this study is to assess the current status of the agricultural sector in Farah Province and to formulate effective development strategies using SWOT analysis. The method of this research is quantitative in terms of data collection and applied in terms of purpose, using SWOT analysis, data were collected through Likert-scale questionnaires from 54 participants including farmers, agricultural specialists, and agriculture related staff. The results show several challenges. These include weak infrastructure, poor water resource management, limited market access, and climate change. These challenges causes' high production costs, low incomes, losses of post-harvest, and unsuitable market conditions, placing farmer in Farah province under considerable economic pressure. Therefore, an accurate evaluation of the present status of the sector, know existing challenges and potentials, and appropriate strategies formulation are importance for Farah province sustainable development. In this regard, SWOT analysis is employed as an effective, practical, and scientific method to provide a clear picture of the sector's strengths, weaknesses, opportunities, and threats.

Keywords: agricultural development, Farah agriculture, EFEM, IFEM, SWOT analysis, strategic planning

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1. INTRODUCTION

Agriculture is very important in Afghanistan. Many people depend on it for jobs, food, and income. It also supports the country's economy. Because of this, it is important for both families and economic stability (FAO, 2020).

Farah Province has good potential for agriculture. It has fertile soil and a suitable climate. Farmers in this area also have good experience. There is also crop diversity. In rural areas, agriculture helps reduce poverty. It also supports social stability where other jobs are limited.

Many studies show that agriculture is linked to economic growth. It also helps reduce poverty and supports rural development. Countries that focus on agriculture often have better productivity and stronger communities (Gürel & Tat, 2017).

However, the situation in Farah is not simple. The sector faces many problems. There is water scarcity and climate change. Farmers have limited access to modern technology. There are not enough storage and processing facilities. Market systems are weak, and transportation is poor. These problems reduce production and affect farmers' income (Batool & Nazir, 2024).

There are inadequate studies about agriculture in Afghanistan, spatially research focused on Farah Province. There is also limited use of SWOT analysis in this area. SWOT helps to study both internal and external factors. This gap makes it harder to develop practical strategies.

This study aims to examine agriculture in Farah Province. It also aims to develop useful strategies using SWOT analysis. The results can help policymakers and organizations make better decisions. In the future, this can improve production, increase farmers' income, and support the local economy (Perkins & Estrada, 2019). This research gives answers to believe questions.

1. What are the main strengths and weakness of the agricultural sector in Farah province?
2. What are the major opportunities and threats affecting the agricultural sector in Farah province?
3. How can SWAT analysis be used to formulate effective strategies for the development of the agricultural sector in Farah province?
4. What strategic actions are required to achieve sustainable agricultural development in Farah province?

2. MATERIALS AND METHODS

This study was conducted in Farah Province, Afghanistan, and employed a quantitative research approach in terms of data collection and an applied approach in terms of purpose. The study focused on evaluating the agricultural sector using a strategic analytical framework. A structured Likert-scale questionnaire was used as the primary data collection instrument. The questionnaire was developed based on a comprehensive review of relevant literature and consultations with agricultural experts.
The study population consisted of farmers, agricultural specialists, and agriculture-related staff, from which a total of 54 respondents were purposively selected. The selection criteria included professional experience, involvement in agricultural activities, and technical expertise. Prior to data collection, informed consent was obtained from all participants to ensure ethical compliance.
The questionnaire was organized into four sections corresponding to the components of SWOT analysis: strengths, weaknesses, opportunities, and threats. To ensure content validity, the instrument was reviewed and validated by two academic experts from the Faculties of Agriculture at Farah University and Nimroz University. After validation, the questionnaires were distributed and completed by the selected respondents.

Data analysis was conducted using the SWOT analytical framework, a widely recognized strategic tool for evaluating internal and external factors and supporting decision-making processes (Gürel & Tat, 2017; David & David, 2017). To improve analytical accuracy, the Internal Factors Evaluation

Matrix (IFEM) and External Factors Evaluation Matrix (EFEM) were constructed. In these matrices, each factor was assigned a weight and rating, and weighted scores were calculated to quantify their relative importance.
Based on the IFEM and EFEM results, four strategic positions were analyzed to determine appropriate development strategies for the agricultural sector in Farah Province. Data were processed and analyzed using Microsoft Excel software.

1. Aggressive Strategy (SO)

In this position, efforts focus on maximizing external opportunities by leveraging internal strengths. This strategy is appropriate when both strengths and opportunities are high.

2. Conservative Strategy (WO)

The objective of this strategy is to utilize external opportunities while simultaneously addressing and improving internal weaknesses. This position is applied when opportunities exist but internal weaknesses constrain development.

3. Competitive Strategy (ST)

In this strategy, existing strengths are used to reduce or counter external threats. This position is suitable when strengths are strong but significant threats are present.

4. Defensive Strategy (WT)

In the defensive strategy, a protective approach is adopted to minimize internal weaknesses and prevent or reduce external threats. This position is relevant when both weaknesses and threats are high and risk reduction is essential for survival.

3. RESULTS

The results presented in Table 1. show that the majority of respondents (51.9%) were between 31 and 40 years of age, indicating that most participants were within an economically active and experienced age group. In terms of education, a large proportion (81.5%) held a bachelor's degree or higher, reflecting a high level of academic background among respondents. Regarding occupation, agriculture lecturers/students and individuals from other related sectors each constituted 40.7% of the sample, while a smaller proportion were directly engaged in farming (11.1%) or employed as agricultural officers (7.4%).

These characteristics indicate that the study benefited from informed participants with substantial academic and professional exposure to the agricultural sector, enhancing the reliability of the findings.

Table 1 Demographic Characteristics and Number of Farmers and Related Participants in the Study

Variable	Category	Frequency	Percentage (%)
Age	22–30 years	22	40.7
	31–40 years	28	51.9
	Above 41 years	4	7.4
	Total	54	100
Education Level	Illiterate	2	3.7
	High school graduate (12th grade)	8	14.8
	Bachelor's degree or higher	44	81.5
	Total	54	100

Occupation	Engaged in farming	6	11.1
	Agricultural officer	4	7.4
	Agriculture lecturer or student	22	40.7
	Other	22	40.7
	Total	54	100

Analysis of Internal Factors

Table 2. presents the evaluation of internal factors (strengths and weaknesses) of the agricultural sector based on the SWOT analysis framework. The analysis was conducted as follows:

1. The first column describes the internal factors, including strengths and weaknesses.
2. The second column represents the weight coefficient, indicating the relative importance of each factor. The value ranges from 0 to 1, and the sum of all weights must not exceed1.
3. The third column shows the rating, which reflects the sector's response to each factor, strengths are assigned ratings of 3 or 4, while weaknesses are assigned ratings of 1 or 2.
4. The fourth column presents the weighted score, calculated by multiplying the weight coefficient by the rating, indicating the overall impact of each factor.
5. Finally, if the total weighted score exceeds 2.5, strengths dominate weaknesses, if it is below 2.5, weaknesses outweigh strengths. For the agricultural sector of Farah Province, the total score is 2.231, indicating that weaknesses outweigh strengths.

The evaluation of internal factors of Farah Province's agricultural sector using the Internal Factors Evaluation (IFE) Matrix shows a total score of 2.231, which indicates that weaknesses currently prevail over strengths. Based on this score, the sector possesses notable strengths while simultaneously facing serious internal weaknesses.

Among the strengths, the most significant factor is the availability of large and flat agricultural lands, with the highest weighted score (0.232), plays a fundamental role in increasing production capacity. In addition, the relative availability of modern agricultural machinery, the use of drip irrigation systems, the presence of university graduates, the distribution of quality seeds and fertilizers, and the availability of young specialists are considered major assets of the agricultural sector. Each of these factors positively contributes to production quality, management efficiency, and the adoption of modern technologies. Furthermore, farmers' experience and traditional skills are regarded as important strengths, as they enhance understanding of local conditions and support the effective organization of agricultural activities.

Despite these strengths, the agricultural sector faces several critical weaknesses that significantly hinder development. Weak agricultural infrastructure, with a weighted score of 0.054, is identified as the most severe constraint, as post-harvest losses and delays in delivering products to markets substantially increase farmers' economic losses. Additionally, the lack of modern technology, absence of storage facilities, insufficient modern irrigation systems, water scarcity, weak marketing structures, and shortages of agricultural tools and machinery directly undermine production quality, farmers' income, and the overall economic stability of the sector.

In particular, water scarcity exacerbated by the climatic conditions of Farah Province is considered a primary cause of reduced agricultural production. Likewise, the absence of storage systems limits the expansion of exports. Overall, the internal factor analysis indicates that although the sector has strong internal potential for growth, urgent reforms are required in water management, marketing, storage, and infrastructure development to enable the sector to fully utilize its strengths and transform weaknesses into opportunities.

Table 2 Evaluation of Internal Factors (Strengths and Weaknesses)

No.	Internal Factors (Strengths and Weaknesses)	Weight	Rating	Weighted Score
1	Farmers' traditional skills are beneficial for agricultural development	0.047	3	0.141
2	Relative availability of modern agricultural machinery increases production	0.059	3	0.177
3	Farmers' experience helps in solving agricultural problems	0.055	3	0.165
4	Presence of young specialists supports the use of new technologies	0.059	3	0.177
5	Relative use of drip irrigation systems increases production	0.056	3	0.168
6	University graduates have the capacity to manage agricultural projects effectively	0.056	3	0.168
7	Availability of large and flat lands is a major strength of Farah's agricultural sector	0.058	4	0.232
8	Relative distribution of quality seeds and fertilizers supports sector development	0.057	3	0.171
9	Water scarcity reduces agricultural production	0.057	1	0.057
10	Lack of modern irrigation systems limits sector development	0.055	1	0.055
11	Absence of storage facilities leads to post-harvest losses of grains	0.055	1	0.055
12	Shortage of cold storage reduces fresh fruit export and preservation capacity	0.054	2	0.108
13	Weak domestic marketing networks reduce farmers' income	0.057	2	0.114
14	Limited export routes reduce global market access for agricultural products	0.054	2	0.108
15	Lack of new technology affects product quality	0.055	1	0.055
16	Weak agricultural infrastructure increases farmers' challenges	0.054	1	0.054
17	Lack of harvesting tools and insufficient agricultural machinery makes farming activities more difficult	0.057	2	0.114
18	Shortage of agricultural machinery lowers farmers' living standards	0.056	2	0.112
Tot		1.00		2.231

Evaluation of External Factors (Opportunities and Threats)

Table 3. presents the assessment of external factors (opportunities and threats) based on the SWOT analysis framework. The evaluation was conducted as follows:

1. The first column describes the external factors, including opportunities and threats.
2. The second column shows the weight coefficient, which reflects the relative importance of each factor. Values range from 0 to 1, and the sum of all weights does not exceed 1.
3. The third column presents the rating, indicating the sector's response to each factor, opportunities are rated 3 or 4, while threats are rated 1 or 2.
4. The fourth column contains the weighted score, calculated by multiplying the weight coefficient by the rating, indicating the overall impact of each factor.
5. Finally, if the total weighted score exceeds 2.5, opportunities dominate threats; if it is below 2.5, threats outweigh opportunities. For the agricultural sector of Farah Province, the total score is 2.342, indicating that threats outweigh opportunities.

The evaluation of external factors of Farah Province's agricultural sector using the External Factors Evaluation (EFE) Matrix resulted in a total score of 2.23, demonstrating that threats currently outweigh opportunities. This score indicates that while the sector possesses notable opportunities for development, it simultaneously faces serious external threats that constrain its overall potential.

Among the opportunity factors, several elements are particularly prominent. The adoption of new agricultural technologies, improved security conditions, construction of the Bakhshabad Dam, attraction of international assistance, and expansion of roads and bridges represent key opportunities that can significantly enhance production levels, water management, export capacity, and marketing efficiency. Notably, the use of new technologies, security stability, and construction of the Bakhshabad Dam each achieved the highest weighted score (0.228), making them the most influential external opportunities and critical drivers for long-term stability and growth of the agricultural sector.

Additionally, expanded access to neighboring countries' markets, implementation of international standards, and development of agricultural projects are considered important opportunities for increasing farmers' income and improving the competitiveness of agricultural products.

On the other hand, the assessment of external threats facing Farah Province's agricultural sector identifies several factors as particularly severe and impactful. Based on weighted scores, global market instability (weighted score: 0.053) and drought (weighted score: 0.054) are classified as first-order threats, as they have direct and negative effects on economic stability and farmers' income. The high weighted scores of these threats indicate that if they are not effectively managed and controlled, they could pose serious risks to the development of the agricultural sector.

Overall, these first-order threats represent critical focal points for strategic decision-making and risk mitigation planning.

Table 3 Evaluation of External Factors (Opportunities and Threats)

No.	External Factors (Opportunities and Threats)	Weight	Rating	Weighted Score
1	Exporting products to neighboring countries promotes agricultural development	0.056	3	0.168
2	Attracting international assistance is beneficial for expanding agricultural projects	0.057	3	0.171
3	Construction of roads and bridges facilitates market access for products	0.056	3	0.168
4	Adoption of new technologies contributes to water conservation	0.057	4	0.228
5	Improved overall security provides opportunities for agricultural development	0.057	4	0.228
6	Construction of the Bakhshabad Dam increases production capacity	0.057	4	0.228
7	Access to international markets is an opportunity for agricultural growth	0.055	3	0.165
8	Expansion of agricultural projects increases employment opportunities for farmers	0.055	3	0.165
9	Implementation of international standards supports export development	0.056	3	0.168
10	Impacts of climate change reduce agricultural production	0.057	1	0.057
11	Drought reduces farmers' income	0.054	1	0.054
12	Reduced rainfall negatively affects product quality	0.055	1	0.055
13	Price volatility of agricultural products increases farmers' challenges	0.053	2	0.106
14	Limited access to agricultural credit hinders farmers' progress	0.055	1	0.055
15	Lack of financial resources limits expansion of agricultural projects	0.053	2	0.106
16	Instability of global markets affects export levels	0.053	1	0.053
17	Weak infrastructure intensifies the impact of threats	0.055	1	0.055
Total		**1.00**		**2.23**

Formulation of Strategies for Agricultural Sector Development

The evaluation of internal and external fundamental factors was conducted using the SWOT matrix in order to identify strategies that align with the objectives of this study and are consistent with existing internal and external conditions.

As indicated by the Internal and External Factor Evaluation Matrices, the total score for internal factors is **2.231**, while the total score for external factors is **2.23**. To determine the primary strategic orientation, these scores were plotted on a four-quadrant SWOT matrix. As shown in **Figure (1),** the main strategy identified for the development of agriculture in Farah Province is a **Defensive Strategy (WT),** marked by a star. This strategic position results from the combination of internal weaknesses and external threats.

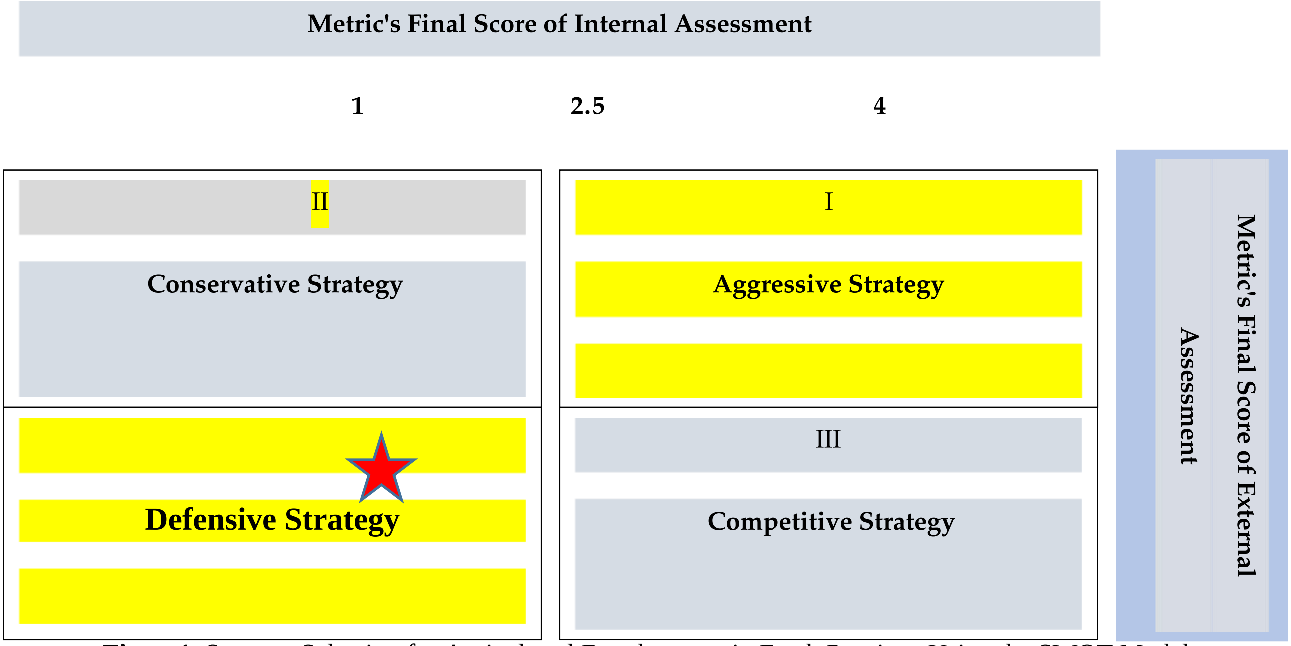

Figure1. Strategy Selection for Agricultural Development in Farah Province Using the SWOT Model

Table 4 Strategies proposed for achieving agricultural development in Farah Province based on the SWOT matrix analysis

• Weaknesses 1. Water resource scarcity reduces agricultural production. 2. Lack of storage facilities causes post-harvest losses of crops. 3. Shortage of cold storage reduces fresh fruit preservation and export capacity. 4. Weak domestic marketing networks reduce farmers' income. 5. Limited export routes restrict global market access. 6. Lack of modern irrigation systems constrains sector development. 7. Insufficient agricultural machinery lowers production levels. 8. Lack of new technology negatively affects product quality. 9. Weak agricultural infrastructure increases farmers' challenges. 10. Lack of harvesting tools increases labor difficulty for farmers.	• Strengths 1. Farmers' traditional skills are beneficial for agricultural development. 2. Relative availability of modern agricultural machinery increases production levels. 3. Farmers' experience contributes to solving agricultural problems. 4. Presence of young specialists facilitates the adoption of new technologies. 5. Relative use of drip irrigation systems increases production efficiency. 6. University graduates have the capacity to effectively manage agricultural projects. 7. Availability of large and flat agricultural lands is a major strength of Farah Province. 8. Relative distribution of quality seeds and fertilizers supports sectoral development.	Internal Factors External Factors
. Competitive Strategy (ST): Using strengths to mitigate threats ✓ Increase production using modern machinery (S2) to reduce price volatility and export risks (T4, T7). ✓ Utilize farmers' skills, experience, and the presence of young specialists and graduates (S1, S3, S4, S6) to counter limitations in credit, financial resources, and infrastructure (T5, T6, T8). ✓ Apply drip irrigation systems and quality seeds and fertilizers (S5, S8) to mitigate threats of climate change, drought, and reduced rainfall (T1, T2, T3). ✓ Utilize large and flat agricultural lands (S7) to increase farmers' income and reduce the impacts of drought (T2).	Aggressive Strategy (SO): Using strengths to maximize opportunities 1. Increase production through relative availability of modern machinery (S2) and expand exports to neighboring and international markets (O1, O7). 2. Strengthen agricultural projects, adoption of international standards, and attraction of international assistance by utilizing farmers' traditional skills, experience, and the presence of young specialists and graduates (S1, S3, S4, S6) (O2, O8, O9).	• **Opportunities** 1. Exporting products to neighboring countries promotes agricultural development. 2. Attraction of international assistance supports expansion of agricultural projects. 3. Construction of roads and bridges facilitates market access. 4. Adoption of new technologies supports water conservation. 5. Improved overall security provides opportunities for sectorial growth. 6. Construction of the Bakhshabad Dam increases production capacity. 7. Access to international markets supports agricultural development. 8. Expansion of agricultural projects increases employment opportunities. 9. Implementation of international standards enhances export potential.

	3. Enhance drip irrigation systems and the use of quality seeds and fertilizers (S5, S8) through new technologies and improved road infrastructure (O4, O3). 4. Expand cultivation on large and flat lands (S7) by utilizing water from the Bakhshabad Dam and improved security conditions (O5, O6).	
Defensive Strategy (WT): Minimizing weaknesses and avoiding threats 1. Efficient use of available water resources (W1) to better manage climate change and reduced rainfall threats (T1, T3). 2. Utilize existing storage facilities and cold rooms (W2, W3) to reduce price volatility and export risks (T4, T7). 3. Rely on existing domestic marketing networks and export routes (W4, W5), and existing irrigation systems (W6) to manage price instability, export risks, drought, and reduced rainfall (T2, T3, T4, T7). 4. Optimize use of existing agricultural machinery and technologies (W7, W8, W10) to control threats related to limited credit and machinery shortages (T5, T9). 5. Improve management of existing agricultural infrastructure (W9) to mitigate infrastructure-related threats (T8).	Conservative Strategy (WO): Using opportunities to reduce weaknesses 1. Reduce weaknesses in marketing networks and limited export routes (W4, W5) by exporting to neighboring countries, accessing international markets, and applying international standards (O1, O7, O9). 2. Address weak infrastructure and lack of new technology (W8, W9) through adoption of new technologies, road construction, and improved security (O3, O4, O5). 3. Reduce water scarcity and lack of modern irrigation systems (W1, W6) through the Bakhshabad Dam and attraction of international assistance (O2, O6).	• **Threats** 1. Climate change impacts reduce agricultural production. 2. Drought decreases farmers' income. 3. Reduced rainfall affects crop quality. 4. Price volatility of agricultural products increases farmers' challenges. 5. Limited access to agricultural credit restricts farmers' progress. 6. Lack of financial resources limits project expansion. 7. Instability of global markets affects export levels. 8. Weak infrastructure intensifies threat impacts. 9. Shortage of agricultural machinery lowers farmers' living standards.

5. Discussion

The results of this study show that agriculture in Farah Province has strong natural potential due to its extensive agricultural land resources, favorable agroecological conditions, and existing farming experience. However, this potential is significantly constrained by structural, environmental, and institutional challenges that limit productivity and long-term sustainability. The findings are consistent with earlier studies that identify water scarcity and climate change as the most serious threats to agricultural development in arid and semi-arid regions. FAO (2023) and ICRC (2024) report that drought and irregular rainfall are major constraints on agricultural livelihoods in Afghanistan. Similarly, UNDP (2021) and World Bank (2022) emphasize that climate change is increasing agricultural risk through higher temperatures, reduced precipitation, and increased evapotranspiration.

A key issue identified in this study is the continued use of traditional irrigation systems, which are inefficient and highly vulnerable to climate variability. FAO (2022) explains that surface irrigation leads to substantial water losses through seepage, runoff, and evaporation, reducing overall efficiency. Jensen (2007) and Burt et al. (2010) also show that poor irrigation management can reduce water-use efficiency by up to 50 percent in similar agroecological contexts. As a result, farmers face increased vulnerability during drought periods and declining agricultural output. To address this, FAO (2022) recommend modern irrigation technologies such as drip and sprinkler systems, which significantly improve water efficiency and resilience. In addition, Ostrom (1990) highlights that effective local water governance and collective action are essential for sustainable irrigation management, particularly in resource-scarce environments. Infrastructure limitations represent another major constraint on agricultural development in Farah Province. The study found that weak transportation systems, limited storage facilities, and poor market access significantly reduce agricultural profitability. These challenges increase post-harvest losses and reduce farmers' bargaining power. Similar findings are reported by World Bank (2021) and FAO (2020), which show that inadequate rural infrastructure is a key barrier to agricultural commercialization in developing countries. Barrett (2008) further explains that weak value chain integration prevents smallholder farmers from transitioning from subsistence to market-oriented production systems. Reardon et al. (2019) also emphasize that investments in rural infrastructure and agro-logistics are essential for improving market access and supporting rural transformation.

Institutional and financial constraints further intensify these challenges. Limited access to credit, weak extension services, and insufficient institutional support reduce farmers' ability to adopt improved agricultural technologies. Anderson and Feder (2007) highlight that agricultural extension systems are critical for knowledge transfer and productivity enhancement, while Davis et al. (2012) show that advisory services significantly improve farm decision-making and farm performance. Financial constraints are also significant. Feder et al. (1985) identify credit constraints and risk aversion as major barriers to agricultural modernization, particularly among smallholder farmers. FAO (2020) emphasize that access to rural finance is essential for investment in improved seeds, fertilizers, and irrigation technologies. The World Bank (2021) further stresses that strengthening rural financial systems is crucial for agricultural transformation in low-income contexts.

Despite these constraints, the study identifies several opportunities for agricultural development. The proposed Bakhshabad Dam is considered a major opportunity due to its potential to increase water availability, expand irrigation coverage, and stabilize agricultural production. Large-scale irrigation infrastructure has been widely recognized as a driver of agricultural intensification and rural development World Bank (2022). In addition, opportunities such as agricultural mechanization, improved seed varieties, and climate-smart agriculture offer important pathways for increasing productivity and resilience. FAO (2020) defines climate-smart agriculture as an approach that increases productivity, strengthens resilience, and reduces emissions where possible. Evidence from Lobell et al. (2011) and Stevenson et al. (2013) shows that improved agricultural technologies can reduce yield variability under climate stress conditions. In Afghanistan, Kakar and Rahimi (2020) further confirm that mechanization and technology adoption significantly improve agricultural output, income diversification, and rural livelihoods.

An important contribution of this study is the integration of SWOT analysis with IFEM and EFEM frameworks. This combined approach provides a more systematic and evidence-based understanding of internal strengths and weaknesses as well as external opportunities and threats. According to David (2017), integrating qualitative and quantitative strategic tools improves the quality of decision-making and policy formulation. In this study, this approach also demonstrates how internal strengths, such as land availability and human capacity, can be leveraged to address external challenges more effectively. Overall, this study highlights the urgent need for integrated agricultural development planning in Farah Province. Coordinated investment in water resource management, infrastructure development, institutional strengthening, and market systems is essential for sustainable agricultural growth. By addressing existing constraints and effectively utilizing available opportunities, agriculture in Farah Province can significantly improve productivity, increase rural incomes, and contribute to long-term economic stability and food security.

6. CONCLUSION

The findings of this study reveal that the agricultural sector in Farah Province possesses several significant strengths, including the availability of suitable agricultural land, adequate human resources, and access to basic agricultural inputs. However, despite these advantages, the sector continues to face considerable structural weaknesses and external challenges that limit its productivity and long-term sustainability. The analysis indicates that persistent issues such as water scarcity, climate variability, inadequate infrastructure, underdeveloped market systems, and limited adoption of modern agricultural technologies remain major constraints to agricultural development in the province.

The application of the SWOT analytical framework, supported by the Internal Factor Evaluation Matrix (IFEM) and External Factor Evaluation Matrix (EFEM), provided a systematic and comprehensive assessment of the agricultural sector. The study clearly illustrates the extent to which internal weaknesses and external threats adversely affect agricultural performance, while also identifying strategic opportunities and practical solutions for sectoral improvement. The results of the study suggest several strategic priorities for achieving sustainable agricultural growth in the province. These include improving water resource management, developing agricultural and rural infrastructure, promoting the adoption of modern technologies, expanding market access, and strengthening the technical and managerial capacities of farmers. In addition, the study highlights important development opportunities through increased investment in irrigation systems, transportation infrastructure, and agricultural markets. Infrastructure projects such as water storage facilities and dam construction are also identified as essential measures for enhancing agricultural resilience and productivity

Author Contributions

Mehrabuddin Rashed conceived the study, collected the data, performed the data analysis, and drafted the manuscript. Mehrabuddin Asif Walizadah contributed to the conceptualization of the study and the development of the methodology. Amir Mohammad Erfani critically reviewed and edited the manuscript. All authors contributed to the writing of the manuscript, reviewed the final version, and approved the submitted manuscript.

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset is not publicly available due to privacy and confidentiality considerations related to the participants.

Conflict of Interest

The authors declare no conflict of interest

Artificial Intelligence (AI) Use Statement

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript.

REFERENCES

Agha, M. (2021). *Challenges and opportunities in Afghanistan's agricultural development*. Kabul: Afghanistan Agricultural Research Institute.

Anderson, J. R., & Feder, G. (2007). Agricultural extension. In R. E. Evenson & P. Pingali (Eds.), *Handbook of agricultural economics* (Vol. 3, pp. 2343–2378).

Barrett, C. B. (2008). Smallholder market participation: Concepts and evidence from eastern and southern Africa. *Food Policy, 33*(4), 299–317.

Batool, S., & Nazir, A. (2024). Agricultural productivity and climate change: Impacts on rural livelihoods in South Asia. *Journal of Environmental Management*, 320, 116143. https://doi.org/10.1016/j.jenvman.2023.116143

Burt, C. M., Clemmens, A. J., Strelkoff, T. S., Solomon, K. H., Bliesner, R. D., Hardy, L. A., Howell, T. A., & Eisenhauer, D. E. (2010). Irrigation performance measures: Efficiency and uniformity. *Journal of Irrigation and Drainage Engineering, 123*(6), 423–442.

Chatterjee, P. (2016). *Strategic management using SWOT analysis*. New Delhi: Sage Publications.

David, F. R., & David, F. R. (2017). *Strategic management: A competitive advantage approach* (16th ed.). Pearson.

Davis, K., Swanson, B., Amudavi, D., Mekonnen, D. A., Flohrs, A., Riese, J., Lamb, C., & Zerfu, E. (2012). *In-depth assessment of the public agricultural extension system of Ethiopia and recommendations for improvement*. IFPRI.

FAO. (2020). *Afghanistan: Food and agriculture challenges and opportunities*. Food and Agriculture Organization of the United Nations.

FAO. (2022). *Irrigation and mechanization in developing countries: Case studies from Asia*. Food and Agriculture Organization of the United Nations.

FAO. (2022). *The state of land and water resources for food and agriculture*. Food and Agriculture Organization.

FAO. (2023). *Afghanistan agricultural livelihoods and food security report*. Food and Agriculture Organization

FAO. (2023). *Climate change impacts on agriculture in Afghanistan*. Food and Agriculture Organization of the United Nations.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change, 33*(2), 255–298.

Gürel, E., & Tat, M. (2017). SWOT analysis: A theoretical review. *Journal of International Social Research*, 10(51), 994–1006.

International Committee of the Red Cross. (2024). *Water scarcity and drought impacts in Afghanistan*. ICRC.

Jensen, M. E. (2007). Beyond irrigation efficiency. *Irrigation Science, 25*(3), 233–245.

Kakar, H., & Rahimi, F. (2020). Agricultural infrastructure development and productivity improvement in Afghanistan. *Asian Journal of Agricultural Research*, 14(3), 45-57.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science, 333*(6042), 616–620.

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press.

Perkins, R., & Estrada, L. (2019). Strategic planning for sustainable agricultural development. *International Journal of Agricultural Sustainability*, 17(4), 321-335.

Reardon, T., Echeverria, R., Berdegué, J. A., Minten, B., Liverpool-Tasie, S. L. O., Tschirley, D., & Zilberman, D. (2019). Rapid transformation of food systems in developing regions: Highlighting the role of agricultural value chains. *Agricultural Economics, 50*(S1), 13–24.

Sabillah, F., Hartono, B., & Syah, R. (2024). Application of SWOT analysis in agricultural strategy formulation. *Journal of Strategic Agriculture*, 5(1), 15-28.

Smith, J., & Miller, T. (2019). Human capital and agricultural development: Evidence from rural Asia. *Journal of Rural Studies*, 68, 112-123.

Stevenson, J. R., Villoria, N., Byerlee, D., Kelley, T., & Maredia, M. (2013). Green revolution research saved an estimated 18 to 27 million hectares from being brought into agricultural production. *Proceedings of the National Academy of Sciences, 110*(21), 8363–8368.

UNDP. (2021). *Climate change and agriculture: Impacts on food security*. United Nations Development Program.

UNDP. (2022). *Strategic planning for agricultural resilience in developing countries*. United Nations Development Program.

World Bank. (2021). *Agricultural value chains and market access in Afghanistan*. World Bank Publications.

World Bank. (2022). *Climate change impacts on agriculture and rural livelihoods in Afghanistan*. World Bank Publications.

World Bank. (2022). *Climate risk and agriculture in Afghanistan*. World Bank Publications.

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Phenological, agronomic, and yield performance of four local common bean varieties under the agro-climatic conditions of Kabul, Afghanistan

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A B S T R A C T

Common bean is an important legume crop cultivated worldwide and exhibits considerable variation in morphological, agronomic, and adaptive traits. In Afghanistan, diverse local and improved bean varieties are grown under different agroecological conditions and contribute significantly to food security and rural livelihoods. However, limited information is available regarding their phenological, agronomic and yield performance, which hinders the identification and recommendation of high-yielding and well-adapted cultivars. Therefore, the study aimed to evaluate the phenological, agronomic, and yield characteristics of four local common bean varieties and identify the most suitable variety for cultivation under agro-climatic conditions of Kabul, Afghanistan. The four local bean varieties evaluated were Nagrabi Kapisa (red large seed), Badakhshi (spotted large seed), Ghaznichi (red small seed), and Logari (cream-colored small seed). The results indicated that Nagrabi (T1) performed superior to the other varieties in most evaluated parameters. Nagrabi bean variety recorded the highest germination percentage (95%), earliest flowering (40.33 days) and maturity (82.67 days), maximum number of branches per plant (11.73), highest number of pods per plant (16.93), longest pod length (11.51 cm), highest number of seeds per pod (5.23), heaviest 100-seed weight (34.06 g), and the highest seed yield (2630.57 kg ha^{-1}). In contrast, Logari (T4) and Ghaznichi (T3) showed comparatively lower performance in most traits. Based on this study, the Nagrabi variety was identified as the most suitable local bean cultivar for cultivation under the agro-climatic conditions of Kabul.

Keywords: agro-climatic conditions of Kabul, agronomic traits, comparison, local common bean varieties, phenological parameters

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1. INTRODUCTION

Common Bean (*Phaseolus vulgaris L.*) is an important legume crop belonging to the family

Fabaceae, widely cultivated across the world due to its high nutritional value, including protein, dietary fiber, vitamins, and essential minerals (Uebersax et al., 2023) and (Lisciani et al., 2024). It is considered one of the most important food legumes in both developed and developing countries because of its ability to contribute significantly to human nutrition and food security (Lisciani et al., 2024). In addition to its dietary importance, common bean plays a vital role in sustainable agriculture through its ability to fix atmospheric nitrogen, thereby improving soil fertility and reducing dependence on synthetic fertilizers (Karavidas et al., 2022) and (Cardoso et al., 2024).

Globally, bean production is influenced by environmental conditions, genetic factors, and agronomic practices. The crop shows considerable adaptability to different agro-ecological zones; however, its productivity is strongly affected by water availability, temperature fluctuations, soil fertility and cultivar selection (Mohammad and Feleke, 2022) and (Daud et al., 2026). In Afghanistan, common bean is an important component of smallholder farming systems, particularly in regions such as Kabul Province, where farmers cultivate beans for both household consumption and income generation. The crop is favored due to its relatively short growth duration and adaptability to local farming systems. However, productivity remains low and unstable due to environmental stress, limited access to improved varieties, and inadequate agronomic management practices (Sarhadi et al.,2017).

Previous studies have reported significant variation in growth and yield performance of bean genotypes under different environmental conditions. For instance, Sarhadi et al. (2017) evaluated the adaptation of local bean varieties under Kabul climatic conditions and reported considerable differences in phenological behavior and yield potential among varieties. Similarly, studies by Hussaini et al. (2021) indicated that water stress significantly affects growth and yield formation in beans, while Qadiri et al, (2023) highlighted the positive role of integrated nutrient management in improving crop performance. Furthermore, Kargiotidou et al, (2018) emphasized that genetic variability among bean genotypes plays a major role in determining yield and its related components, particularly pod number and seed development. Sadiq et al. (2023) also reported that plant density, cultivar and agronomic practices significantly influence yield potential in bean production systems. Despite these findings, there is still limited and insufficient comparative information on the performance of local bean varieties under the specific agro-climatic conditions of Kabul, particularly regarding detailed evaluation of phenological traits, growth characteristics, and yield components under uniform field conditions. Therefore, systematic evaluation of locally available bean varieties is essential to identify high-performing genotypes suitable for sustainable production in the region.

This study is significant because it provides updated comparative information on the performance of local bean varieties under Kabul conditions, which can support farmers, researchers, and extension workers in selecting high-yielding and well-adapted varieties. The findings will also contribute to improving food security and sustainable agricultural production in agro-climatic condition of Kabul. (limited information regarding the comparison of phonological, agronomic and yield characteristics of local bean varieties in agro-climatic conditions of Kabul). Farmers mainly depend on traditional practices and regional knowledge when selecting varieties, which can lead to low productivity and inefficient resource use. Without experiments, it is difficult to identify which local bean varieties are best suited for Kabul's environment in terms of phonological, agronomic and yield characteristics. This knowledge gap hinders efforts to improve bean production. Therefore, the study aimed to compare the phonological, agronomic and yield characteristics of four local bean varieties under Kabul's climatic conditions to determine the most productive types.

2. MATERIALS AND METHODS

This research was conducted at the Agriculture Faculty research farm of Kabul University, during the summer growth season in two field experiments, location (A) and location (B), from the 28 April

2025 to 29 August 2025. Randomized Complete Block Design (RCBD) was used with three replications. Four local bean varieties were used as treatments: Nagrabi (T1), Badakhshi (T2), Ghaznichi (T3), and Logari (T4). Seeds of these varieties were obtained from local farmers and seed sources within their respective production areas. Each replication consisted of four plots, one for each bean variety, resulting in a total of 12 plots per location. Each plot measured 2 × 2 m (4 m²), the experimental area included four rows which arranged to maintain 50 cm distance between each row and 20 cm distance between each individual plant.

Table 1 Morphological and agronomic characteristics of four local common bean varieties

Variety Name	Seed Size	Seed Color	Growth Habit	Agronomic Characteristics	picture
Nagrabi (Kapisa) common bean variety	Large	Red	Determinate	Early maturing	
Badakhshi common bean variety	Large	Spotted (Ablaq)	Semi-determinate	Intermediate maturity	
Ghaznichi (Maqur) common bean variety	Small	Red	Indeterminate	Late-maturing	
Logari common bean variety	Small	Cream-colored (Shirayi)	Indeterminate	Late-maturing	

Source: The common bean varieties used in this study were obtained from the Badam Bagh Research Directorate, Kabul, Afghanistan, under the Ministry of Agriculture, Irrigation and Livestock (MAIL).

The experimental field was thoroughly prepared through deep ploughing, followed by additional ploughing, hoeing, debris removal, and land leveling to create a fine and uniform seedbed. The field was then divided into three blocks and twelve plots, with furrows prepared for sowing. To enhance soil fertility, 280 kg ha^{-1} of DAP, 1.5 t ha^{-1} of organic manure and 180 kg ha^{-1} of urea were applied, with urea supplied in split doses. Bean seeds were treated with Vitawax fungicide before sowing to protect against soil-borne diseases and improve seedling establishment. A pre-sowing germination test (100 seeds per variety) was conducted under moist tissue conditions at room temperature. Results indicated high seed viability, with germination rates ranging from 96% to 100%, confirming the suitability of all seed lots for field planting. Prior to sowing, the field was irrigated and seeds were soaked for 18 hours to promote rapid germination. Planting was carried out on 28 April 2025 at a depth of 5 cm, maintaining a spacing of 20 cm between plants and 50 cm between rows. Weed control was performed manually twice during the growing season to reduce competition for resources and maintain field hygiene. Variety-specific seed rates were used, ranging from 25 to 33 kg ha^{-1}. Crop protection measures focused on monitoring and manually controlling cutworm (Agrotis spp.) infestations, which posed a threat to young seedlings. Thinning was conducted 25 days after sowing to maintain the recommended plant spacing and ensure uniform growth. Irrigation management included pre-sowing irrigation followed by regular applications at 7-10 day intervals, resulting in a total of 17 irrigations throughout the growing season to maintain adequate soil moisture and support optimum crop development.

Data on germination, growth, phenology, and yield attributes were collected using standard procedures. Germination percentage was determined 10 days after sowing by counting seeds that produced a visible radicle or shoot and calculating the proportion of germinated seeds relative to the total seeds sown. Days to start flowering and days to start maturity were recorded from sowing to the appearance of the first open flower and the first signs of pod browning, respectively, using observations from five representative plants per plot. Plant height was measured at harvest from the base of the plant to the tip of the main stem on five selected plants, while the numbers of branches and pods per plant were determined by counting all primary and secondary branches and total pods on the same sampled plants. Pod length, pod diameter, and seeds per pod were assessed using ten randomly selected pods from representative plants in each plot, and mean values were calculated. For seed weight, a random sample of 100 seeds from each replication was weighed using a precision electronic balance after harvest, threshing, and cleaning. Seed yield was determined by harvesting a 1 m^2 area within each plot, drying the seeds to a uniform moisture content, recording the seed weight, and converting the values to kilograms per hectare (kg ha^{-1}) using standard conversion methods. All measurements were averaged to obtain representative values for each plot and treatment.

Analysis of variance (ANOVA) was conducted to assess collected data through their Randomized Complete Block Design (RCBD) experimental setup. Mean was compared using the Tukey Honest Significant Difference (HSD) test at the 5% probability level comparisons were conducted to compare the means statistical analysis conducted through STAR (Statistical Tool for Agricultural Research) software.

3. RESULTS

Various plant parameters such as germination percentage (10 DAS), days to flowering, days to maturity, Plant height, branches per plant, pods per plant, pod length, seeds per pod, pod diameter, 100-seed weight and seed yield (kg ha^{-1}) were evaluated.

Germination% 10 DAS

Nagrabi demonstrated the highest germination performance, which indicating variation in seed vigor and establishment ability, followed by Badakhshi and Ghaznichi, while Logari showed the lowest germination percentage.

Table 2 Comparison of varieties in germination% 10 DAS

Treatments	Germination% 10 DAS
T1 (Nagrabi)	95.0 ^{a}
T2 (Badakhshi)	77.4 ^{b}
T3 (Ghaznichi)	67.1 ^{c}
T4 (Logari)	59.3 ^{d}

Values presented are treatment means based on three replications (n = 3). Means followed by the same letter within a column are not significantly different at the 5% probability level according to the Tukey Honest Significant Difference (HSD) test ($P \leq 0.05$). Different letters within a column indicate significant differences among bean varieties for the respective parameter.

Phenological parameters

For days to flowering and days to maturity significant differences ($p \leq 0.05$) were observed between treatments. Nagrabi was the earliest flowering and maturing variety, while Logari and Ghaznichi required a longer time to complete their growth cycle. Badakhshi showed intermediate performance. These differences reflect the genetic variability among the varieties in their growth and developmental characteristics.

Table 3 Comparison of varieties in phenological parameters

Treatments	Days to Flowering	Days to Maturity
T1 (Nagrabi)	40.33 [d]	82.67 [d]
T2 (Badakhshi)	48.43 [c]	89.00 [c]
T3 (Ghaznichi)	60.50 [a]	101.33 [b]
T4 (Logari)	56.67 [b]	110.33 [a]

Values presented are treatment means based on three replications (n = 3). Means followed by the same letter within a column are not significantly different at the 5% probability level according to the Tukey Honest Significant Difference (HSD) test ($p \leq 0.05$). Different letters within a column indicate significant differences among bean varieties for the respective parameters.

Growth Traits

Significant differences were observed among the varieties for both traits. Logari and Ghaznichi produced the tallest plants, indicating greater vegetative growth, whereas Nagrabi exhibited the shortest plants. In contrast, Nagrabi developed the highest number of branches per plant, while Ghaznichi produced the fewest branches. Badakhshi and Logari showed intermediate branching performance. These results suggest that varietal differences influenced plant architecture, with taller varieties not necessarily producing a greater number of branches.

Table 4 Comparison of varieties in Agronomic treats

Treatments	Plant Height (cm)	Number of Branches Per Plant
T1 (Nagrabi)	37.13 [c]	11.73 [a]
T2 (Badakhshi)	54.67 [b]	9.17 [ab]
T3 (Ghaznichi)	71.07 [a]	4.63 [c]
T4 (Logari)	76.8 [a]	7.47 [b]

Values presented are treatment means based on three replications (n = 3). Means followed by the same letter within a column are not significantly different at the 5% probability level according to the Tukey Honest Significant Difference (HSD) test ($P \leq 0.05$). Different letters within a column indicate significant differences among bean varieties for the respective parameters.

Reproductive characteristics

Table.4 shows significant differences among the bean varieties for yield and yield-related traits. Nagrabi produced the highest number of pods per plant, longest pods, greatest number of seeds per pod, highest 100-seed weight, and the highest grain yield, demonstrating superior yield performance. Badakhshi exhibited intermediate values for most traits and ranked second in grain yield. Ghaznichi showed moderate performance, while Logari recorded the lowest values for most yield components and consequently produced the lowest grain yield. Pod diameter was generally similar among most varieties, although Logari exhibited a significantly smaller pod diameter. These results indicate that variations in grain yield were largely associated with differences in pod production, seed set, pod size, and seed weight among the tested varieties.

Table 5 Comparison of varieties in reproductive traits

Treatments	Pods per Plant	Pod Length (cm)	Seeds per Pod	Pod Diameter (cm)	100-Seed Weight (g)	Grain yield (kg ha^{-1})
T1 (Nagrabi)	16.93 ^{a}	11.51 ^{a}	5.23 ^{a}	3.53 ^{a}	34.06 ^{a}	2630.57 ^{a}
T2 (Badakhshi)	13.40 ^{b}	9.85 ^{ab}	4.75 ^{ab}	3.32 ^{a}	31.80 ^{ab}	1876.33 ^{b}
T3 (Ghaznichi)	10.37 ^{bc}	8.56 ^{bc}	3.98 ^{bc}	3.34 ^{a}	23.93 ^{c}	1568.00 ^{c}
T4 (Logari)	9.00 ^{c}	6.43 ^{c}	3.37 ^{c}	2.60 ^{b}	25.67 ^{bc}	1231.43 ^{d}

Values presented are treatment means based on three replications (n = 3). Means followed by the same letter within a column are not significantly different at the 5% probability level according to the Tukey Honest Significant Difference (HSD) test ($P \leq 0.05$). Different letters within a column indicate significant differences among bean varieties for the respective parameters.

5. Discussion

Nagrabi showed the highest germination performance, indicating superior seed vigor, faster metabolic activation, and better reserve mobilization during early establishment. This advantage suggests stronger physiological readiness for rapid seedling emergence under agro-climatic conditions of Kabul. Similar genetic control of germination and seed vigor in common bean was reported by Kusaksiz et al. (2022), who emphasized varietal differences in early establishment ability. **(**T3**)** and **(**T4**)** exhibited lower germination percentages within the first 10 days due to their delayed germination behavior and late-maturing nature in some varieties may be associated with reduced seed vigor and sensitivity to environmental conditions, which is consistent with the findings of Teshale et al. (2020), who reported poor establishment under stress-prone environments.

Earliest flowering was exhibited in Nagrabi bean variety, reflecting a shorter vegetative phase and faster transition to reproductive development. This early phenology is advantageous in Kabul's semi-arid climate, where terminal drought or temperature stress can reduce yield in late-maturing types. The early flowering response likely indicates better adaptation and efficient accumulation of thermal units. Raggi et al. (2019) confirmed strong genetic control over flowering time in common bean, while Bhakta et al. (2017) reported that temperature and photoperiod strongly influence floral initiation. Similar variation among growth habits was also observed by Neupane et al. (2011).

The earliest maturity recorded in Nagrabi demonstrates its ability to complete its life cycle efficiently under limited moisture conditions, allowing it to escape late-season stress. This trait is particularly valuable in semi-arid environments where water availability declines toward the end of the growing season. Similar findings were reported by Yanda and Tryphone (2022), who associated early maturity with drought avoidance strategies. Kusaksiz et al. (2022) also noted that early-maturing genotypes are better adapted to short-season environments, whereas late-maturing types prioritize biomass accumulation under favorable conditions.

The tallest plants observed in Ghaznichi and Logari indicate lengthen vegetative growth and more indeterminate growth habit, while Nagrabi showed shorter plant height which could be associated with early maturity and more efficient resource allocation to reproductive organs. Similar patterns were reported by Kusaksiz et al. (2022), who distinguished indeterminate tall types from determinate short types. This suggests that assimilates in Nagrabi are preferentially allocated to reproductive structures rather than vegetative biomass.

Nagrabi produced the highest number of branches, indicating superior plant architecture and greater potential for reproductive site formation. This higher branching capacity directly contributed to increased pod formation and yield potential. Kusaksiz et al. (2022) similarly reported that highly branched genotypes produce more reproductive nodes and higher yields. In contrast, reduced branching in some varieties may be linked to genetic limitations or suboptimal assimilate distribution.

The highest pod number per plant recorded in Nagrabi, which reflects improved flower retention and stronger source–sink relationships during reproductive development. This superiority is likely associated with its higher branching and early flowering traits, which extend pod formation duration. Mekonnen et al. (2019) reported that pod formation is strongly influenced by genotype × environment interaction, while Girma et al. (2021) confirmed that higher branching increases pod production.

Longer pods in Nagrabi indicate better assimilate translocation and stronger reproductive development compared to other varieties. This suggests more efficient nutrient uptake and partitioning during pod filling. Similar effects of favorable agronomic conditions on pod elongation were reported by Olawale et al. (2021) and Singh and Kumar (2019), while Adebayo et al. (2020) emphasized the importance of soil fertility in improving pod structural development.

The highest seed number per pod showed Nagrabi, indicating efficient fertilization and strong assimilate supply during seed formation. This trait reflects better reproductive efficiency and sinks strength. Togay et al. (2005) reported that nitrogen and phosphorus significantly improve seed set, while Khalid et al. (2018) and Kusaksiz et al. (2022) confirmed strong genetic control over this trait. In contrast, Ghaznichi's lower seed set, reflects the lower end of reported ranges, likely due to limited resource allocation and suboptimal reproductive efficiency.

Greater pod diameter in Nagrabi and some other varieties indicates improved pod filling capacity and stronger sink development. This trait reflects better nutrient availability and physiological efficiency during reproductive growth. Similar findings were reported by Olawale et al. (2021), who highlighted the role of improved agronomic practices in enhancing pod size, while Singh and Kumar (2019) emphasized genetics and environmental influence on pod structure.

Higher 100-seed weight in Nagrabi indicates superior assimilate partitioning and efficient seed filling during the reproductive stage. This suggests stronger photosynthetic activity and effective translocation of nutrients to developing seeds. Similar variation influenced by genotype and agronomic practices was reported by Sadiq et al. (2023), while Avens (2021) demonstrated the effect of spacing on seed weight.

The highest seed yield in Nagrabi is the cumulative result of its superior performance in all yield components, including higher pod number, better seed set, and higher seed weight. This indicates a well-balanced source-sink relationship and strong adaptation to semi-arid conditions. FAO (2022) reported that environmental conditions and genotype strongly influence bean yield.

6. CONCLUSION

The present study evaluated the performance of four local bean varieties under the agro-climatic conditions of Kabul by assessing germination, phenological, growth traits and yield components. The results revealed clear and significant variation among the tested varieties, Nagrabi (T1) consistently demonstrated superior performance across nearly all parameters. It achieved the highest germination percentage (95%w), indicating excellent seed vigor and viability, and exhibited the earliest flowering (40.33 days) and earliest maturity (82.67 days), which are critical advantages under Kabul's relatively short growing season and water limited conditions. Moreover, Nagrabi (T1) excelled in yield contributing traits, recording the highest number of branches per plant (11.73), maximum number of pods per plant (16.93), longest pod length (11.51 cm), highest number of seeds per pod (5.23), heaviest (100) seed weight (34.06 g) and the highest seed yield (2630 kg ha^{-1}). Based on our findings in the research area and agro-climatic conditions of Kabul, we suggest that the Nagrabi (T1) variety of bean showed the best performance. In contrast, Logari (T4) and Ghaznichi (T3) exhibited weaker performance in most growth and yield parameters, including low germination rates, delayed flowering and maturity, fewer branches, and reduced seeds weight. Their lower adaptability suggests that these varieties are less suited to the specific climatic and soil conditions of Kabul. Badakhshi (T2) showed moderate performance across traits, performing better than Ghaznichi (T3) and Logari (T4) but not reaching the productivity level of Nagrabi (T1).

It is recommended to investigate how different fertilization systems and irrigation approaches and intercropping methods affect plant development in local environments to improve bean production and environmental sustainability.

Author Contributions

Mehrabuddin Rashed contributed to the conceptualization of the study, development of the methodology, experimental design, data collection, data analysis, interpretation of results, and preparation of the original manuscript draft. Abdul Khalil Afghani contributed to the supervision of the research, provided guidance throughout the study, and critically reviewed and edited the manuscript.

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset is not publicly available because it contains experimental observations and measurements generated during the study and has not been deposited in a public data repository.

Conflict of Interest

The authors declare no conflict of interest.

Artificial Intelligence (AI) Use Statement

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript

REFERENCES

Adebayo, A. A., Olawale, J. O., & Yusuf, M. A. (2020). Effects of agronomic practices on pod development and yield of common bean (Phaseolus vulgaris L.). Journal of Crop Science and Biotechnology, 23(2), 115–123.

Al-Kindi Publisher. (2023). Yield response of common bean to planting density and nutrient management. *Agricultural Research Reports*, 12(1), 45–53.

Avens Online. (2020). Nitrogen and phosphorus fertilization effects on common bean yield performance. *Avens Journal of Agricultural Science*, 8(3), 210–218.

Avens Online. (2021). Effect of plant spacing on seed weight and yield of common bean. *Avens Journal of Plant Production*, 9(2), 134–142.

Bhakta, M., Sharma, P., & Singh, R. (2017). Environmental regulation of flowering time in common bean (*Phaseolus vulgaris* L.). *Plant Physiology Reports*, 22(4), 301–309.

Cardoso, A. M., da Silva, C. V. F., & Padua, V. L. (2024). Microbial insights into biofortified common bean cultivation. Sci, 6(1), 6.

Cardoso, E. J. B. N., Silva, R. M., Pereira, L. F., & Santos, M. A. (2024). Nitrogen fixation and sustainable production of common bean (*Phaseolus vulgaris L.*). *Agronomy*, 14(3), 512–528.

Daud, M., Rahimi, S., Ahmadzai, A., & Khan, M. A. (2026). Environmental factors affecting growth and productivity of common bean (*Phaseolus vulgaris L.*). *Journal of Crop Improvement*, 40(1), 25–39.

FAO. (2022). Climate change impacts on bean production and water management strategies. Food and Agriculture Organization of the United Nations.

Girma, A., Tadesse, T., & Wolde, S. (2021). Influence of plant architecture on yield performance of common bean varieties. *African Journal of Agricultural Research*, 16(5), 621–629.

Hussaini, M., Rahman, K., & Ali, S. (2021). Drought stress effects on growth and yield of common bean. *Journal of Arid Agriculture Studies*, 14(1), 55–63.

Kargiotidou, A., Papadopoulos, I., & Georgiadis, N. (2018). Genetic variability and yield performance in common bean genotypes. *Crop Breeding and Genetics Journal*, 10(2), 88–97.

Khalid, M., Khan, M., & Rahman, A. (2018). Nutrient management effects on growth and yield of common bean. *International Journal of Agronomy and Agricultural Research*, 12(3), 101–110.

Kusaksiz, E., Yildiz, M., & Demir, A. (2022). Morphological and yield variability in common bean genotypes. *Field Crops Research Journal*, 28(1), 45–56.

Lisciani, S., Marconi, S., Le Donne, C., Camilli, E., Aguzzi, A., Gabrielli, P., Gambelli, L., Kunert, K., Marais, D., Vorster, B. J., Alvarado-Ramos, K., Reboul, E., Cominelli, E., Preite, C., Sparvoli, F., Losa, A., Sala, T., Botha, A.-M., & Ferrari, M. (2024). Legumes and common beans in sustainable diets: Nutritional quality, environmental benefits, spread and use in food preparations. *Frontiers in Nutrition*, 11, Article 1385232.

Mekonnen, S., Abebe, T., & Desta, B. (2019). Genotype and environment interaction effects on common bean yield components. *Ethiopian Journal of Crop Science*, 7(2), 77–86.

Neupane, D., Shrestha, J., & Pandey, S. (2011). Flowering behavior of bush and climbing beans under different environments. *Journal of Tropical Agriculture*, 49(2), 112–118.

Olawale, J. O., Adebayo, A. A., & Bello, M. O. (2021). Influence of fertilizer application on pod development in legumes. *Journal of Plant Nutrition and Soil Science*, 19(3), 201–209.

Qadiri, S., Ahmad, Z., & Noor, H. (2023). Integrated nutrient management and its effects on crop productivity. *Agricultural Systems Review*, 15(2), 89–98.

Raggi, L., Terzi, V., & Galasso, I. (2019). Genetic control of flowering time in common bean (*Phaseolus vulgaris* L.). *Frontiers in Plant Science*, 10, 1234.

Sadiq, F., Rahimi, A., & Ahmadzai, H. (2023). Plant density effects on yield performance of common bean in Afghanistan. *Journal of Sustainable Agriculture*, 18(1), 33–41.

Sarhadi, A., Ahmadi, H., & Rahmanzai, M. (2015). Adaptation of local bean varieties under Kabul climatic conditions. *Kabul University Journal of Agricultural Sciences*, 4(1), 23–31.

Singh, R., & Kumar, P. (2019). Agronomic practices influencing pod size and yield in legumes. *International Journal of Plant Production*, 13(2), 145–152.

Teshale, A., Mekonnen, Y., & Alemu, D. (2020). Effects of drought stress on growth and yield of common bean. *Journal of Dryland Agriculture*, 11(1), 66–74.

Togay, N., Togay, Y., & Dogan, Y. (2005). Fertilizer effects on yield and yield components of bean. *Asian Journal of Plant Sciences*, 4(6), 569–572.

Uebersax, M. A., Cichy, K. A., Porch, T. G., Singh, S. P., Xia, E., & Sidhu, J. S. (2023). Dry beans (*Phaseolus vulgaris L.*) as a vital component of sustainable agriculture and food security. *Legume Science*, 5(1), e155.

Wortmann, C. S. (2006). Phaseolus vulgaris L. production systems and agronomy. *Field Crops Research*, 97(2–3), 219–231.

Yanda, P., & Tryphone, G. (2022). Maturity variation among common bean genotypes under field conditions. *African Crop Science Journal*, 30(1), 55–63.

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Prebiotics in poultry production: mechanisms of action, gut microbiota modulation, health benefits, and potential alternatives to antibiotic growth promoters

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A B S T R A C T

The poultry industry is increasingly challenged by antimicrobial resistance, rising feed costs, and the growing demand for sustainable production systems, accelerating the search for effective alternatives to antibiotic growth promoters (AGPs). This narrative review synthesizes current evidence on the classification, mechanisms of action, and practical applications of prebiotics in poultry nutrition. Relevant literature published in peer-reviewed journals was systematically identified through major scientific databases using predefined search terms, with studies selected based on their relevance to poultry production, gut health, immune function, and growth performance. Prebiotics, including fructans (inulin and fructooligosaccharides), galacto-oligosaccharides, mannan-oligosaccharides, resistant starch, lactulose, and other functional oligosaccharides, have demonstrated considerable potential to beneficially modulate intestinal microbiota and improve host physiology. Their beneficial effects are primarily mediated through the selective stimulation of beneficial microorganisms, enhanced short-chain fatty acid production, improved intestinal barrier integrity, immune modulation, and increased nutrient digestibility. These mechanisms contribute to improved growth performance, feed efficiency, disease resistance, and overall poultry health. However, inconsistent responses among studies indicate that the efficacy of prebiotics is influenced by multiple factors, including prebiotic type and dosage, bird genotype and age, dietary composition, management practices, and environmental conditions. This review critically evaluates these variations, identifies current knowledge gaps, and highlights emerging opportunities for precision prebiotic supplementation and microbiome-based nutritional strategies. Overall, prebiotics represent promising functional feed additives for reducing antibiotic dependency and supporting sustainable poultry production, although further well-designed studies under commercial production conditions are required to optimize their practical application.

Keywords: feed additives, growth performance, intestinal micro-biota, poultry, prebiotics

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1. INTRODUCTION

Poultry production has become one of the fastest-growing sectors of animal agriculture due to its high efficiency in converting feed into high-quality animal protein. Poultry meat is widely consumed because of its favorable nutritional profile, including lower levels of saturated fat compared with many red meats, affordability, and availability (Jilo & Hasan, 2022). However, the rapid expansion of the poultry industry has created several challenges, including maintaining productivity, controlling intestinal disorders, reducing production costs, and ensuring food safety (Efremova, 2018).

For many decades, AGPs have been used in poultry production to enhance growth performance, improve feed efficiency, and reduce bacterial challenges. However, the extensive and prolonged use of antibiotics has contributed to the emergence of antimicrobial-resistant microorganisms, which represents a major concern for animal production, public health, and environmental sustainability (Reznichenko et al., 2021). Therefore, global efforts have focused on identifying safe and effective alternatives to AGPs that can maintain productivity while minimizing antimicrobial resistance risks (Solis-Cruz et al., 2019).

Among various functional feed additives, prebiotics have received increasing attention due to their ability to regulate intestinal microbial ecosystems and improve host health. Prebiotics are non-digestible compounds that are selectively utilized by beneficial microorganisms in the gastrointestinal tract, resulting in the production of bioactive metabolites, particularly short-chain fatty acids (SCFAs) (Gibson et al., 2017; Bevilacqua et al., 2024). These metabolites contribute to intestinal homeostasis by influencing microbial composition, intestinal barrier integrity, nutrient utilization, and immune regulation (Xia et al., 2024).

A wide range of prebiotic compounds, including fructans (inulin and fructooligosaccharides), galacto-oligosaccharides (GOS), mannan-oligosaccharides (MOS), resistant starch, lactulose, and pectic oligosaccharides, have been investigated in poultry nutrition. Previous studies have demonstrated that dietary prebiotics can enhance beneficial microbial populations, increase SCFA production, improve intestinal morphology, and support immune function in poultry (Abd El-Hack et al., 2022; Ali et al., 2023). For example, mannan-oligosaccharides and β-glucans have been associated with improved growth performance and immune responses, particularly under environmental stress conditions such as heat stress (Sayed et al., 2023).

Despite the increasing number of studies investigating prebiotics in poultry, their effectiveness is not always consistent. Differences in outcomes may be related to prebiotic type, chemical structure, inclusion level, bird species, age, dietary composition, and environmental conditions (Johnson et al., 2025). Moreover, although several studies have evaluated individual prebiotic compounds, a comprehensive understanding of their mechanisms of action, comparative effectiveness, and practical application in commercial poultry production remains limited.

Therefore, this review aims to provide an updated overview of prebiotics in poultry nutrition, focusing on their classification, biological mechanisms, effects on gut microbiota, nutrient utilization, immune function, production performance, and their potential role as alternatives to antibiotic growth promoters.

2. METHODOLOGY

This review was conducted as a narrative review to evaluate the current knowledge regarding the application, mechanisms, and effects of prebiotics in poultry production. A comprehensive literature search was performed using major scientific databases, including PubMed, ScienceDirect, Scopus, Web of Science, and Google Scholar, to identify relevant studies related to dietary prebiotics and their effects on poultry health and productivity. The literature search was conducted using combinations of the following keywords and Boolean operators: different types of prebiotics and poultry growth performance, gut microbiota intestinal health, immune response and antibiotic alternatives.

Studies were selected based on predefined inclusion criteria, including: (1) research conducted on poultry species, (2) evaluation of dietary prebiotic supplementation, (3) investigation of outcomes related to growth performance, intestinal microbiota, nutrient utilization, immune responses, disease resistance, or product quality, and (4) publication in peer-reviewed scientific journals. Recent studies published mainly between 2015 and 2026 were prioritized to incorporate current advances in prebiotic research.

Studies were excluded when they focused exclusively on non-poultry species, human nutrition, non-dietary applications of prebiotics, or lacked sufficient information regarding prebiotic type, dosage, or biological outcomes. Relevant information, including prebiotic source, supplementation level, bird species, experimental duration, and reported effects, was extracted and systematically organized. Finally, the collected information was qualitatively analyzed to identify major trends, biological mechanisms, research limitations, and future opportunities regarding the use of prebiotics as functional feed additives and alternatives to antibiotic growth promoters in sustainable poultry production.

3. Classification and Sources of Prebiotics Used in Poultry Nutrition

Prebiotics are non-digestible functional feed ingredients that are selectively utilized by beneficial intestinal microorganisms, resulting in improved microbial balance, enhanced intestinal function, and better physiological responses in poultry. Based on their chemical structure and biological activity, prebiotics used in poultry nutrition are mainly classified into fructans (inulin and fructooligosaccharides, FOS), galacto-oligosaccharides (GOS), mannan-oligosaccharides (MOS), xylo-oligosaccharides (XOS), isomalto-oligosaccharides (IMO), resistant starch (RS), lactulose, pectic oligosaccharides (POS), β-glucans, and other non-digestible oligosaccharides (Gibson et al., 2017; Abd El-Hack et al., 2022).

Fructans, including inulin and fructooligosaccharides, are among the most extensively studied prebiotics in poultry nutrition. These carbohydrate compounds are fermented by intestinal microorganisms and promote the production of short-chain fatty acids (SCFAs), which contribute to intestinal microbial balance and improved gut function (Franco-Robles & López, 2015; Hernández & Plou, 2023). Supplementation of fructan-based prebiotics has been associated with improved intestinal microbiota composition and enhanced nutrient utilization in poultry (Ferrocino et al., 2023).

Galacto-oligosaccharides (GOS) are another important group of prebiotics produced through enzymatic conversion of lactose. GOS selectively stimulate beneficial bacteria and contribute to improved intestinal barrier function and microbial stability (Vera et al., 2016; Ambrogi et al., 2023). Recent studies have indicated that GOS supplementation can support intestinal health and increase SCFA production in poultry (Mei et al., 2022).

Mannan-oligosaccharides (MOS), mainly derived from yeast cell walls, are widely used as functional feed additives in poultry production. MOS can modulate intestinal microbial populations, reduce pathogen colonization, and improve growth performance and immune responses. Previous studies have demonstrated beneficial effects of MOS supplementation on broiler performance and intestinal health (Ali et al., 2023; Nawaz et al., 2024).

Resistant starch (RS) is considered an important prebiotic substrate because it escapes digestion in the upper gastrointestinal tract and reaches the hindgut, where it is fermented by microorganisms into SCFAs, particularly butyrate. In poultry, resistant starch has been associated with improved gut microbial activity, intestinal health, and metabolic regulation (Tan et al., 2021; Hussain et al., 2025).

Other prebiotic compounds, including xylo-oligosaccharides (XOS), isomalto-oligosaccharides (IMO), lactulose, pectic oligosaccharides (POS), and β-glucans, have also received increasing attention in poultry nutrition. XOS and IMO influence beneficial microbial populations and intestinal fermentation, whereas lactulose contributes to microbial balance and digestive health (Morgan et al., 2022; Mookiah et al., 2014; Sizova et al., 2025). Pectic oligosaccharides derived from plant materials represent emerging prebiotic compounds with potential roles in regulating intestinal microorganisms and supporting immune responses (Singh et al., 2020; Tang et al., 2025). β-glucans, often obtained from yeast sources, have demonstrated immunomodulatory and microbiota-regulating properties in poultry (Sayed et al., 2023).

Although different prebiotic classes vary in their chemical structures and biological functions, their effectiveness in poultry depends on several factors, including molecular characteristics, supplementation level, bird species, age, dietary composition, and environmental conditions. Therefore, understanding the specific properties of each prebiotic category is essential for optimizing their application in sustainable poultry production.

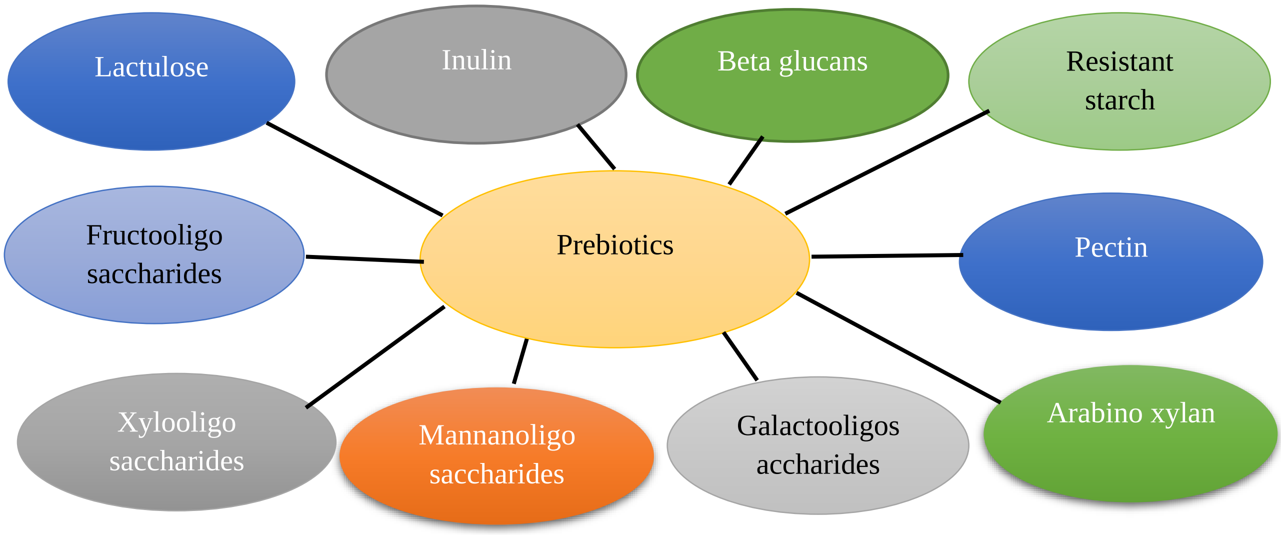

Figure 1. Different types of prebiotics (Obayomi et al., 2024).

4. Mechanisms of Action of Prebiotics in Poultry

Prebiotics exert their beneficial effects in poultry through multiple interconnected mechanisms, primarily involving the regulation of intestinal microbiota, production of microbial metabolites, enhancement of intestinal barrier function, modulation of immune responses, and inhibition of pathogenic microorganisms. The biological responses induced by prebiotics depend largely on their chemical structure, fermentation characteristics, and interaction with the gastrointestinal microbiome.

4.1. Modulation of Intestinal Microbiota

One of the primary mechanisms of prebiotics is the selective stimulation of beneficial intestinal microorganisms, particularly *Lactobacillus* and *Bifidobacterium*, while limiting the proliferation of harmful bacteria. Because poultry cannot enzymatically digest most prebiotic compounds, these substrates reach the lower gastrointestinal tract, where they are selectively fermented by resident microorganisms. This microbial regulation contributes to improved intestinal microbial balance and enhanced gut ecosystem stability (Gibson et al., 2017; Xia et al., 2024).

Supplementation of prebiotics such as fructooligosaccharides, mannan-oligosaccharides, and galacto-oligosaccharides has been reported to increase beneficial bacterial populations and reduce pathogenic microorganisms, including *Salmonella* and *Escherichia coli*, in poultry (Pourabedin & Zhao, 2015; Micciche et al., 2018). The ability of prebiotics to promote favorable microbial communities represents a key mechanism underlying their role as alternatives to antibiotic growth promoters. The application of prebiotics in poultry production represents a scientifically robust strategy to address the global imperative of reducing antibiotic growth promoters (AGPs) while maintaining animal health, performance, and food safety. Their multifaceted mechanisms of action are not isolated effects but interconnected biological processes that collectively enhance gut ecosystem homeostasis. The primary mechanism begins with the selective modulation of the intestinal microbiota. Prebiotics, defined as non-digestible food ingredients that beneficially affect the host by selectively stimulating the growth and/or activity of beneficial bacteria in the colon, serve as a substrate for specific commensal microbes such as *Bifidobacterium* and *Lactobacillus* species (Yue et al., 2025).

4.2. Production of Short-Chain Fatty Acids and Regulation of Intestinal Environment

The fermentation of prebiotics by intestinal microorganisms produces short-chain fatty acids (SCFAs), including acetate, propionate, and butyrate. These metabolites play important roles in maintaining intestinal health by lowering intestinal pH, enhancing epithelial cell energy supply, and creating unfavorable conditions for pathogenic bacterial growth (Morgan, 2023). Butyrate, in particular, serves as an important energy source for intestinal epithelial cells and contributes to maintaining intestinal integrity. Increased SCFA production following prebiotic supplementation has been associated with improved gut function and reduced pathogen colonization in poultry (Tan et al., 2021; Al-baadani et al., 2025). Second, and perhaps more importantly, SCFAs act as key signaling molecules and energy sources for the host. Butyrate, in particular, is the preferred energy source for colonocytes, the cells lining the intestinal tract. Its provision is essential for maintaining the health, proliferation, and functional integrity of these epithelial cells (Ducatelle et al., 2023)6. Furthermore, SCFAs like butyrate and propionate can modulate host gene expression through mechanisms such as histone deacetylase (HDAC) inhibition and activation of G-protein-coupled receptors (GPCRs), influencing a wide array of cellular processes from metabolism to inflammation (Oke et al., 2025)7.

4.3. Improvement of Intestinal Barrier Integrity and Morphology

Prebiotics improve intestinal structure by influencing villus development, crypt depth, and epithelial integrity. Enhanced villus height and increased villus height-to-crypt depth ratio indicate improved absorptive capacity and nutrient utilization. These structural improvements facilitate better digestion and absorption of nutrients while strengthening protection against intestinal challenges (Rehman et al., 2020; Ali et al., 2023). Furthermore, prebiotic-induced changes in microbial metabolites can enhance intestinal barrier function by supporting tight junction integrity and reducing intestinal inflammation. These effects contribute to improved nutrient availability and overall poultry performance. This metabolic support directly translates into the improvement of intestinal barrier integrity and morphology. A healthy, well-nourished epithelium forms a tight, impermeable barrier against the translocation of harmful bacteria, toxins, and undigested antigens—a condition often referred to as "leaky gut" when compromised (Sayed et al., 2023). Prebiotic supplementation has been consistently shown to enhance key morphological features of the gut, including increased villi height and a higher villi height-to-crypt depth ratio in the small intestine (Yaqoob et al., 2021). These structural improvements significantly expand the absorptive surface area of the gut, which is fundamental for efficient nutrient uptake. Concurrently, prebiotics strengthen the barrier at a molecular level by upregulating the expression of tight junction proteins (e.g., claudins, occludin, ZO-1) that seal the paracellular spaces between epithelial cells, thereby reinforcing the physical barrier (Teng & Kim, 2018).

4.4. Immune Modulation

Prebiotics influence both innate and adaptive immune responses through interactions between intestinal microorganisms and host immune cells. By promoting beneficial bacteria and increasing microbial metabolites, prebiotics enhance immune system development and improve resistance against environmental and pathogenic challenges. Dietary supplementation with MOS, β-glucans, and other oligosaccharides has been associated with increased immunoglobulin production, improved immune organ development, and enhanced disease resistance in poultry (Sayed et al., 2023; Bayat et al., 2025). These immunomodulatory effects make prebiotics valuable components of antibiotic-free poultry production systems. The immune system is profoundly intertwined with gut health, and prebiotics exert significant immunomodulatory effects. They do not simply stimulate the immune system in a non-specific manner; rather, they help calibrate it towards a state of balanced responsiveness. By promoting a healthy microbiota and providing SCFAs, prebiotics support the development and function of regulatory T cells (Tregs), which are crucial for maintaining immune tolerance to commensal bacteria and dietary antigens while preventing excessive inflammatory responses (Swaggerty et al., 2022). This is achieved through SCFA-mediated signaling that promotes an anti-inflammatory milieu in the gut-associated lymphoid tissue (GALT). Additionally, prebiotics can enhance the production of secretory immunoglobulin A (sIgA), a key antibody that provides immune exclusion by trapping pathogens and toxins in the mucus layer, preventing their attachment to the epithelium (Tellez-Isaias et al., 2024). This refined immune status makes birds more resilient to infections and environmental stressors, such as heat stress, which can otherwise lead to immunosuppression (Sayed et al., 2023).

4.5. Inhibition of Pathogenic Microorganisms

Prebiotics can reduce pathogenic bacterial colonization through several mechanisms, including competitive exclusion, alteration of intestinal pH, increased SCFA production, and enhancement of mucosal defense. Certain prebiotics, particularly MOS, can bind bacterial surface structures and reduce attachment of pathogens to intestinal epithelial cells. Studies have demonstrated that prebiotic supplementation can decrease intestinal *Salmonella* populations and improve microbial safety in poultry products (Micciche et al., 2018; Abd El-Hack et al., 2022). Therefore, prebiotics provide a multifaceted approach for controlling intestinal pathogens without contributing to antimicrobial resistance. The inhibition of pathogenic microorganisms is a synergistic outcome of several aforementioned mechanisms. The lowered pH from SCFA production creates a direct chemical barrier. The competitive exclusion by a thriving population of beneficial bacteria limits the ecological niche available for pathogens. Moreover, some beneficial bacteria stimulated by prebiotics can produce their own antimicrobial substances, such as bacteriocins, which directly kill or inhibit competing pathogenic strains (Ashfaq et al., 2020). This multi-pronged approach makes it significantly harder for pathogens like *Salmonella* to establish a foothold and proliferate within the avian gastrointestinal tract, thereby reducing the risk of both clinical disease in the bird and the potential for foodborne pathogen contamination in the final product (Abd El-Hack et al., 2022).

4.6. Enhancement of Nutrient Utilization and Metabolism

By improving intestinal morphology, microbial balance, and digestive processes, prebiotics contribute to enhanced nutrient utilization. Increased populations of beneficial microorganisms support nutrient metabolism and improve the availability of minerals and other dietary components. Previous studies have reported that prebiotics such as MOS, β-glucans, and inulin improve nutrient digestibility, nitrogen utilization, and metabolic efficiency in poultry (Leone & Ferrante, 2023; Ferrocino et al., 2023). Finally, the enhancement of nutrient utilization and metabolism is the ultimate driver of improved growth performance, which is the primary economic goal in poultry production. The improved gut morphology (taller villi, greater surface area) directly facilitates more efficient digestion and absorption of nutrients from the feed (Yaqoob et al., 2021). A stable, healthy gut environment also reduces the energetic cost associated with chronic low-grade inflammation and immune activation, allowing more dietary energy to be directed towards growth and muscle deposition (Yadav & Jha, 2019). Furthermore, a balanced microbiota contributes to the host's metabolic capacity by synthesizing certain vitamins (e.g., B vitamins, vitamin K) and aiding in the breakdown of complex dietary components that the host enzymes cannot fully digest on their own (Fathima et al., 2022). Together, these mechanisms allow prebiotic-fed birds to achieve feed conversion ratios and weight gains that can rival those previously obtained with AGPs, making them a viable and sustainable cornerstone of modern, antibiotic-free poultry production systems (Adhikari & Kim, 2017; Yang et al., 2025).

5. Effects of Prebiotics on Poultry Production

Prebiotics have gained increasing attention in poultry nutrition because of their ability to improve production efficiency, maintain intestinal health, and support disease resistance without contributing to antimicrobial resistance. Their beneficial effects are mainly associated with modulation of intestinal microbiota, increased production of microbial metabolites, improved nutrient utilization, and regulation of immune responses. However, the effectiveness of prebiotics depends on factors such as prebiotic type, inclusion level, bird species, age, dietary composition, and environmental conditions (Abd El-Hack et al., 2022; Bevilacqua et al., 2024).

5.1. Improvement of Growth Performance and Feed Efficiency

Growth performance and feed efficiency are among the most important indicators for evaluating the effectiveness of functional feed additives in poultry production. Several studies have demonstrated that prebiotic supplementation can improve body weight gain (BWG) and feed conversion ratio (FCR) by creating a favorable intestinal environment and enhancing nutrient utilization. Mannan-oligosaccharides (MOS), fructooligosaccharides (FOS), and other oligosaccharides have been reported to improve broiler growth performance through stimulation of beneficial microorganisms and reduction of intestinal microbial disturbances (Ali et al., 2023; Nawaz et al., 2024). MOS supplementation has shown positive effects on body weight gain and feed efficiency, with responses comparable to antibiotic growth promoters, indicating its potential as a natural alternative to AGPs (Ali et al., 2023). Furthermore, prebiotic supplementation may improve performance under environmental stress conditions. Dietary administration of MOS and β-glucans in heat-stressed broilers enhanced growth rate, maintained beneficial microbial populations, and improved immune responses, suggesting that prebiotics can support production stability under challenging conditions (Sayed et al., 2023). Similarly, prebiotic supplementation during heat stress has been associated with improved growth performance and feed utilization efficiency (Awad et al., 2020).

5.2. Enhancement of Nutrient Digestibility and Utilization

Prebiotics improve nutrient utilization by modifying intestinal microbial activity, enhancing intestinal morphology, and increasing the efficiency of nutrient absorption. The fermentation products generated by beneficial bacteria contribute to improved digestive processes and nutrient availability. Supplementation with MOS and β-glucans has been shown to enhance ileal nutrient digestion and nitrogen utilization by improving intestinal structure and microbial activity (Leone & Ferrante, 2023). Inulin supplementation has also been reported to increase intestinal microbial functional capacity, which may contribute to improved nutrient uptake and gut health in broilers (Ferrocino et al., 2023).

In addition, prebiotics may influence mineral utilization. Wheat-derived prebiotic compounds have been associated with improved iron status through changes in intestinal conditions and enhanced mineral availability (Tako et al., 2014). Similarly, prebiotic supplementation has been reported to increase copper utilization in poultry (Leblebicier & Aydoğan, 2018).

5.3. Improvement of Gut Health and Intestinal Microbial Balance

The gastrointestinal tract plays a central role in poultry productivity, and maintaining microbial balance is essential for efficient digestion, nutrient absorption, and disease prevention. Prebiotics regulate intestinal microbiota by selectively promoting beneficial bacteria and suppressing harmful microorganisms. Dietary supplementation with FOS, MOS, and other oligosaccharides increases beneficial bacterial populations, particularly *Lactobacillus* and *Bifidobacterium*, while reducing pathogenic bacteria. These microbial changes enhance SCFA production, decrease intestinal pH, and create unfavorable conditions for pathogen growth (Pourabedin & Zhao, 2015; Morgan, 2023). Prebiotics also improve intestinal morphology by increasing villus height and enhancing the villus height-to-crypt depth ratio, which contributes to greater absorptive capacity and intestinal integrity (Rehman et al., 2020; Ali et al., 2023). These structural improvements support better nutrient utilization and overall production performance.

5.4. Enhancement of Immune Function and Disease Resistance

Prebiotics influence poultry immunity through interactions between intestinal microorganisms and host immune systems. By improving microbial balance and increasing beneficial microbial metabolites, prebiotics enhance both intestinal and systemic immune responses. Supplementation with MOS, β-glucans, and other prebiotic compounds has been associated with increased immunoglobulin levels, improved immune organ development, and enhanced resistance against infectious challenges in poultry (Sayed et al., 2023; Bayat et al., 2025). These effects demonstrate the potential of prebiotics to strengthen natural defense mechanisms in antibiotic-free production systems.

5.5. Reduction of Antibiotic Dependency

The global increase in antimicrobial resistance has accelerated the search for alternatives to antibiotic growth promoters in poultry production. Prebiotics provide a promising strategy because they improve intestinal health through ecological regulation rather than direct bacterial elimination. Unlike antibiotics, prebiotics selectively stimulate beneficial microorganisms and enhance intestinal conditions that limit pathogen development. This mechanism reduces pathogen pressure while maintaining microbial diversity within the gastrointestinal tract (Ricke, 2018; Solis-Cruz et al., 2019). Previous studies have reported that prebiotic supplementation can improve productivity and disease resistance while reducing the need for antibiotics in poultry production systems (Andrew Selaledi et al., 2020). Furthermore, agricultural and industrial by-product-derived prebiotics have been proposed as sustainable solutions for improving animal health and reducing dependence on antimicrobial agents (Ravanal et al., 2025).

5.6. Effects on Poultry Product Quality

In addition to improving growth and health parameters, prebiotics may influence poultry product quality through their effects on nutrient metabolism, intestinal function, and lipid regulation. Dietary inulin supplementation has been reported to maintain favorable meat physicochemical properties while providing a potential alternative to antibiotic growth promoters (Guaragni et al., 2020). Moreover, improvements in intestinal health and nutrient utilization associated with prebiotic supplementation may contribute indirectly to enhanced carcass characteristics and production quality (Tavaniello et al., 2018).

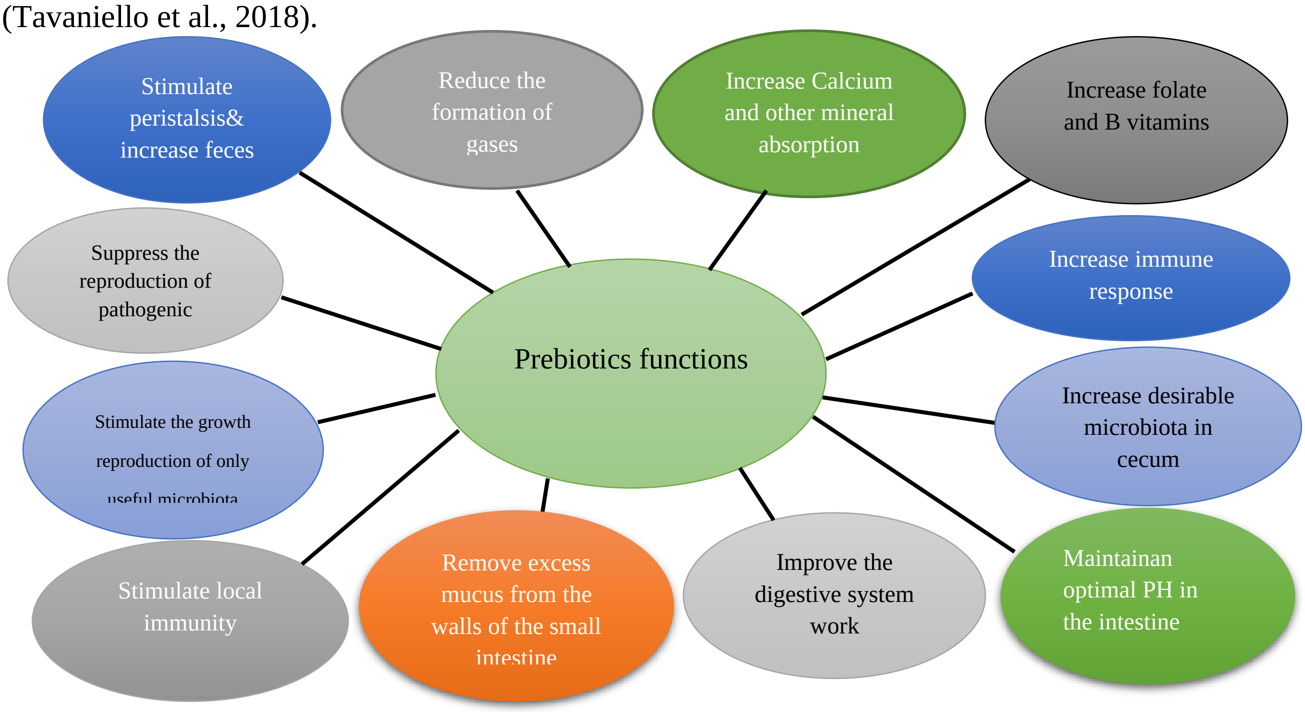

Figure 2. The main functions of prebiotics in poultry.

Table 1 Effects of dietary supplementation with different types of prebiotics on poultry gut microbiota and SCFAs concentrations

Effect	Name of Prebiotics	Amount (mg/kg)	Species	Age	Reference
Feeding 10,000 mg/kg FOS led to a reduction in the viable count of *Salmonella enteritidis*.	Fructo oligosaccharides	0,5000,10000 (mg/kg) of feed	Layer White Leghorn hens	60–65to weeks	Adhikari et al.,2018
Feeding 2,000 mg/kg resulted in increased ileal protein digestibility	Xylo-oligosaccharides	0, 50, 2000 (mg/kg)	Layer	39–47 weeks	Morgan et al.,2022
Increased acetate with 3500 mg/kg SBO.	Soybean oligosaccharides	3500,5000 (mg/kg)	Broiler	0–42days	Liu et al.,2021
Reduced pH of ileal and cecal, especially at the highest dose, without changing their concentration.	Fructo oligosaccharides	2000 (mg/kg)	Turkeys	0-56days	Juśkiewicz et al.,2006
Increased caecal *lactobacilli* and *bifidobacteria*, reduced *E. coli*, and elevated caecal VFA and non-VFA concentrations	isomalto-oligosaccharides +Probiotics+ Symbiotics	5000 IMO (mg/kg)	Broiler-(Ross 308)	0–42days	Mookiah et al.,2014
Increased *Lactobacillus* levels accompanied by reduced total coliforms and pH, along with improved ileum morphology.	Nutrition yeast (NY)	2000 (mg/kg)	Broiler-(Ross 308)	0–42days	Bayat et al.,2025
Enhanced propionic acid production with XOS	Xylo-oligosaccharides	0.250	Broiler- Ross	0–21days	Craig et al.,2020

6. Current Challenges and Research Gaps

Although prebiotics have demonstrated promising effects in poultry production, several challenges remain regarding their consistent application under commercial conditions. Variations in experimental outcomes among studies indicate that the effectiveness of prebiotics is influenced by multiple factors, including chemical structure, molecular size, degree of polymerization, inclusion level, bird genotype, age, diet composition, and environmental conditions (Gibson et al., 2017; Abd El-Hack et al., 2022).

One of the major challenges is the variation in responses among different prebiotic sources. Different prebiotic compounds do not produce identical biological effects because their fermentation characteristics and interactions with intestinal microorganisms vary. For example, MOS, FOS, GOS, and resistant starch may influence microbial populations through different pathways, making it difficult to establish universal recommendations regarding the most effective prebiotic type or dosage for specific poultry production systems (Pourabedin & Zhao, 2015; Bevilacqua et al., 2024).

Another important limitation is the lack of standardized dosage recommendations. Although many studies have reported beneficial effects of prebiotics, supplementation levels differ considerably among experiments. Excessive or insufficient inclusion rates may reduce their effectiveness or fail to produce measurable improvements in poultry performance. Therefore, dose–response studies under commercial production conditions are required to determine optimal inclusion levels for different poultry categories (Nawaz et al., 2024; Ali et al., 2023).

The complex interaction between prebiotics and intestinal microbiota represents another research challenge. The response of poultry to prebiotic supplementation depends on the existing microbial community, environmental conditions, and host factors. Advances in microbiome analysis have improved understanding of these interactions; however, further research is needed to identify specific microbial populations responsible for beneficial responses and to develop precision-based prebiotic strategies (Ferrocino et al., 2023; Xia et al., 2024).

The economic feasibility and practical application of prebiotics also require further investigation. Although prebiotics can improve poultry health and productivity, production costs, availability of raw materials, processing methods, and stability during feed manufacturing may affect their commercial adoption. The development of cost-effective prebiotic sources from agricultural and industrial by-products may provide sustainable solutions for large-scale poultry production (Ravanal et al., 2025).

Furthermore, limited information is available regarding the long-term effects of continuous prebiotic supplementation on poultry health, microbiome stability, and product quality. Most current studies focus on short-term experimental periods, whereas commercial poultry production requires evaluation throughout the entire production cycle. Long-term investigations are necessary to confirm safety, consistency, and economic benefits.

Finally, future studies should focus on precision nutrition approaches, including the integration of prebiotics with microbiome-based technologies, probiotics, enzymes, and other functional feed additives. Such approaches may improve predictability and maximize the benefits of prebiotics as sustainable alternatives to antibiotic growth promoters in poultry production systems (Sayed et al., 2023; Ravanal et al., 2025).

7. Future Perspectives and Research Directions

The increasing demand for sustainable poultry production systems and the global movement toward reducing antibiotic use have created new opportunities for the application of prebiotics as functional feed additives. Although prebiotics have demonstrated beneficial effects on poultry performance, intestinal health, and immunity, future research should focus on improving their predictability, efficiency, and practical application under commercial production conditions.

One important research direction is the development of precision prebiotic strategies. Since different prebiotic compounds produce variable responses depending on their chemical structure, fermentation characteristics, and interaction with intestinal microorganisms, future studies should identify specific prebiotics that target particular microbial populations and production objectives. The integration of microbiome sequencing and advanced bioinformatics approaches may help determine the most effective prebiotic–microbiota interactions and support personalized nutritional strategies for different poultry categories (Ferrocino et al., 2023; Xia et al., 2024).

Another promising area is the investigation of combined applications of prebiotics with other functional feed additives, including probiotics, enzymes, phytogenic compounds, and organic acids. These combinations may produce synergistic effects by simultaneously improving microbial balance, nutrient utilization, and immune responses. However, further research is required to determine optimal combinations, inclusion levels, and practical benefits under field conditions (Sayed et al., 2023; Ravanal et al., 2025).

Future studies should also emphasize the development of cost-effective and sustainable prebiotic sources. Agricultural residues and industrial by-products may represent valuable sources of novel prebiotic compounds; however, their extraction methods, consistency, safety, and biological effectiveness require further evaluation before large-scale application in poultry feed production (Ravanal et al., 2025).

The use of advanced analytical technologies, including metagenomics, metabolomics, and molecular approaches, will provide deeper insights into the mechanisms through which prebiotics influence host–microbiota interactions. These approaches may facilitate the identification of microbial biomarkers associated with improved growth performance, disease resistance, and feed efficiency.

Furthermore, future research should evaluate the long-term effects of prebiotic supplementation throughout the complete production cycle, including impacts on growth, reproductive performance, product quality, microbiome stability, and economic efficiency. Large-scale commercial trials are necessary to validate experimental findings and determine the feasibility of prebiotics under diverse production systems.

Overall, future advances in prebiotic research should move from general supplementation approaches toward targeted, microbiome-driven nutritional strategies. Such developments will strengthen the role of prebiotics as sustainable alternatives to antibiotic growth promoters and contribute to the advancement of environmentally responsible poultry production systems.

8. CONCLUSION

Prebiotics represent promising functional feed additives for improving the sustainability and efficiency of poultry production systems. Their ability to selectively stimulate beneficial intestinal microorganisms contributes to improved microbial balance, enhanced intestinal function, and better host responses. Different prebiotic classes, including fructans, galacto-oligosaccharides, mannan-oligosaccharides, resistant starch, lactulose, and other oligosaccharides, have demonstrated beneficial effects on poultry performance, nutrient utilization, intestinal integrity, and immune regulation. The beneficial effects of prebiotics are mainly associated with modulation of gut microbiota, increased production of short-chain fatty acids, reduction of intestinal pH, improvement of intestinal morphology, and limitation of pathogenic bacterial colonization. These mechanisms support their potential as alternatives to antibiotic growth promoters by enhancing natural disease resistance and maintaining productivity without increasing antimicrobial resistance risks (Ricke, 2018; Solis-Cruz et al., 2019). However, variations in responses among studies indicate that the effectiveness of prebiotics depends on factors such as compound type, dosage, bird characteristics, dietary composition, and environmental conditions. Therefore, future research should focus on precision-based prebiotic applications, microbiome-driven approaches, long-term safety evaluations, and cost-effective strategies for commercial poultry production. Overall, prebiotics provide a valuable approach for developing antibiotic-free and sustainable poultry production systems. Their integration with advanced nutritional technologies and evidence-based feeding strategies may further enhance their role in improving poultry health, productivity, and environmental sustainability.

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7. REFERENCES

Abbas, M., Saeed, F., Anjum, F. M., Tufail, T., Bashir, M. S., & Ishtiaq, A. (2017). Natural polyphenols: An overview Natural polyphenol: An overview. International Journal of Food Properties, 20(8), 1689–1699. https://doi.org/10.1080/10942912.2016.1220393

Abd El-Hack, M. E., El-Saadony, M. T., Shafi, M. E., Alshahrani, O. A., Saghir, S. A. M., Al-wajeeh, A. S., … Abdel-Moneim, A. M. E. (2022). Prebiotics can restrict Salmonella populations in poultry: a review. Animal Biotechnology, 33(7), 1668–1677. https://doi.org/10.1080/10495398.2021.1883637

Adhikari, P., Cosby, D. E., Cox, N. A., Franca, M. S., Williams, S. M., Jr, R. M. G., Ritz, C. W., & Kim, W. K. (2015). Effect of dietary fructooligosaccharide supplementation on internal organs Salmonella colonization , immune response , ileal morphology , and ileal immunohistochemistry in laying hens challenged with Salmonella enteritidis. Poultry Science, 97(7), 2525–2533. https://doi.org/10.3382/ps/pey101

Adhikari, P. A., & Kim, W. K. (2017). Overview of Prebiotics and Probiotics: Focus on Performance, Gut Health and Immunity – A Review. Annals of Animal Science, 17(4), 949–966. https://doi.org/10.1515/aoas-2016-0092

Ahmed, M. M. N., & Ismail, Z. S. H. (2018). APPLICATION OF PREBIOTICS AS FEED ADDITIVES IN POULTRY NUTRITION-A REVIEW. 5623(38).

Aït-Aissa, A., & Aïder, M. (2014). Lactulose: production and use in functional food, medical and pharmaceutical applications. Practical and critical review. International journal of food science and technology, 49(5), 1245-1253.

Ajuwon, K. M. (2015). Toward a better understanding of mechanisms of probiotics and prebiotics action in poultry species 1. Poultry Science, 25(2), 277–283. https://doi.org/10.3382/japr/pfv074

Al-baadani, H. H., Aboragah, A. A., Alharthi, A. S., & Alhotan, R. A. (2025). Interaction effect of prebiotic products as feed additives and rearing systems on performance , slaughter yield and intestinal health of broiler chickens. Journal of Applied Poultry Research, 34(2), 100535. https://doi.org/10.1016/j.japr.2025.100535

Aleli, A. T. (2023). Efficacy of Garlic (Allium Sativum) Supplement on Productive Performances and Egg Qualities of Layers: A Review. Animal and Veterinary Sciences, 11(6), 168-171.

Ali, A., Qureshi, A. S., Rehan, S., Deeba, F., Usman, M., & Ateeq, M. K. (2023). Prebiotic, probiotic, and antibiotic growth promoters use in commercial broilers: A comparative study. Journal of the Hellenic Veterinary Medical Society, 74(3), 5929-5936.

Ali, S., Hamayun, M., Siraj, M., Afzal, S., Kim, H., & Lee, B. (2025). Recent advances in prebiotics : Classification , mechanisms , and health applications. Future Foods, 12(June), 100680. https://doi.org/10.1016/j.fufo.2025.100680

Ambrogi, V., Bottacini, F., Cao, L., Kuipers, B., & Sinderen, D. Van. (2023). Galacto-oligosaccharides as infant prebiotics : production , application , bioactive activities and future perspectives. Critical Reviews in Food Science and Nutrition, 63(6), 753–766. https://doi.org/10.1080/10408398.2021.1953437

Andrew Selaledi, L., Mohammed Hassan, Z., Manyelo, T. G., & Mabelebele, M. (2020). The Current Status of the Alternative Use to Antibiotics in Poultry Production: An African Perspective. Antibiotics, 9(9), 594. https://doi.org/10.3390/antibiotics9090594

Ashfaq, I., Amjad, H., Ahmad, W., Nasir, A., Ali, A., Ali, W. R., Khaliq, S., Hayat, A., Ali, H., Sattar, F., Ghauri, M. A., & Anwar, M. A. (2020). Growth Inhibition of Common Enteric Pathogens in the Intestine of Broilers by Microbially Produced Dextran and Levan Exopolysaccharides. Current Microbiology, 77(9), 2128–2136. https://doi.org/10.1007/s00284-020-02091-3

Atuahene, D., Sam, B. A., Idan, F., Sana, S. S., Knop, R., Suthar, T., Kumar, H., & Shaikh, A. M. (2025). Probiotics , Prebiotics , and Synbiotics in Pigs and Poultry : A Review of Gut Health , Performance , and Environmental Outcomes. 1–29.

Awad, E. A., Zulkifli, I., Ramiah, S. K., Khalil, E. S., & Abdallh, M. E. (2021). Prebiotics supplementation: an effective approach to mitigate the detrimental effects of heat stress in broiler chickens. World's Poultry Science Journal, 77(1), 135–151. https://doi.org/10.1080/00439339.2020.1759222

Babbar, N., Dejonghe, W., Gatti, M., Sforza, S., & Elst, K. (2016). Pectic oligosaccharides from agricultural by-products: production, characterization and health benefits. Critical Reviews in Biotechnology, 36(4), 594–606. https://doi.org/10.3109/07388551.2014.996732

Bednarczyk M, Stadnicka K, Kozłowska I, et al. Influence of different prebiotics and mode of their administration on broiler chicken performance. Animal 2016; 10:12719. https://doi.org/10.1017/S1751731116000173

Bayat, M., Kuhi, H. D., Mehr, M. R., Hossein-zadeh, N. G., Kuhi, D., Mehr, R., & Hossein-zadeh, G. (2025). Original Article Effect of Dietary Prebiotic Supplementation on the Immune Response and Intestinal Health Following Eimeria Infection of Broiler Chicken. 19(4), 767–784.

BeMiller, J. N. (2020). Resistant starch. In Science and Technology of Fibers in Food Systems (pp. 153-183). Cham: Springer International Publishing.

Bevilacqua, A., Campaniello, D., Speranza, B., Corbo, M. R., Racioppo, A., & Sinigaglia, M. (2024). An Update on Prebiotics and on Their Health Effects.

Bloom, P. P., & Tapper, E. B. (2023). Lactulose in cirrhosis : Current understanding of efficacy , mechanism , and practical considerations. 0(July), 1–9. https://doi.org/10.1097/HC9.0000000000000295

Chu, N., Ling, J., Jie, H., Leung, K., & Poon, E. (2022). The potential role of lactulose pharmacotherapy in the treatment and prevention of diabetes. September, 1–10. https://doi.org/10.3389/fendo.2022.956203

Demirci, M. (2026). probiotic & enzyme combination on performance ,. 53–65.

Ducatelle, R., Goossens, E., Eeckhaut, V., & Van Immerseel, F. (2023). Poultry gut health and beyond. Animal Nutrition, 13, 240–248. https://doi.org/10.1016/j.aninu.2023.03.005

Efremova, A. (2018). Role of poultry industry in public food supply. 7(2), 29–36. https://doi.org/10.22630/ESARE.2018.2.2

Fathima, S., Shanmugasundaram, R., Adams, D., & Selvaraj, R. K. (2022). Gastrointestinal Microbiota and Their Manipulation for Improved Growth and Performance in Chickens. Foods, 11(10), 1401. https://doi.org/10.3390/foods11101401

Fara, A., Sabater, C., Palacios, J., Montilla, A., Zárate, G., & Requena, T. (2020). Function Prebiotic galactooligosaccharides production from lactose and lactulose by Lactobacillus delbrueckii. 5875–5886. https://doi.org/10.1039/d0fo00942c

Ferrocino, I., Biasato, I., Dabbou, S., Colombino, E., Rantsiou, K., & Squara, S. (2023). lactiplantibacillus pentosus and inulin meal inclusion boost the metagenomic function of broiler chickens.

Franco-robles, E., & López, M. G. (2015). Implication of Fructans in Health : Immunomodulatory and Antioxidant Mechanisms. 2015. https://doi.org/10.1155/2015/289267

Froebel, L. K., Jalukar, S., Lavergne, T. A., Lee, J. T., & Duong, T. (2016). Administration of dietary prebiotics improves growth performance and reduces pathogen colonization in broiler chickens. 6668–6676. https://doi.org/10.3382/ps/pez537

Gibson, G. R., Hutkins, R. W., & Prescott, S. L. (2017). The International Scientific Association for Probiotics and Prebiotics (ISAPP) Consensus Statement on the Definition and Scope of Prebiotics.

Guaragni, A., Boiago, M. M., Bottari, N. B., Morsch, V. M., Lopes, T. F., & da Silva, A. S. (2020). Feed supplementation with inulin on broiler performance and meat quality challenged with Clostridium perfringens: Infection and prebiotic impacts. Microbial pathogenesis, 139,103889.

Gutiérrez, T. J., & Tovar, J. (2021). Update of the concept of type 5 resistant starch (RS5): Self-assembled starch V-type complexes. Trends in Food Science & Technology, 109, 711-724.

Gorlov, I. F., Slozhenkina, M. I., Mosolova, D. A., Viktorovna, L., Komarova, Z. B., Nikulin, V. N., & Struk, E. A. (2024). Lactulose with synergists supplementation improving a health of chicks and reducing the environmental burden in poultry industry. 7710(June), 429–438.

Hernández, L., & Plou, F. J. (2023). Fructans: the terminology. In The book of fructans (pp. 3-10). Academic Press.

Hussain, R., Noor, M., Khalid, S., Basharat, N., Arif, M. S., Iffat, A., Shoukat, M. F., Naveed, K., Zeb, H., & Mehmood, A. (2025). A comprehensive review on resistant starch , its types , sources, application and health benefits. 14(2), 531–542.

Ibrahim, N. S., Ahmed, A. B. N., & Abdel-Raheem, G. S. (2021). Impact of dietary supplementation of prebiotics on the growth performance and immunity in broilers fed low protein diets. Assiut Veterinary Medical Journal, 67(171), 103-119.

Intanon, M., Arreola, S.L., Pham, N.H., Kneifel, W., Haltrich, D., Nguyen, T.H., 2014. Nature and biosynthesis of galacto-oligosaccharides related to oligosaccharides in human breast milk. FEMS Microbiol. Lett. 353, 89-97.

Ivanova, S., Sukhikh, S., Popov, A., Shishko, O., Nikonov, I., Kapitonova, E., Krol, O., Larina, V., Noskova, S., & Babich, O. (2024). Medicinal plants : A source of phytobiotics for the feed additives. Journal of Agriculture and Food Research, 16(March), 101172. https://doi.org/10.1016/j.jafr.2024.101172

Jacob, J. P., & Pescatore, A. J. (2014). Barley β -glucan in poultry diets. 2(3). https://doi.org/10.3978/j.issn.2305-5839.2014.01.02

Jilo, S. A., & Hasan, L. A. (2022). The importance of poultry meat in medicine: A review. Journal of World's Poultry Research, 12(4), 258-262.

Johnson, A., Hwang, A. H., Bueno, A. I., Miller, A. B. E. A., Valeris-chacin, A. R., Nault, A. C. A. J., Singer, R. S., & Ae, T. J. J. (2025). Original Article — Efficacy of Prebiotics and Probiotics on Growth Performance in Turkeys : A Systematic Review. 45–57.

Juśkiewicz, J., Jankowski, J., Zduńczyk, Z., & Mikulski, D. (2006). Performance and gastrointestinal tract metabolism of turkeys fed diets with different contents of fructooligosaccharides. Poultry science, 85(5), 886-891.

Khosravi, A., Boldaji, F., Dastar, B., Amir, M., Torshizi, K., Alemi, M., & Hoseinifar, S. H. (2025). OPEN A Symbiotics improves performance and gut health in broiler chickens. 1–12. https://doi.org/10.1016/j.psj.2025.105878

Kumar, V., Bahuguna, A., Kumar, S., & Kim, M. (2025). Xylooligosaccharides mediated gut microbiome modulation: prebiotics to postbiotics. Critical Reviews in Biotechnology , 45(5), 1098–1116. https://doi.org/10.1080/07388551.2025.2460852

Leblebicier, Ö. D. Y., & Aydoğan, İ. (2018). The effects of mannan oligosaccharide and chitosan oligosaccharide on performance and blood parameters of broilers. Journal of Poultry Research, 15(1), 18-22.

biotics on performance , animal welfare and environmental impact . A review. Science of the Total Environment, 901(April), 165951. https://doi.org/10.1016/j.scitotenv.2023.165951

Liang, S., Sun, Y., & Dai, X. (2018). A Review of the Preparation , Analysis and Biological Functions of Chitooligosaccharide. https://doi.org/10.3390/ijms19082197

Lipiński, K., Mazur, M., Antoszkiewicz, Z., & Purwin, C. (2017). Polyphenols in monogastric nutrition-a review.

Liu, H. Y., Li, X., Zhu, X., Dong, W. G., & Yang, G. Q. (2021). Animal The international journal of animal biosciences Soybean oligosaccharides attenuate odour compounds in excreta by modulating the caecal microbiota in broilers. 15. https://doi.org/10.1016/j.animal.2020.100159

Liu, Y. S., Zhang, Y. Y., Xing, T., Li, J. L., Wang, X. F., Zhu, X. D., … Gao, F. (2020). Glucose and lipid metabolism of broiler chickens fed diets with graded levels of corn resistant starch. British Poultry Science, 61(5), 599–607. https://doi.org/10.1080/00071668.2020.1774511

Lockyer, S., & Nugent, A. P. (2017). Health effects of resistant starch. Nutrition bulletin, 42(1), 10-41.

Malli, I., Awadh, A., & Shakoori, A. (2025). The efficacy of probiotics and prebiotics in reducing fecal and cloacal colonization of Salmonella spp . in chickens : a systematic review and meta-analysis. World's Poultry Science Journal, 81(2), 459–480. https://doi.org/10.1080/00439339.2025.2492562

Mansouri, M., Hammami, N., Yahia, A., Saidani, K., Boumahdi, Z., Tarzaali, D., & Mimoune, N. (2025). Impact of prebiotic supplementation on the zootechnical and health performance in broiler chickens. 2025(12), 442–451.

Mehdi Y, LétourneauMontminy MP, Gaucher ML, et al. Use of antibiotics in broiler production: Global impacts and alternatives. Anim Nutr 2018;4:1708. https://doi.org/10.1016/ j.aninu.2018.03.002

Mei, Z., Yuan, J., & Li, D. (2022). Biological activity of. September, 1– https://doi.org/10.3389/fmicb.2022.993052

Micciche, A. C., Foley, S. L., Pavlidis, H. O., Mcintyre, D. R., & Ricke, S. C. (2018). A Review of Prebiotics Against Salmonella in Poultry : Current and Future Potential for Microbiome Research Applications. 5(August), 1–11. https://doi.org/10.3389/fvets.2018.00191

Mnisi, C. M., Dibakoane, S. R., Mpofu, B. I., Kumalo, I., Sekano, K., Mhlongo, G., Wokadala, O. C., & Mlambo, V. (2025). Green banana resistant starch as a candidate prebiotic in poultry diets : Mechanisms , limitations , and prospects. Poultry Science, 104(11), 105878. https://doi.org/10.1016/j.psj.2025.105878

Mnisi, C. M., Mlambo, V., Montso, P. K., Manyeula, F., Kumanda, C., & Moreki, J. C. (2024). Nutraceuticals as components of sustainable poultry production systems for food and nutrition security in Africa : a review. Agriculture & Food Security, 1–12. https://doi.org/10.1186/s40066-024-00477-1

Mohammed, M. A. (2025). Use of Probiotics , Prebiotics , and Synbiotic in Poultry Nutrition : A review. 196–209.

Mookiah, S., Sieo, C. C., Ramasamy, K., Abdullah, N., & Ho, Y. W. (2014). Effects of dietary prebiotics, probiotic and synbiotics on performance, caecal bacterial populations and caecal fermentation concentrations of broiler chickens. Journal of the Science of Food and Agriculture, 94(2), 341-348.

Morgan, N. K. (2023). Advances in prebiotics for poultry: role of the caeca and oligosaccharides. Animal production science, 63(18), 1911-1925.

Morgan, N. K., Wallace, A., Bedford, M. R., & González-Ortiz, G. (2022). Impact of fermentable fiber, xylo-oligosaccharides and xylanase on laying hen productive performance and nutrient utilization. Poultry science, 101(12), 102210.

Mukherjee, S., Patel, P., & John, S. (2024). Lactulose. In StatPearls [Internet]. StatPearls Publishing.

Nawaz, A., Usman, M., Ali, M., Ahmad, A., Jahangir, M., Şahin, T., ... & Sarmad, M. (2024). Effects of prebiotics on metabolic activity in broilers. BIOLOGICAL AND CLINICAL SCIENCES RESEARCH JOURNAL Учредители: Medeye Publishers, 2024(1), 1075.

Obayomi, O. V., Olaniran, A. F., & Owa, S. O. (2024). Unveiling the role of functional foods with emphasis on prebiotics and probiotics in human health: A review. Journal of Functional Foods, 119, 106337.

Obianwuna, U. E., Chang, X., Okoleh, V. U. O., Onu, P. N., Zhang, H., Qiu, K., & Wu, S. (2024). Phytobiotics in poultry : revolutionizing broiler chicken nutrition with plant - derived gut health enhancers. 9, 1–33. https://doi.org/10.1186/s40104-024-01101-9

Oke, O. E., Fasasi, L. O., Opowoye, I. O., & Akosile, O. A. (2025). The role of gut microbiota-derived metabolites in modulating poultry immunometabolism. Frontiers in Physiology, 16. https://doi.org/10.3389/fphys.2025.1700406

Oni, O. O., Alabi, J. O., & Adebayo, R. M. (2020). Comparative efficacy of lactose and mannan-oligosaccharides on performance, nutrient digestibility and health status of broiler chicks. Indian J. Poult. Sci, 55(2), 121-128.

Pashaei, M., Fayçal, Z., Kahrizi, D., & Ercisli, S. (2024). Medicinal Plants and Natural Substances for Poultry Health: A Review. The Journal of Poultry Sciences and Avian Diseases, 2(2), 36-49.

Pitino, R., Marchi, M. De, Manuelian, C. L., Johnson, M., Simoni, M., Righi, F., & Tsiplakou, E. (2021). Plant Feed Additives as Natural Alternatives to the Use of Synthetic Antioxidant Vitamins on Yield , Quality , and Oxidative Status of Poultry Products : A Review of the Literature of the Last 20 Years.

Plamada, D., & Vodnar, D. C. (2022). Polyphenols—Gut Microbiota Interrelationship: A Transition to a New Generation of Prebiotics. Nutrients, 14(1), 137. https://doi.org/10.3390/nu14010137

Pourabedin, M., & Zhao, X. (2015). Prebiotics and gut microbiota in chickens. FEMS microbiology letters, 362(15), fnv122.

Purnamasari, L., dela Cruz, J. F., & dela Cruz, K. J. V. (2022). The potential of beta-glucan as feed additives in broiler chickens: A review. Jurnal Ilmu Peternakan Terapan, 6(1), 18-28.

Ravanal, M. C., Contador, C. A., Wong, W., Zhang, Q., Roman-benn, A., Ah-hen, K. S., Ulloa, P. E., & Lam, H. (2025). Prebiotics in animal nutrition : Harnessing agro-industrial waste for improved gut health and performance. Animal Nutrition, 21, 179–192. https://doi.org/10.1016/j.aninu.2024.11.025

Rehman, A., Arif, M., Sajjad, N., Alagawany, M., El-hack, M. E. A., Alhimaidi, A. R., Elnesr, S. S., Almutairi, B. O., Amran, R. A., Hussein, E. O. S., & Swelum, A. A. (2019). Dietary effect of probiotics and prebiotics on broiler performance , carcass , and immunity. Poultry Science, 99(12), 6946–6953. https://doi.org/10.1016/j.psj.2020.09.043

Reznichenko, A. A. (2019, August). The use of prebiotics in broiler poultry as an alternative to antibacterial drugs. In IOP Conference Series: Earth and Environmental Science (Vol. 315, No. 2, p. 022037). IOP Publishing.

Reznichenko, A., Reznichenko, L., Dorozhkin, V., Noskov, S., & Vodianitskaia, S. (2021). Prospects of the use of prebiotics in broiler poultry farming as an alternative to antibiotics. 00156, 1–5.

Ricke, S. C. (2018). Impact of Prebiotics on Poultry Production and Food Safety. 91, 151–159.

Ricke, S. C., Lee, S. I., Kim, S. A., & Park, S. H. (2019). Prebiotics and the poultry gastrointestinal tract microbiome. Poultry Science, 99(2), 670–677. https://doi.org/10.1016/j.psj.2019.12.018

Ruangpanit, Y., Rassmidatta, K., Philatha, A., & Saothong, P. (2025). Effects of fructooligosaccharide administration routes on growth performance , gut integrity , microbiota , and meat quality in broiler chickens exposed to reused litter. Poultry Science, 104(11), 105899. https://doi.org/10.1016/j.psj.2025.105899

Sarmad, M., Umar, M., Zunaira, N. U., Asif, H., Usman, M., Faiz, A., ... & Buzdar, J. A. Use of Natural Feed Additives in Broiler Birds: Updated Knowledge. Complementary and Alternative Medicine: Feed Additives, 9.

Sarangi NR, Babu LK, Kumar A, Pradhan CR, Pati PK, Mishra JP. Effect of dietary supplementation of prebiotic, probiotic, and synbiotic on growth performance and carcass characteristics of broiler chickens. Vet World 2016; 9:3139. https:// doi.org/10.14202/vetworld.2016.313319

Sayed, Y., Hassan, M., Salem, H. M., Amry, K. Al, & Eid, G. E. (2023). Prophylactic influences of prebiotics on gut microbiome and immune response of heat - stressed broiler chickens. Scientific Reports, 1–17. https://doi.org/10.1038/s41598-023-40997-7

Slawinska, A., Dunislawska, A., Plowiec, A., Radomska, M., Lachmanska, J., Siwek, M., Tavaniello, S., Maiorano, G., 2019. Modulation of microbial communities and mucosal gene expression in chicken intestines after galactooligosaccharides delivery In Ovo. PLOS ONE. 14, e0212318.

Sciences, V. I. (2025). Effects of galacto-oligosaccharides on growth performance and gut health in broiler chickens. 23(January 2023), 1–14. https://doi.org/10.12982/VIS.2025.029

Shani, M. A., & Irani, M. (2024). Feeding strategy and prebiotic supplementation: Effects on immune responses and gut health in the early life stage of broiler chickens. Research in Veterinary Science, 171, 105226.

Singh, R. P., Prakash, S., Bhatia, R., Negi, M., Singh, J., Bishnoi, M., & Kondepudi, K. K. (2020). Generation of structurally diverse pectin oligosaccharides having prebiotic attributes. Food Hydrocolloids, 108, 105988.

Sizova, E. A., & Shoshin, D. E. (2025). Influence of lactulose as a composition of organic-mineral feed additive on broiler chicken productivity , feed digestibility , and microbiome. 18, 2095–2105. https://doi.org/10.14202/vetworld.2025.2095-2105

Solis-Cruz, B., Hernandez-Patlan, D., Hargis, B. M., & Tellez, G. (2019). Use of prebiotics as an alternative to antibiotic growth promoters in the poultry industry. In Prebiotics and Probiotics-Potential Benefits in Nutrition and Health. IntechOpen.

Swaggerty, C. L., Bortoluzzi, C., Lee, A., Eyng, C., Pont, G. D., & Kogut, M. H. (2022). Potential Replacements for Antibiotic Growth Promoters in Poultry: Interactions at the Gut Level and Their Impact on Host Immunity (pp. 145–159). https://doi.org/10.1007/978-3-030-85686-1_8

Tako, E., Glahn, R. P., Knez, M., & Stangoulis, J. C. (2014). The effect of wheat prebiotics on the gut bacterial population and iron status of iron deficient broiler chickens. Nutrition Journal, 13(1), 58.

Tan, F. P., Beltranena, E., & Zijlstra, R. T. (2021). Resistant starch: Implications of dietary inclusion on gut health and growth in pigs: A review. Journal of animal science and biotechnology, 12(1), 124.

Tang, W., Han, T., Liu, W., He, J., & Liu, J. (2025). Pectic oligosaccharides: enzymatic preparation, structure, bioactivities and application. Critical Reviews in Food Science and Nutrition, 65(11), 2117–2133. https://doi.org/10.1080/10408398.2024.2328175

Tavaniello, S., Maiorano, G., Stadnicka, K., Mucci, R., Bogucka, J., & Bednarczyk, M. (2017). Prebiotics offered to broiler chicken exert positive effect on meat quality traits irrespective of delivery route. Poultry Science, 97(8), 2979–2987. https://doi.org/10.3382/ps/pey149

Tellez-Isaias, G., Hernandez-Patlan, D., Solis-Cruz, B., El-Ashram, S., & Al-Olayan, E. (2024). The use of probiotics and prebiotics to improve gut function and immunity in poultry: unlocking the secrets of avian wellness (pp. 367–389). https://doi.org/10.19103/AS.2024.0143.18

Teng, P.-Y., & Kim, W. K. (2018). Review: Roles of Prebiotics in Intestinal Ecosystem of Broilers. Frontiers in Veterinary Science, 5. https://doi.org/10.3389/fvets.2018.00245

Tingirikari, J. M. R. (2018). Microbiota-accessible pectic poly-and oligosaccharides in gut health. Food & function, 9(10), 5059-5073

Uçar, A., & Türkoğlu, M. (2018). Efficiency of Poultry Production in terms of Quality and Balanced Nutrition. Turkish Journal of Agriculture - Food Science and Technology, 6(1), 69–72. https://doi.org/10.24925/turjaf.v6i1.69-72.1739

Varasteh, S., Braber, S., Akbari, P., Garssen, J., & Fink-, J. (2015). Differences in Susceptibility to Heat Stress along the Chicken Intestine and the Protective Effects of Galacto- Oligosaccharides. 1–18. https://doi.org/10.1371/journal.pone.0138975

Vera, C., Córdova, A., Aburto, C., Guerrero, C., Suárez, S., & Illanes, A. (2016). Synthesis and purification of galacto-oligosaccharides: state of the art. World journal of microbiology & biotechnology, 32(12), 197. https://doi.org/10.1007/s11274-016-2159-4

Versluys, M. (2017). The fructan syndrome : Evolutionary aspects and common themes among plants and microbes. September, 16–38. https://doi.org/10.1111/pce.13070

Xia, J., Cui, Y., Guo, Y., Liu, Y., & Deng, B. (2024). The Function of Probiotics and Prebiotics on Canine Intestinal Health and Their Evaluation Criteria.

Yadav, S., & Jha, R. (2019). Strategies to modulate the intestinal microbiota and their effects on nutrient utilization, performance, and health of poultry. Journal of Animal Science and Biotechnology, 10(1), 2. https://doi.org/10.1186/s40104-018-0310-9

Yang, X., Bist, R. B., Subedi, S., Guo, Y., & Chai, L. (2025). The Application of Probiotics and Prebiotics in Poultry Production and Impacts on Environment : A Review.

Yaqoob, M. U., El-hack, M. E. A., Hassan, F., El-saadony, M. T., Khafaga, A. F., Batiha, G. E., Yehia, N., Elnesr, S. S., Alagawany, M., El-tarabily, K. A., & Wang, M. (2021). The potential mechanistic insights and future implications for the effect of prebiotics on poultry performance , gut microbiome , and intestinal morphology. Poultry Science, 100(7), 101143. https://doi.org/10.1016/j.psj.2021.101143

Yoo, S., Jung, S.-C., Kwak, K., & Kim, J.-S. (2024). The Role of Prebiotics in Modulating Gut Microbiota: Implications for Human Health. International Journal of Molecular Sciences, 25(9), 4834. https://doi.org/10.3390/ijms25094834

Yue, T., Lu, Y., Ding, W., Xu, B., Zhang, C., Li, L., Jian, F., & Huang, S. (2025). The Role of Probiotics, Prebiotics, Synbiotics, and Postbiotics in Livestock and Poultry Gut Health: A Review. Metabolites, 15(7), 478. https://doi.org/10.3390/metabo15070478

Zaman, S. A., & Sarbini, S. R. (2016). The potential of resistant starch as a prebiotic. Reviews in Biotechnology, 36(3), 578–584. https://doi.org/10.3109/07388551.2014.993590

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