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Machine Learning-Based Agricultural Crop Yield Prediction for Sustainable Economic Development in Afghanistan

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Abstract. *Afghanistan's economy remains heavily dependent on rain-fed and irrigated agriculture, a sector that employs the majority of the rural workforce yet is increasingly threatened by rising temperatures, erratic precipitation, and recurrent drought, so timely and reliable crop yield forecasts are essential for food-security planning, market stabilization, and rural income protection, even though conventional statistical and agronomic estimation methods struggle to capture the nonlinear interactions among climatic, soil, and management variables that drive yield variability. This paper develops a conceptual machine learning (ML)-based framework for crop yield prediction adapted to the data, infrastructure, and institutional conditions of Afghanistan, using a narrative synthesis of recent literature on machine learning and deep learning approaches to crop yield estimation together with Afghanistan-specific studies on climate change and agricultural productivity. The synthesis yields a four-layer framework, comprising data, processing, model, and decision layers, together with an implementation pipeline spanning data collection, preprocessing, feature selection, model training, validation, and advisory deployment, accommodating heterogeneous inputs including meteorological records, satellite-derived vegetation indices, soil parameters, and historical yield statistics, and comparing ensemble methods (Random Forest, XGBoost), kernel-based methods (Support Vector Machines), and deep architectures (CNN, LSTM, and CNN-LSTM hybrids) reported in the literature. The discussion shows how such a framework could support the Ministry of Agriculture, Irrigation and Livestock and development partners in strengthening early-warning systems, guiding input allocation, and advancing Sustainable Development Goal 2 in a fragile, data-scarce environment; because the paper is conceptual and does not report primary empirical results, it concludes with a discussion of implementation barriers, including connectivity, data governance, and capacity constraints, and directions for future empirical validation using field-level Afghan agricultural data. By improving the potential timeliness and spatial specificity of crop-yield information, the framework could support evidence-based planning related to sustainable food production, agricultural resilience, and climate-risk management. These potential contributions are aligned particularly with SDG 2 (Zero Hunger), while their actual magnitude remains subject to future empirical validation using Afghan agricultural data.*

Keywords: *Crop Yield Prediction; Food Security; Machine Learning; Precision Agriculture; Sustainable Development*

1. Introduction

Agriculture remains the structural backbone of Afghanistan's economy and the primary livelihood source for the majority of its rural population, contributing close to a quarter of national gross domestic product and employing an estimated seven in ten rural

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workers (Wafa et al., 2024). Wheat alone is cultivated on roughly 85% of the country's cropped area, and food grains as a whole account for nearly three-quarters of total cropped land, leaving national food security tightly coupled to the performance of a narrow set of staple crops (Wafa et al., 2024). This dependence has become increasingly precarious. Afghanistan is repeatedly ranked among the countries most exposed to climate variability, with recurrent drought, erratic precipitation, and rising mean temperatures already measurably reducing cereal productivity (World Bank Group, 2021; WFP & UNEP, 2016).

Empirical studies of Afghan agriculture document the scale of this exposure. Panel and downscaling analyses project that mean wheat yields could fall by more than a fifth over the coming decades under continued warming, with comparable declines projected for barley and rice (Wafa et al., 2024), while a one-degree Celsius rise in mean temperature has already been associated with measurable reductions in wheat and barley yields per hectare (Sharma et al., 2015). Precipitation trends across the country are spatially uneven, declining in the southwest and northwest while shifting unpredictably elsewhere (Aliyar & Esmailnejad, 2022), and Afghanistan's glacier-fed river systems, which underpin much of the country's irrigation, are themselves under strain from rapid climate warming (Shokory et al., 2023). Composite climatic assessment indicators combining temperature, precipitation, and radiation variables have proven useful elsewhere in Asia for tracking how shifting climate regimes translate into cereal-yield risk (Xu et al., 2019), an approach with direct relevance to Afghanistan's own wheat-dependent agro-climatic zones. Farmers report direct awareness of these shifts and have already begun adapting cropping calendars and water use in response (Sarwary et al., 2021), yet these autonomous adaptations are rarely informed by predictive tools capable of anticipating yield outcomes before the growing season ends. The socio-economic consequences are substantial: reduced yields translate directly into higher food prices, lower agricultural wages, and deepening food insecurity for a population in which roughly a quarter already experiences acute food insecurity (Savage et al., 2009; World Bank Group, 2021).

Outside Afghanistan, a large and rapidly growing body of research has demonstrated that machine learning (ML) methods can substantially improve the accuracy of crop yield prediction relative to conventional agronomic and statistical models. A systematic review of the field found that ensemble tree-based methods and, increasingly, deep learning architectures now dominate the literature, owing to their capacity to model nonlinear interactions among weather, soil, and management variables that simple regression models cannot capture (van Klompenburg et al., 2020). Random Forest and gradient-boosted models such as XGBoost have been applied successfully to a range of staple and cash crops, including potato and maize in Rwanda (Kuradusenge et al., 2023), sugarcane using ensemble learning on meteorological data (Kumar et al., 2024), and winter wheat combining satellite-derived solar-induced chlorophyll fluorescence with XGBoost and Random Forest algorithms (Joshi et al., 2023). Reviews of the broader remote-sensing and machine-learning literature likewise report that integrating vegetation indices such as the Normalized Difference Vegetation Index with weather and soil covariates consistently improves predictive accuracy over single-source models (Bharadiya et al., 2023; Modi et al., 2022), and comparable remote-sensing-driven models have been proposed specifically to strengthen food-insecurity early warning in resource-constrained settings (Shafi et al., 2023).

Deep learning architectures extend these gains by directly modeling the temporal and spatial dependencies inherent in crop growth. Long Short-Term Memory (LSTM) networks, designed to retain information across long input sequences (Hochreiter & Schmidhuber, 1997), have been combined with Convolutional Neural Networks (CNNs) to jointly capture spatial and temporal signal in satellite and weather time series, as demonstrated in county-level soybean yield prediction in the United States (Sun et al., 2019) and in hybrid CNN-LSTM models with attention mechanisms applied to wheat and rice (Kalmani et al., 2025). These advances build on the broader deep learning paradigm that has reshaped pattern recognition across scientific domains (Goodfellow et al., 2016; LeCun et al., 2015), and they are increasingly complemented by Internet of Things (IoT) sensor networks and low-cost remote sensing platforms that make continuous, field-level data collection feasible even for smallholder producers in low- and middle-income countries (Goel et al., 2022; United Nations Development Programme [UNDP], 2021).

Despite this global momentum, the application of machine learning to crop yield prediction in Afghanistan remains largely unexplored in the published literature. Most ML-based yield studies originate from data-rich agricultural systems in South and Southeast Asia, East Africa, and North America (Kuradusenge et al., 2023; Kumar et al., 2024; Nguyen et al., 2023), where meteorological networks, satellite ground-truthing programs, and agricultural census infrastructure are considerably more mature than in Afghanistan. Precision agriculture adoption research from Vietnam illustrates that even where the underlying technology is available, institutional support, cooperative structures, and extension capacity are decisive for whether smallholder farmers actually benefit from predictive tools (Nguyen et al., 2023), a consideration of direct relevance to Afghanistan's fragmented and infrastructure-constrained agricultural sector. This gap between a mature global methodology and an underserved national context motivates the present paper.

From a sustainability perspective, the proposed framework is particularly relevant to SDG 2 (Zero Hunger), as improved crop-yield information could support more informed food-production planning and agricultural risk assessment. It may also contribute indirectly to sustainable and resilient agricultural production by helping identify yield risks associated with climatic variability and by supporting more timely agricultural decision-making. However, these are potential contributions of the proposed framework rather than empirically demonstrated impacts, and their effectiveness must be established through future validation using representative Afghan agricultural data.

This paper does not report an empirical yield-prediction model trained on Afghan field data; rather, it develops a conceptual, literature-grounded framework intended to guide such empirical work. Specifically, the paper (1) synthesizes recent machine learning and deep learning literature on crop yield prediction alongside Afghanistan-specific evidence on climate change and agricultural productivity; (2) proposes a four-layer ML-based framework, together with an implementation pipeline, adapted to Afghanistan's data availability and institutional context; and (3) discusses the framework's implications for food security, farmer income, and Sustainable Development Goal 2, along with the practical barriers that would need to be addressed before field-level deployment. The intended contribution is a structured starting point for researchers and agricultural authorities seeking to design, fund, and eventually validate ML-based yield prediction systems in the Afghan context.

2. Methods

2.1. Research Design

This study adopted a conceptual, literature-grounded, and design-oriented research approach to develop a machine learning (ML)-based framework for agricultural crop yield prediction in Afghanistan. The study did not collect, process, or analyze a primary agricultural, field-level, meteorological, or remote-sensing dataset. Instead, the proposed framework was developed through a structured synthesis of relevant scholarly literature and the contextual mapping of potential data sources, machine-learning algorithms, data-processing procedures, and validation strategies to the Afghan agricultural environment.

The methodological process consisted of four interconnected stages: (1) literature identification and synthesis, (2) identification and characterization of Afghanistan-relevant data sources, (3) comparative assessment of candidate ML algorithms, and (4) development of a future empirical validation strategy. The resulting methodology was designed to provide a practical foundation for subsequent empirical research using field-level agricultural data from Afghanistan.

2.2. Literature Search Strategy

The literature synthesis comprised two complementary evidence domains. The first domain focused on international research concerning machine learning, deep learning, remote sensing, and crop-yield prediction. The second domain focused on Afghanistan-specific and regionally comparable research concerning climate change, agricultural productivity, food security, and agricultural technology adoption.

The primary literature search covered studies published between 2015 and 2025. Seminal methodological studies published outside this period were retained when they provided foundational knowledge concerning specific machine-learning or deep-learning methods. Searches were conducted using Scopus-indexed and open-access scholarly sources, with particular attention to relevant agricultural, environmental, remote-sensing, and machine-learning journals.

The principal search terms included combinations of:

- "crop yield prediction"
- "crop yield forecasting"
- "agricultural yield prediction"
- "machine learning"
- "deep learning"
- "remote sensing"
- "precision agriculture"
- "crop yield" AND "climate change"
- "Afghanistan" AND "agriculture"
- "Afghanistan" AND "crop yield"
- "Afghanistan" AND "climate change"

The search focused on studies providing evidence relevant to at least one of the following components: data sources, preprocessing, feature selection, predictive algorithms, model validation, or agricultural decision support.

2.3. Inclusion and Exclusion Criteria

To improve transparency and reproducibility, studies were selected according to predefined inclusion and exclusion criteria.

Table 1. Inclusion and exclusion criteria for literature selection

Criterion	Inclusion criteria	Exclusion criteria
Publication period	Primarily studies published from 2015–2025	Older studies unless they provide seminal methodological foundations
Publication type	Peer-reviewed journal articles and recognized scholarly publications	Non-scholarly opinion articles and sources without sufficient methodological information
Research topic	Crop-yield prediction, agricultural productivity, ML/DL, remote sensing, climate-related agricultural modelling	Studies unrelated to agricultural prediction
Methodological relevance	Studies describing algorithms, input variables, preprocessing, feature selection, or validation	Studies without relevant methodological information
Geographic relevance	Afghanistan, comparable developing-country contexts, or transferable international agricultural systems	Studies with no meaningful relevance to the framework
Evidence type	Primary empirical studies and relevant systematic/review studies	Duplicated or insufficiently documented studies
Algorithm relevance	RF, XGBoost, SVM, CNN, LSTM, CNN-LSTM, and related approaches	Algorithms with no relevance to crop-yield prediction

Priority was given to recent primary research reporting comparative model performance, while high-quality review studies were used to identify broader methodological trends and algorithmic developments.

2.4. Literature Screening and Synthesis

The literature screening process was conducted in sequential stages. First, potentially relevant publications were identified through keyword-based searches. Duplicate records and publications that were clearly unrelated to crop-yield prediction or agricultural modelling were removed.

The remaining studies were screened based on their titles and abstracts. Publications considered potentially relevant were subsequently examined in greater methodological detail. The full-text assessment focused on the type and characteristics of input data, predictive algorithms, spatial and temporal dimensions, preprocessing procedures, validation approaches, reported strengths and limitations, and applicability to data-constrained agricultural environments.

Table 2. Literature screening and evidence-synthesis procedure

Stage	Procedure	Main purpose
1. Identification	Keyword-based searches of scholarly sources	Identify potentially relevant studies
2. Initial screening	Remove duplicates and clearly irrelevant records	Improve relevance of the evidence base
3. Title and abstract screening	Examine research objectives and methodological relevance	Identify potentially eligible studies
4. Full-text assessment	Examine data, algorithms, validation, and findings	Determine methodological eligibility
5. Evidence synthesis	Compare relevant findings across studies	Develop the conceptual framework

Review studies were primarily used to establish the broader state of research, whereas primary empirical studies were emphasized when assessing algorithmic strengths, limitations, and reported predictive performance. The literature was used as the conceptual and methodological evidence base for framework development and was not treated as a dataset for model training.

3. Results and Discussion

3.1. Proposed ML-based framework for Afghan agriculture

Figure 1 presents the proposed four-layer framework. The Data Layer aggregates the four input categories identified in Section 2: meteorological records, satellite-derived vegetation indices, soil and field-management data where available, and historical yield and market statistics. The Processing Layer performs the data-cleaning, normalization, and feature-engineering steps that the reviewed literature consistently identifies as prerequisites for reliable model performance, including imputation of missing meteorological readings, a persistent challenge in conflict-affected and infrastructure-limited settings, and construction of derived features such as growing-degree days and vegetation-index trends. The Model Layer hosts the candidate algorithms compared in Section 3.2, allowing multiple model families to be trained and validated in parallel rather than committing prematurely to a single architecture. The Decision Layer translates model outputs into yield forecasts, early-warning risk alerts, and advisory content intended for dissemination to farmers, extension agents, and policymakers. A feedback loop returns observed field outcomes to the Data Layer, enabling periodic retraining as new seasons of data accumulate, an important feature given how quickly climate conditions in Afghanistan are shifting (Aliyar & Esmailnejad, 2022; Habib-ur-Rahman et al., 2022).

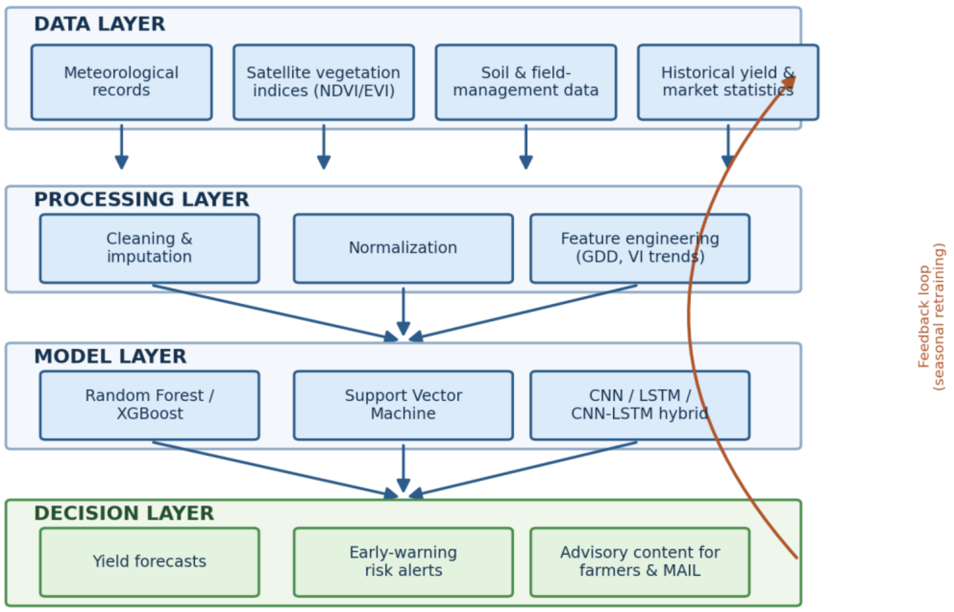

Figure 1. Proposed four-layer ML-based crop yield prediction framework for Afghan agriculture.

The proposed framework is organized into four interconnected layers: Data, Processing, Model, and Decision. The architecture is designed specifically for the Afghan agricultural context, where data availability, spatial coverage, infrastructure, and institutional capacity may vary substantially across provinces. Rather than assuming that a single algorithm or data source is universally optimal, the framework establishes a sequential pathway through which heterogeneous agricultural data are collected, quality-controlled, harmonized, transformed into predictive features, evaluated using alternative machine-learning algorithms, and ultimately translated into decision-support information.

The framework is therefore designed as an adaptable architecture rather than a fixed predictive model. Its implementation can accommodate differences in crop type, agro-climatic conditions, data availability, and computational capacity across Afghan provinces. The four layers are interconnected through a continuous data-to-decision pipeline, allowing model performance to be evaluated and the modelling configuration to be adjusted when geographic or temporal transferability is insufficient.

3.2. Comparative assessment of candidate algorithms

Table 3 summarizes the algorithm families most frequently reported in the crop yield prediction literature reviewed for this paper, together with their typical data requirements and reported comparative strengths. Ensemble tree-based methods such as Random Forest (Breiman, 2001) and XGBoost (Chen & Guestrin, 2016) recur across the literature as strong baseline choices because they handle heterogeneous, tabular agro-climatic data well and require comparatively modest training data, an important consideration given Afghanistan's limited historical digital records. Random Forest models combining satellite vegetation indices with meteorological covariates have outperformed linear regression, support vector regression, and XGBoost in at least one recent comparative study (Kuradusenge et al., 2023), while ensemble learning has also proven effective for meteorologically driven forecasting of sugarcane yield (Kumar et al., 2024). Support Vector Machines (Cortes & Vapnik, 1995) remain competitive where training data are limited, though the literature indicates they are increasingly outperformed by tree-based and deep learning methods as data volume grows (Joshi et al., 2023). Deep learning architectures, particularly CNN-LSTM hybrids, achieve the strongest reported performance where sufficiently long historical time series and spatial imagery are available, capturing both the temporal dynamics of a growing season and the spatial patterns visible in satellite imagery (Kalmani et al., 2025; Sun et al., 2019), but they are correspondingly more data- and computation-intensive, a constraint that matters directly for Afghanistan's nascent digital agricultural infrastructure.

Table 3. Comparative summary of machine learning algorithms reported in the crop yield prediction literature

Algorithm	Typical Data Inputs	Reported Comparative Strength	Representative Studies
Random Forest	Tabular weather, soil, and vegetation-index data; moderate sample size	Robust to noise and missing values; strong baseline with limited tuning	Breiman (2001); Kuradusenge et al. (2023)
XGBoost	Tabular multi-source data; benefits from engineered features	High accuracy via gradient boosting; efficient on structured data	Chen & Guestrin (2016); Joshi et al. (2023)
Support Vector Machine	Small-to-moderate structured datasets	Effective with limited training samples; sensitive to kernel choice	Cortes & Vapnik (1995)
CNN	Satellite imagery, spatial vegetation-index maps	Captures spatial patterns in remote sensing data	Sun et al. (2019)
LSTM	Sequential weather and phenological time series	Models temporal dependencies across the growing season	Hochreiter & Schmidhuber (1997)
CNN-LSTM hybrid	Combined spatial imagery and temporal weather series	Highest reported accuracy where sufficient historical data exist	Kalmani et al. (2025); Sun et al. (2019)

The comparative evidence indicates that algorithm selection should be determined by the characteristics of the available dataset rather than by predictive accuracy reported in other geographical settings alone. Afghanistan presents a combination of limited ground observations, fragmented agricultural records, heterogeneous agro-climatic conditions, and uneven computational capacity. Consequently, the most complex algorithm is not necessarily the most appropriate option for every province or crop.

Random Forest provides a practical starting point when sample sizes are moderate and predictors include a mixture of climatic, soil, management, and remote-sensing variables. Its relatively strong robustness and feature-importance capabilities make it useful as a baseline model and for settings where interpretability is important. XGBoost may provide greater predictive flexibility for structured datasets with nonlinear relationships, although careful hyperparameter tuning is required.

SVM may be advantageous where the number of observations is relatively limited because it can perform effectively in high-dimensional nonlinear problems. However, its performance depends strongly on kernel selection and parameter optimization. Deep-learning approaches such as CNN, LSTM, and CNN-LSTM hybrids become more attractive when sufficiently large and consistent spatial or temporal datasets are available. Their ability to learn complex spatial and temporal representations may provide advantages for satellite time series and long-term climate observations, but their computational and data requirements make them less appropriate for severely data-constrained settings.

Therefore, the framework recommends a tiered algorithm-selection strategy. RF and SVM can serve as practical baseline models for limited or moderate datasets; XGBoost can be prioritized when larger structured datasets are available; and CNN, LSTM, or CNN-LSTM models can be evaluated when sufficiently large, high-quality spatial and temporal datasets are available. Final selection should be based on independent validation rather than assumed superiority.

3.3. Afghanistan-Specific Operationalization

The practical implementation of the framework requires integration of data sources that are realistically accessible within Afghanistan or through open international platforms. Meteorological observations can provide temperature, precipitation, humidity, and related climatic variables, while satellite products can provide spatially continuous vegetation information. Soil and management variables can complement these sources where field-level information is available.

A major consideration is that the spatial and temporal resolution of these datasets may not be consistent. Meteorological observations may be available at individual stations, agricultural statistics may be reported at administrative levels, and satellite observations may provide spatially continuous information at different resolutions. Consequently, all datasets should be harmonized before model training.

The framework does not assume complete national coverage of all variables. Instead, it allows the modelling system to operate according to the level of data availability in each target region. Where field-level data are available, they should be prioritized. Where field observations are limited, satellite and reanalysis products can provide complementary information, subject to appropriate validation.

Data fragmentation and missing observations represent important implementation challenges. Missingness should first be quantified and its spatial and temporal patterns assessed. Limited missing observations may be treated using scientifically appropriate imputation procedures, whereas systematic or extensive gaps should be retained as uncertainty or excluded when data quality is insufficient. This approach reduces the risk of introducing artificial patterns into the training dataset.

3.4. Implementation pipeline

Figure 2 sets out the six-stage pipeline through which the framework in Section 3.1 would be operationalized. Data collection would draw on the sources identified in Section 2, with satellite-derived indices offering a practical entry point given that they require no in-country sensor investment. Preprocessing and feature selection stages address data quality and dimensionality, both flagged repeatedly in the literature as determinants of downstream model accuracy (van Klompenburg et al., 2020). Model training and validation would proceed using standard cross-validation and error metrics such as RMSE, MAE, and R^2, consistent with reporting conventions in the reviewed studies, allowing the candidate algorithms in Table 3 to be benchmarked against one another once Afghan field data become available. The final deployment stage envisions delivering forecasts and risk alerts through low-bandwidth channels, such as SMS or basic mobile applications, mirroring approaches found effective for smallholder farmers in other developing-country contexts (UNDP, 2021).

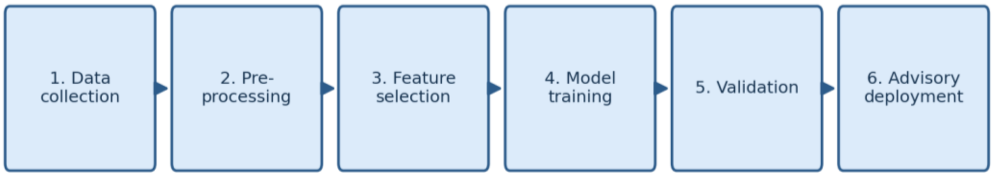

Figure 2. Six-stage implementation pipeline for deploying the proposed framework.

3.5. Implications for sustainable economic development and implementation barriers

A functioning ML-based yield prediction system would support several strands of Afghanistan's sustainable development agenda simultaneously. At the household level, earlier and more accurate yield forecasts could inform planting decisions, input allocation, and off-farm income planning, directly supporting farmer welfare in a sector where reduced yields already translate into lower agricultural wages (World Bank Group, 2021). At the national level, aggregated forecasts could strengthen early-warning capacity for MAIL and international partners such as FAO, whose wheat programme has already demonstrated measurable food-security gains through more conventional interventions such as certified-seed distribution (FAO, 2025), and could complement humanitarian planning against the flood and drought shocks that are already driving food insecurity (World Bank Group, 2021). These applications align directly with Sustainable Development Goal 2 (Zero Hunger) and with the broader recognition that precision agriculture, when adequately supported institutionally, can raise both productivity and resilience for smallholder producers (Nguyen et al., 2023; UNDP, 2021).

Realizing these benefits, however, depends on addressing barriers that the literature identifies as binding constraints in comparable low-resource settings. Data scarcity and fragmentation are likely the most immediate obstacle: Afghanistan's historical yield and meteorological records are incomplete relative to the datasets underpinning most published ML models, which typically draw on multi-decade national statistical systems (van Klompenburg et al., 2020). Rural connectivity and electricity access constrain both sensor-based data collection and advisory dissemination, a challenge documented broadly in precision agriculture adoption studies from other developing countries (UNDP, 2021; Goel et al., 2022). Institutional capacity is a further constraint; extension services and cooperative structures play a decisive mediating role in whether predictive tools reach and are trusted by smallholder farmers, as shown in adoption research from Vietnam (Nguyen et al., 2023). Finally, model outputs generated primarily from satellite and reanalysis data, in the likely absence of dense in-country sensor networks in the near term, would require careful validation against ground-truth yield measurements before being used for operational decision-making, underscoring that the framework proposed here is a starting point for empirical work rather than a substitute for it.

3.6. Future Empirical Validation and Geographic Transferability

Although the present study does not train or evaluate a predictive model using primary Afghan agricultural data, the proposed framework establishes a clear pathway for future empirical validation. Future research should evaluate candidate algorithms using independent observations and should avoid relying exclusively on random train-test splits because agricultural observations from neighboring locations or consecutive years may be spatially and temporally correlated.

Model performance should be evaluated using RMSE, MAE, and R^2. These metrics provide complementary information regarding prediction error and explained variance. RMSE gives greater weight to large prediction errors, MAE provides an interpretable measure of average prediction error, and R^2 indicates the proportion of observed yield variability explained by the model.

Validation should include both temporal and spatial components. Temporal validation can be conducted by training models on earlier agricultural seasons and testing them on subsequent seasons. Spatial validation can involve training models using observations from selected provinces or agro-climatic zones and testing them on geographically independent provinces or zones.

Overfitting should be assessed by comparing training, validation, and independent test performance. A substantial reduction in performance on unseen data would indicate potential overfitting. Cross-validation, hyperparameter tuning, regularization, and early stopping for deep-learning models may be applied as appropriate.

Geographic transferability should be assessed by comparing model performance across Afghan provinces and agro-climatic zones. If a model performs well in one region but demonstrates substantial degradation in another, regional modelling, transfer learning, or domain-adaptation approaches may be considered. This procedure is particularly important because differences in elevation, temperature, precipitation, irrigation, soil characteristics, and cropping systems may affect the relationships between predictors and crop yield.

3.7. Practical Implications for Agricultural Decision-Making in Afghanistan

The proposed framework has potential practical value for agricultural planning in Afghanistan because it provides a structured pathway for integrating climate, satellite, soil, management, and historical yield information. Rather than replacing agricultural expertise, the framework is intended to provide additional evidence for decisions concerning crop production, input allocation, and climate-related risk management.

The potential value of the framework is particularly relevant in regions where agricultural production is strongly influenced by precipitation variability, drought, temperature fluctuations, and irrigation constraints. Earlier estimates of crop yield conditions could help agricultural authorities and development partners identify areas that may require closer monitoring or targeted intervention.

However, these potential benefits should not be interpreted as empirically demonstrated outcomes of the present study. The framework has not yet been tested using a nationally representative Afghan field-level dataset. Its practical effectiveness will depend on data quality, institutional coordination, computational infrastructure, technical capacity, and the ability of predictive models to maintain acceptable performance across different provinces and agricultural environments.

The proposed approach therefore emphasizes gradual implementation, beginning with pilot studies in selected provinces or agro-climatic zones. Evidence from these pilots could subsequently inform broader national deployment if the models demonstrate sufficient accuracy, robustness, and geographic transferability.

3.7. Limitations

This study has several limitations that should be considered when interpreting its contribution. First, the proposed framework is conceptual and literature-grounded; therefore, it does not provide empirical estimates of crop-yield prediction accuracy in Afghanistan. The relative performance of the candidate algorithms is derived from published evidence and methodological assessment rather than direct experimentation with Afghan field-level data.

Second, the availability, completeness, and consistency of agricultural and environmental data may vary substantially across Afghan provinces. Fragmented observations, differences in spatial and temporal resolution, and missing records may affect the reliability of future model training.

Third, algorithmic performance reported in other countries cannot automatically be generalized to Afghanistan because agricultural systems, climate conditions, soil characteristics, irrigation practices, and data environments differ across geographical contexts. Consequently, the proposed algorithm recommendations should be regarded as hypotheses for future empirical testing rather than definitive rankings.

Finally, geographic and temporal transferability remains an empirical question. Future research should therefore evaluate the proposed framework using independent field-level observations and spatially and temporally separated validation datasets before the framework is adopted for operational agricultural decision-making.

Conclusions

This study developed a conceptual machine learning-based framework for agricultural crop-yield prediction adapted to the data, technological, and institutional conditions of Afghanistan. Through the synthesis of relevant literature, the framework integrates four principal layers—data, processing, model, and decision—to provide a structured pathway from heterogeneous agricultural information to potential decision-support applications.

The framework recognizes that no single machine-learning algorithm is universally optimal for the Afghan context. Algorithm selection should depend on sample size, computational requirements, interpretability, data quality, and the degree of agro-climatic heterogeneity. Random Forest, XGBoost, and SVM may provide practical options for structured and relatively limited datasets, while CNN, LSTM, and CNN-LSTM architectures may become more appropriate when large and consistent spatial or temporal datasets are available.

The framework also emphasizes that future implementation should address data fragmentation through spatial and temporal harmonization, appropriate missing-data treatment, feature engineering, and rigorous quality assessment. Most importantly, future empirical studies should evaluate models using RMSE, MAE, and R^2 and should incorporate independent spatial and temporal validation to determine overfitting, robustness, and geographic transferability across Afghan provinces.

The proposed framework should therefore be considered a methodological foundation rather than a validated operational prediction system. Its effectiveness remains to be demonstrated through empirical research using representative Afghan agricultural datasets. Such validation would provide the evidence necessary to determine whether machine-learning-based yield prediction can reliably support agricultural planning, food-security monitoring, climate-risk management, and more resilient agricultural production in Afghanistan.

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Conflicts of Interest

The authors declare no conflict of interest.

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