Computational Molecular Biology 2026, Vol.16, No.3, 146-158
http://bioscipublisher.com/index.php/cmb

Review Article Open Access

Prediction of Eggplant Yield Based on Fertilization and Climate Variables

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Computational Molecular Biology, 2026, Vol.16, No.3 doi: 10.5376/cmb.2026.16.0011
Received: 24 Mar., 2026
Accepted: 28 Apr., 2026
Published: 12 May, 2026

Preferred citation for this article:
Li G.F., 2026, Prediction of eggplant yield based on fertilization and climate variables, Computational Molecular Biology, 16(3): 146-158 (doi: 10.5376/cmb.2026.16.0011)

Abstract With the intensification of climate change and the continuous transformation of agricultural production methods, the extent to which eggplant yields are jointly influenced by fertilizer management and climatic conditions has become increasingly evident. Focusing on fertilization factors and climatic variables as the core subjects of inquiry, this study systematically analyzes the mechanisms by which temperature, precipitation, humidity, and fertilizer inputs affect eggplant yield formation, while also exploring the interactive effects between climate and fertilization. To this end, regional meteorological data, soil nutrient data, and field yield data were collected to construct an eggplant yield prediction model based on a combination of statistical analysis and machine learning techniques. The research focuses on variable selection, feature engineering, model training, and the optimization of predictive performance, while also comparing the differences in predictive accuracy and stability between regression models and machine learning algorithms. The results indicate that temperature fluctuations, soil moisture conditions, and nitrogen fertilizer inputs are critical factors influencing eggplant yields, and that the coupled effects of these multiple factors can significantly enhance the accuracy of the prediction model. A case study further validates the model's applicability within regional agricultural production contexts, providing a scientific basis for precision fertilization management, agricultural risk assessment, and smart farming decision-making. This study holds significant theoretical and practical implications for improving eggplant production efficiency, optimizing resource utilization, and fostering sustainable agricultural development.

Keywords Eggplant yield prediction; Fertilization management; Climate variables; Machine learning; Precision agriculture

1 Introduction

Eggplant (*Solanum melongena* L.) is a widely cultivated vegetable valued for its nutritional quality, including minerals, vitamins, and antioxidant phenolics that contribute to human health and dietary diversity (Başay et al., 2025). It also plays an important economic role, providing income for smallholders and contributing substantially to vegetable production in many countries, yet yields in several regions remain below global averages (Oladosu et al., 2021; Dollison and Tapas, 2024). At the same time, agriculture faces mounting pressure from climate change, with shifts in temperature and rainfall patterns already constraining productivity and threatening food and nutrition security, especially in vulnerable regions (Chioti et al., 2022; Kuradusenge et al., 2023). In this context, improving the stability and predictability of eggplant yield under varying fertilization regimes and climate conditions is critical for both farmers' livelihoods and broader food system resilience.

Fertilization management is a central lever for enhancing eggplant productivity, fruit quality, and nutritional value. Numerous studies show that optimizing macro- and micronutrient supply-through mineral NPK fertilizers, organic amendments, and foliar micronutrients-can significantly increase growth, yield components, and nutrient content of eggplant fruits and seeds (Bana et al., 2022). Integrated nutrient management approaches, combining chemical fertilizers with biofertilizers and micronutrients, have further improved yield and quality, and have been successfully modeled using data-driven techniques such as artificial neural networks to identify key nutritional predictors of yield and protein content (Thingujam et al., 2020). However, many fertilization recommendations are still static, and rarely account for interactions with variable weather, despite the fact that fertilization efficiency and crop response can be strongly modulated by temperature and moisture regimes (Gad, 2023; Chandio et al., 2025).

Climate variability and change are increasingly recognized as major drivers of year-to-year yield fluctuations across a wide range of crops. Analyses of long-term data link changes in temperature, rainfall, and the length of the rainy season to substantial variations in yields, with higher temperatures and drought often reducing productivity, while adequate or increased rainfall can partially offset these negative effects (Chioti et al., 2022). At the same time, recent work has demonstrated that combining environmental variables (such as temperature, precipitation, and evaporation) with fertilizer use data in predictive models can greatly improve crop yield forecasting performance, supporting more informed agronomic decisions (Burdett and Wellen, 2022; Krishnadoss and Ramasamy, 2024). Despite this progress, there is a notable gap regarding eggplant-specific yield prediction frameworks that jointly consider fertilization practices and climate variables, even though eggplant is sensitive to both soil fertility and temperature stress, including low-temperature constraints in certain seasons (Osman et al., 2021; Badshah et al., 2024).

This study addresses these gaps by developing a predictive framework for eggplant yield based on fertilization and climate variables, with the goal of supporting climate-smart nutrient management. Building on evidence that data-driven and machine learning models (such as random forests, ensemble approaches, and neural networks) can accurately capture complex, nonlinear relationships among weather, input use, and yields in other crops and regions, this work tailors such concepts to eggplant systems. The specific objectives are to quantify the combined and individual effects of fertilization regimes and key climate factors (e.g., temperature and rainfall) on eggplant yield, construct and evaluate predictive models that use these variables to estimate yield, and identify the most influential features governing yield variability to inform practical management guidelines. By integrating fertilization and climate information into a unified predictive approach, the study aims to contribute a scalable tool and empirical insights that can enhance fertilizer recommendations, reduce climate-related yield risks, and ultimately support more sustainable and resilient eggplant production.

2 Influence of Climate Variables on Eggplant Production

2.1 Effects of temperature variability on yield formation

Open-field work using growing degree days (GDD) shows that eggplant accessions requiring fewer accumulated heat units to first fruiting achieve higher productivity; in a Caribbean environment without temperature extremes (<15 °C or >35 °C), yields above 80 t ha^{-1} were obtained, indicating that thermally suitable sites allow full yield potential expression (Pacheco et al., 2019). Greenhouse studies reveal curvilinear temperature responses of fruit number and total yield, with lower yields when temperatures deviate from an optimum that depends on light intensity, reinforcing the non-linear nature of temperature-yield relationships.

Physiological research indicates that temperatures below about 17 °C slow growth, and near 10 °C induce metabolic disturbances, impairing membrane stability, water relations, chloroplast development, and photosynthetic efficiency, all of which ultimately reduce fruit set and yield (Shimira and Taşkın, 2022). Conversely, excessive heat accelerates development and can depress fruit set in vegetable crops, shortening the period for photoassimilate accumulation and causing yield loss, so yield prediction must account for both cold and heat stress windows around the crop's optimal growth range.

2.2 Impact of rainfall and soil moisture on crop productivity

A multi-year field trial in a moderate climate showed that eggplant yield depended strongly on both air temperature and total rainfall, with the highest yields obtained when high mean temperatures coincided with evenly distributed rainfall; periods of very low or absent rainfall shortened the harvest period and delayed first fruiting. In the Colombian Caribbean, rainfall largely met crop evapotranspiration, supplemented by irrigation to maintain soil at field capacity, and under these favorable moisture conditions no critical drought episodes occurred, supporting high yields across genotypes.

Deficit irrigation studies using field capacity (FC) as a benchmark demonstrate that, under subsurface infiltration irrigation, reducing soil moisture from 80% to 60% FC during early and mid stages can be tolerated with limited yield reduction, but deficits during the prime fruit stage markedly decrease yield and plant growth traits (Li et al., 2024). Complementary deficit drip irrigation work on sandy clay loam soils found maximum yield and irrigation water use efficiency at about 75% FC, with both lower and higher soil moisture leading to reduced productivity, indicating an optimum soil moisture band for yield formation (Ouma et al., 2024).

2.3 Relationship between humidity conditions and plant health

Eggplant health is strongly influenced by humidity through its effects on fungal and bacterial disease development. In humid subtropical environments, high relative humidity and moderate temperatures were associated with substantial incidences of Phomopsis fruit rot and Cercospora leaf spot, with fruit rot increasing roughly tenfold over 30 days under mean temperatures around 23.7 °C and 55.5% relative humidity, and leaf spot rising fivefold when average temperature was 18.2 °C with morning humidity near 88%. Broader reviews of eggplant fungal diseases emphasize that environmental factors-particularly moisture and temperature-interact with host genetics to drive pathogenesis and yield loss, underscoring humidity as a key variable in risk-based yield prediction (Kaniyassery et al., 2022).

For Alternaria leaf spot, field monitoring across sowing dates showed disease intensity to be positively and significantly correlated with both maximum and minimum temperatures, but negatively correlated with morning and noon relative humidity; rainfall also showed a negative (though non-significant) association with disease intensity (Sharma et al., 2025). Other pathosystems, such as Verticillium wilt under greenhouse conditions, demonstrate that disease severity significantly reduces early and total yield and plant biomass, while irrigation frequency (and thus soil moisture regime) also affects plant performance, indicating that combined humidity, soil moisture, and pathogen pressure must be integrated into plant health and yield models.

3 Interaction Between Fertilization and Climate Factors in Yield Formation

3.1 Coupling effects of water and fertilizer management

Water-fertilizer coupling directly shapes crop growth environments by synchronizing soil moisture and nutrient availability, thereby affecting yield formation, resource use efficiency, and environmental impacts (Xing et al., 2024). In eggplant systems under mulched drip irrigation, factorial combinations of irrigation levels and nitrogen rates show that both water, nitrogen, and their interaction significantly alter evapotranspiration, yield, and water productivity, with mild water deficit plus moderate nitrogen achieving the highest yield and water productivity (Zhou et al., 2023). Similar coupling principles have been generalized across crops, where appropriate water-fertilizer ratios enhance soil physical structure, microbial activity, and nutrient mineralization, thus improving crop performance while reducing fertilizer loss and environmental pressure.

Studies in cold and arid oasis environments further indicate that eggplant yield, fruit quality, and water- and nitrogen-use efficiency are jointly governed by irrigation-nitrogen interactions, with mild water deficit (60%-70% field capacity) and moderate nitrogen rates outperforming both lower and higher inputs (Li et al., 2025). These results align with broader reviews of water-fertilizer coupling, which report that optimized coupling improves soil structural stability, microbial diversity, and enzyme activity, and that intelligent drip fertigation systems can enhance water use efficiency while lowering nutrient leakage and pollution risks (Xing et al., 2024). Together, this evidence highlights water-fertilizer coupling as a key mechanism through which management and climate-modulated water supply co-determine yield.

3.2 Climate-dependent fertilizer efficiency

Fertilizer efficiency is strongly modulated by climatic conditions, particularly temperature and rainfall regimes that influence nitrogen uptake pathways, losses, and crop demand. Long-term simulations for wheat-maize rotations under future climate scenarios show that, even with unchanged cultivars, warming and altered rainfall patterns reduce annual nitrogen use efficiency by about 15%, with manure-amended systems partly buffering these negative impacts by sustaining soil organic matter and nutrient supply. In rice systems, meta-analysis across climatic gradients finds that mean seasonal temperature and precipitation, along with fertilizer N rate and soil properties, jointly explain regional differences in agronomic efficiency, N recovery, and reactive nitrogen losses, underscoring that identical fertilizer rates can perform very differently under contrasting climates (Cai et al., 2022).

Experimental warming studies using 15N tracers confirm that modest temperature increases can lower fertilizer nitrogen recovery and increase nitrogen losses even when grain yield remains unchanged, indicating a hidden decline in fertilizer efficiency under warming. At a broader scale, analyses of nitrogen fertilizer use and climate interactions for maize reveal that higher temperatures and extreme heat days can diminish the yield benefits of nitrogen, while favorable growing-degree days and adequate precipitation enhance the marginal return to N, with optimal nitrogen rates shifting across climate gradients (Huang et al., 2024). These findings demonstrate that fertilizer recommendations and efficiency metrics cannot be treated as static, but must be adjusted to local and evolving climate conditions.

3.3 Synergistic effects of multi-factor agricultural inputs

Yield responses to fertilization rarely depend on nutrients alone; instead, they emerge from combined effects of climate, soil, and multiple input levels. Meta-analysis of maize fertilization across Northeast China shows that moderate NPK rates increase yield by about 20% and improve protein and fat content, but the magnitude of yield and quality gains depends on precipitation, temperature, soil pH, and soil nutrient status, with soil organic matter and available phosphorus identified as dominant drivers of fertilization benefits (Gao et al., 2025). At the process level, a global synthesis of nutrient interactions indicates that most macronutrient combinations act synergistically on yield when both are deficient, whereas certain divalent cation combinations can be antagonistic, implying that multi-nutrient strategies must be designed to exploit synergy while avoiding negative interactions.

Multi-factor management that couples irrigation, nitrogen, and delivery method can further amplify positive interactions. A large meta-analysis across Chinese cropping systems shows that drip fertigation-combining precise water and N supply-raises yield by 12%, water productivity by 26%, and nitrogen use efficiency by 34%, while reducing evapotranspiration compared with traditional irrigation and broadcasting fertilization (Li et al., 2021). Complementary analyses of irrigation-nitrogen combinations in maize and wheat demonstrate that joint application of irrigation and N typically increases yield by 9%-17% relative to controls, though the effect size varies with climate and soil, highlighting the importance of context-specific optimization of multiple inputs (Cui et al., 2024). Such evidence supports modeling approaches that integrate fertilization, water management, and climate variables when predicting yield and designing climate-resilient fertilization regimes.

4 Construction of Eggplant Yield Prediction Models

4.1 Selection of fertilization and climate variables

The selection of input variables is crucial for robust eggplant yield prediction, particularly when combining fertilization and climate information. Systematic reviews of crop-yield ML studies show that temperature, rainfall, soil type, humidity, and fertilizer-related variables are among the most frequently and successfully used features for yield estimation (Jabed and Murad, 2024; Shawon et al., 2024). Other work that jointly models environmental and chemical inputs demonstrates that precipitation, temperature, evaporation, wind speed, and chemical (fertilizer) use together can explain a large share of yield variability, supporting their inclusion in compact yet informative feature sets (Krishnadoss and Ramasamy, 2024).

At the same time, models that explicitly incorporate nutrient levels (e.g., NPK) with climatic variables such as temperature, rainfall, and humidity can generate highly accurate crop recommendations and yield responses, indicating that these variables effectively capture plant-environment-management interactions (Dey et al., 2024). Broader ML applications in agriculture reinforce that features related to soil fertility, water availability, and weather conditions (including meteorological variables and season) are central drivers of crop output and must therefore be prioritized in variable selection for eggplant yield prediction under different fertilization regimes (Figure 1) (Gupta et al., 2022; Sharma et al., 2023).

4.2 Data processing and feature engineering

Accurate prediction requires careful preprocessing to transform raw agronomic and climatic records into machine-learning-ready datasets. Studies on crop yield prediction typically perform data cleaning, normalization, and integration of heterogeneous sources (weather, inputs, yield) as early steps, sometimes engineering new targets such as yield per area from production and land area data to better reflect productivity (Iniyan et al., 2023;

Sarikonda et al., 2025). To avoid bias and overfitting, workflows also emphasize correct partitioning schemes and prevention of information leakage, along with modular feature creation from weather, soil, remote sensing, and crop-model outputs (Paudel et al., 2020; Morales and Villalobos, 2023).

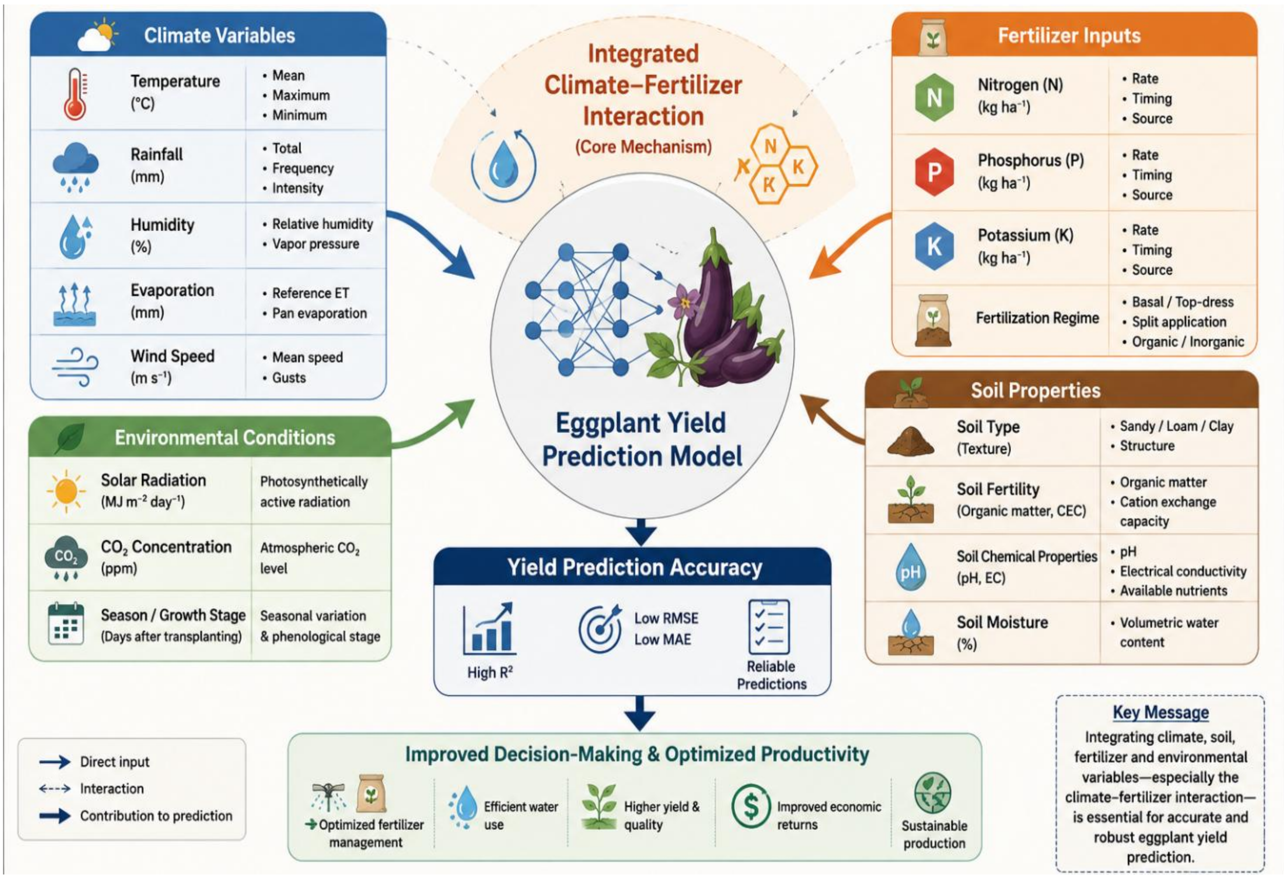

Figure 1 Conceptual framework of key input variables used in machine learning-based eggplant yield prediction models. Climate, soil, fertilizer, and environmental variables jointly influence prediction accuracy and crop productivity responses

Feature selection and extraction are key to reducing redundancy and improving generalization. Relief-based feature selection and linear discriminant analysis have been used to isolate the most discriminative predictors before training support vector machines, k-nearest neighbors, and random forests for yield classification or regression (Gupta et al., 2022). Hybrid approaches combine correlation-based filters, clustering, and recursive feature elimination to build reduced, information-rich datasets that, together with optimized support vector regressors, substantially improve prediction accuracy while lowering computational cost, illustrating the value of systematic feature engineering pipelines (Abdel-Salam et al., 2024).

4.3 Development of statistical and machine learning models

A wide range of statistical and ML algorithms has been applied to crop yield prediction, offering guidance for constructing eggplant-specific models. Linear regression, random forest, gradient boosting trees, and related methods are among the most widely used, with random forest and boosting-based techniques often achieving strong performance across diverse environments and crops (Mahesh and Soundrapandiyan, 2024; Shawon et al., 2024). Ensemble models that integrate multiple learners (e.g., Extra Trees, gradient boosting, or stacked approaches) have repeatedly reached very high R^2 and low error metrics, suggesting that ensemble strategies are promising for capturing complex fertilization-climate-yield relationships (Iniyan et al., 2023; Nossam et al., 2024).

For eggplant specifically, machine learning models using spectral vegetation indices, days after planting, and irrigation-related coefficients have successfully predicted yield; principal component analysis-based inputs combined with artificial neural networks achieved very high accuracy, indicating that nonlinear models can effectively exploit engineered features (Taşan et al., 2022). Gradient-boosting families (CatBoost, LightGBM, XGBoost) have also shown excellent performance for general crop yield prediction and for eggplant yield based on genotype-related variables, where CatBoost provided accurate and robust forecasts, highlighting the suitability of tree-based boosting for eggplant yield modeling under varying environmental and management conditions (Islam et al., 2023; Mahesh and Soundrapandiyan, 2024).

5 Evaluation and Optimization of Yield Prediction Performance

5.1 Comparison of regression and machine learning algorithms

Crop yield prediction studies consistently show that machine learning algorithms often outperform simple regression when relationships between climate, management, and yield are nonlinear and complex. Comparative evaluations across linear regression, decision trees, random forests, support vector machines, and neural networks report that ensemble methods such as Random Forest and Gradient Boosting generally achieve higher accuracy and better generalization than traditional linear models, especially when diverse environmental and management variables are included (Kurmi and Singh, 2025). However, linear models remain competitive when relationships are close to linear, offering advantages in interpretability and lower computational cost (Nazir et al., 2025).

Broader multi-crop comparisons confirm that advanced tree-based models and k-nearest neighbors often provide lower error and higher correlation with observed yields than multiple linear regression, particularly when many climatic and soil predictors are used. Recent work further extends comparisons to deep learning (e.g., LSTM and Bi-LSTM), showing that optimized recurrent networks can substantially reduce prediction error relative to support vector regression and time-series models such as ARIMA and VAR, demonstrating the value of capturing temporal dependencies in climate and yield series (Kumar et al., 2023).

5.2 Accuracy assessment using evaluation indicators

Evaluation of yield prediction models relies on multiple complementary indicators to capture both error magnitude and explanatory power. Common metrics include root mean squared error (RMSE), mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2), which together provide a comprehensive view of prediction bias, dispersion, and goodness-of-fit (Kurmi and Singh, 2025; Nazir et al., 2025). Studies comparing regression and machine learning approaches typically rank models by minimizing RMSE and MAE while maximizing R^2, revealing clear performance hierarchies among algorithms under different data conditions (Pant et al., 2025).

Large-scale forecasting frameworks and ensemble systems also employ normalized RMSE (NRMSE) and additional agreement indices to compare machine-learning baselines against operational forecasting systems or process-based crop models, emphasizing reproducibility and robustness across crops, regions, and seasons (Paudel et al., 2020; Singh et al., 2025). In practice, these metrics are often computed under cross-validation or using independent test years, allowing rigorous assessment of generalization and facilitating fair comparison of alternative algorithms for integrating fertilization and climate variables in yield prediction (Sowmya and Prasad, 2024).

5.3 Optimization of model parameters and prediction stability

Model performance and stability depend strongly on appropriate hyperparameter tuning and feature selection. Grid-search and other systematic optimization methods applied to tree-based ensembles such as Random Forest and Gradient Boosting have been shown to significantly improve RMSE, MAE, and R^2 compared with default configurations, with tuned ensembles delivering more robust rice yield predictions under variable climatic conditions (Hoque et al., 2024; Sowmya and Prasad, 2024). Similarly, combining multiple tuned base learners in stacked or adaptive ensembles can further reduce prediction error relative to any single model, demonstrating the benefits of leveraging diverse algorithmic strengths (Sánchez et al., 2014).

Advanced frameworks integrate hybrid feature selection and metaheuristic optimization to enhance both accuracy and efficiency. For example, coupling clustering and correlation-based filters with feature selection methods, followed by hyperparameter optimization of support vector regression via an improved Crayfish Optimization

Algorithm, yields superior crop yield predictions compared with standard SVR and other regressors (Abdel-Salam et al., 2024). Deep learning approaches also rely on systematic hyperparameter optimization and cross-validation, where careful selection of optimizers and network configurations (e.g., Bi-LSTM with Adam) enhances prediction accuracy and reduces error variability across crops, thereby improving prediction stability over time and across environmental conditions (Kumar et al., 2023).

6 Identification of Key Determinants Affecting Eggplant Yield

6.1 Contribution analysis of fertilizer inputs

Quantifying the contribution of fertilizer inputs to yield is central for identifying leverage points in eggplant production. Pot experiments with graded nitrogen (N) and phosphorus (P_2O_5) rates showed that N applications significantly affected nearly all growth and yield components, whereas P_2O_5 influenced fewer variables; yield gains were mainly driven by fruit number and fruit weight, with optimal responses at 100-150 kg/ha of both N and P_2O_5. A separate fertigation study using factorial N and K rates found that leaf area and agronomic efficiency of N declined at higher N and K levels, indicating diminishing returns and highlighting the importance of moderate N doses and balanced K supply for efficient production.

Longer-term field experiments confirm that not only fertilizer quantity but also source and combination determine yield contributions. In a four-year eggplant trial, applying 100% recommended NPK together with farmyard manure increased fruit yield by 47% compared with mineral fertilizer alone, while also enhancing soil organic carbon and available N, P, and K, and improving agronomic efficiency and nutrient recovery (Nisar et al., 2025). In multi-crop vegetable systems on organic soils, random forest models using soil, management, and meteorological features revealed little response to added P and only null to moderate response to added N in high-P conditions, suggesting that excess P is common and that fertilizer contribution depends strongly on existing soil fertility and N-P stoichiometry (Parent, 2024).

6.2 Sensitivity analysis of climate variables

Sensitivity analyses from global and regional studies provide a framework for evaluating how climate variables modulate eggplant yield response to fertilization. Non-parametric elasticity analysis for major crops showed that yields are most sensitive to mean air temperature, with precipitation exerting a smaller but still relevant influence; the sign and magnitude of temperature elasticity varied by crop and region, with many wheat and rice systems experiencing negative yield responses to warming (Liu et al., 2020). A machine-learning study of climate extremes found that growing-season mean climate and extremes together explained up to 49% of yield anomaly variance, and that temperature-related extremes were generally more influential than precipitation-related indices, although irrigation partly mitigated heat damage.

Variance-based sensitivity analysis applied to a process-based wheat model demonstrated that yield sensitivity shifts between water-controlling factors (precipitation, soil hydraulic properties) and nitrogen-controlling factors depending on which resource is limiting under a given climate-soil-management scenario (Hao et al., 2024). In arid and semi-arid Jordan, combining machine learning with Sobol' indices showed that climate-related variables explained a large fraction of yield variance for sensitive crops like wheat, whereas more resilient crops such as barley exhibited much lower climate-driven variance, underlining the crop- and context-specific nature of climate sensitivity (Xu et al., 2025).

6.3 Identification of dominant yield-limiting factors

Disentangling dominant yield-limiting factors requires integrating fertilizer response with plant nutritional physiology and climate constraints. Nutrient-solution omission experiments in eggplant showed that withholding individual macronutrients reduced vegetative growth, dry matter, and photosynthesis, with nitrogen and calcium identified as the most growth-limiting elements despite potassium being most demanded quantitatively (Flores et al., 2015). Greenhouse studies on N and P_2O_5 rates further indicated that yield was more affected by N than by P, with excessive doses reducing performance, suggesting that sub-optimal N supply or imbalanced N:P ratios can act as primary yield constraints even when total fertilizer input is high

At larger scales and across crops, feature-importance and explainable-AI analyses consistently rank temperature, rainfall, and macronutrient levels among the most influential predictors of yield, revealing strong interactions between climate drivers and NPK supply (Meng et al., 2021; Mohan et al., 2025). In a maize yield prediction framework integrating fertilizer systems with multi-source data, random forest feature importance highlighted fertilizer variables, maximum temperature, and precipitation as key determinants, with different fertilizer systems shifting which factors were most limiting under given climatic conditions (Meng et al., 2021). Together, these results indicate that for eggplant, dominant yield-limiting factors are likely to be inadequate or poorly balanced N (and Ca), interacting with temperature and water availability, rather than single inputs considered in isolation.

7 Case Study on Regional Eggplant Yield Prediction

7.1 Overview of the selected experimental region

The experimental region represents a semi-arid to arid environment where eggplant production is constrained by high evaporative demand, limited and seasonally concentrated rainfall, and strong sensitivity of yield to microclimate modification. In cold and arid oasis conditions, such as the Hexi irrigation area of northwest China, annual precipitation is only about 183-285 mm, evaporation exceeds 1600 mm, and sunshine duration approaches 3000 h, creating a dry atmosphere where irrigation and fertilization strategies are critical to sustain eggplant productivity (Li et al., 2025). Comparable semi-arid vegetable regions, for example Carnarvon in Western Australia, face high temperatures and intense solar radiation during spring-summer, which damage crops and shorten the production season unless protective cultivation is adopted (Nguyen et al., 2022).

Within these environments, protected and controlled systems are increasingly used to create favorable microclimates for eggplant. Shade-net houses in Carnarvon, using moderate shade factors around 21%, altered light intensity and microclimatic conditions in ways that promoted taller, bushier plants and higher fruit yield compared with open-field cultivation (Figure 2) (Nguyen et al., 2022). Similarly, controlled and semicontrolled greenhouse systems in arid regions have shown that adjusting temperature, light, and nutrient sources (inorganic fertilizers, compost, and their mixtures) can strongly influence eggplant growth, yield, and water-use efficiency, providing locally specific data to calibrate yield models for such climates (Abbas et al., 2025).

7.2 Application of the prediction model to field data

Regional yield prediction relies on integrating field experiments that quantify responses to water and fertilizer regimes under real climate variability. In the Hexi oasis, split-plot experiments across two seasons with three irrigation levels (50%-60%, 60%-70%, 70%-80% field capacity) and three nitrogen rates (215, 270, 325 kg/ha) generated detailed yield, quality, and resource-use data, enabling identification of an optimal mild water deficit (60%-70% FC) with moderate nitrogen (270 kg/ha) under mulched drip irrigation (Li et al., 2025). These structured datasets, including soil properties and multi-year climate records, are well suited for training and validating regional prediction models that link fertilization and climate variables to eggplant yield.

Advanced modeling frameworks in other crops illustrate how multi-layered, multi-farm datasets can be used to forecast yield at field and regional scales. In Western Australia, yield monitor data for wheat, barley, and canola over three seasons were combined with weather and soil-related predictors to build random forest models at 100 m resolution, achieving concordance correlation coefficients of 0.89-0.92 and RMSE of 0.36-0.42 t/ha . Applying similar machine learning workflows to eggplant, using experimental and commercial field data from protected and open-field systems, allows spatially explicit yield forecasts that support regional fertilizer and irrigation decisions.

7.3 Implications for precision fertilization and farm management

Results from regional case studies highlight that optimal eggplant yield can be achieved with water- and nitrogen-saving strategies tailored to local climate, providing a basis for precision fertilization. In the cold, arid Hexi region, mild water deficit with moderate nitrogen significantly increased yield, fruit quality, and water- and nitrogen-use efficiency relative to unfertilized, fully irrigated controls, demonstrating that blanket high-input strategies are neither necessary nor efficient (Li et al., 2025). Parallel work in deficit drip irrigation on sandy clay loam soils showed that maintaining soil moisture at 75% field capacity maximized yield (≈39 t/ha) and irrigation water-use efficiency, with further increases in water supply reducing both yield and efficiency (Ouma et al., 2024).

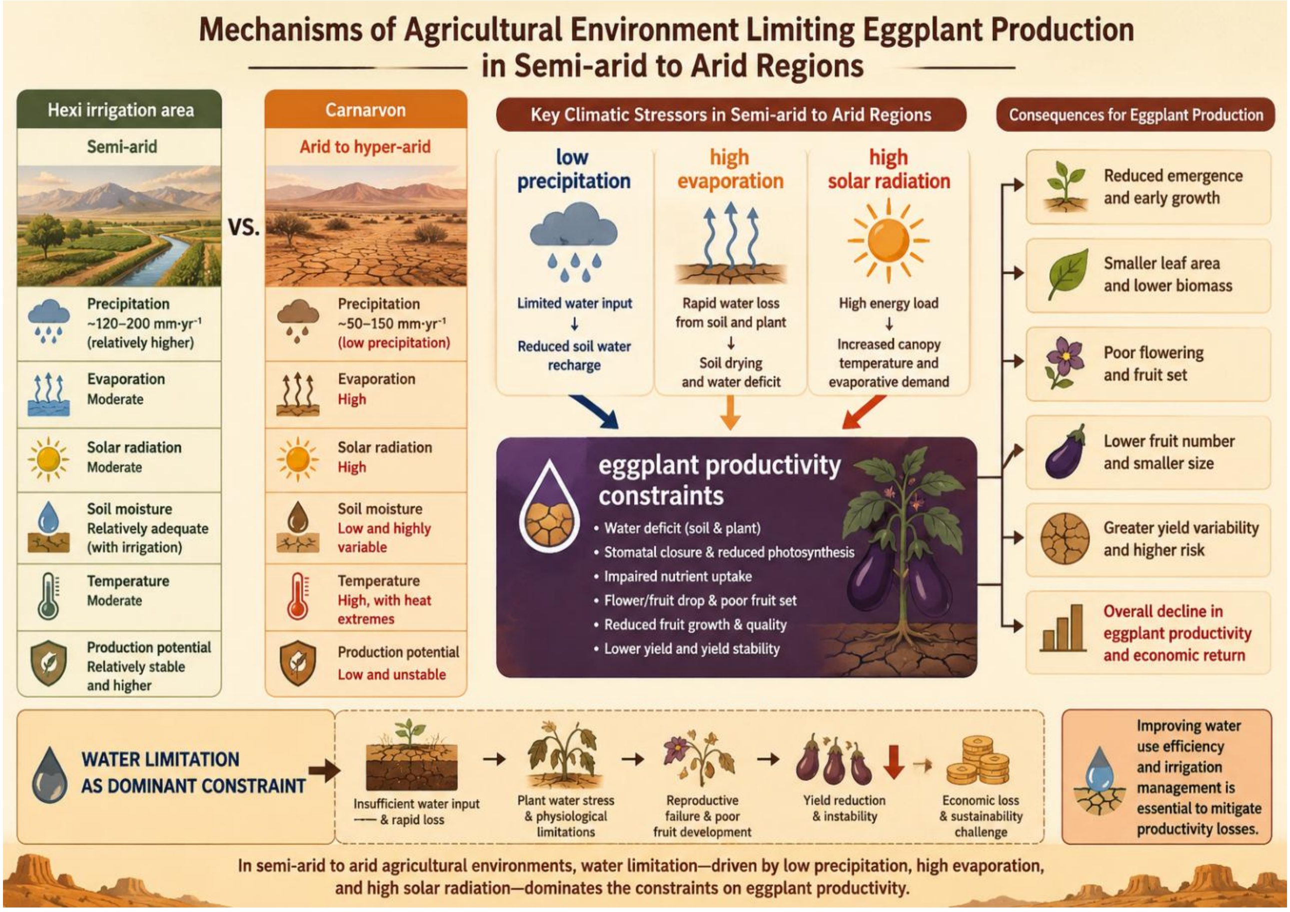

Figure 2 Schematic representation of climatic constraints on eggplant production in semi-arid to arid environments (e.g., Hexi irrigation area and Carnarvon). High evaporative demand, low precipitation, and strong solar radiation jointly limit crop productivity

These findings align with broader advances in precision water-fertilizer management. Reviews of precise water and fertilizer application technologies emphasize that integrating advanced sensors, remote sensing, and machine learning enables variable-rate fertigation and micro-irrigation that improve nutrient uptake, water-use efficiency, and environmental outcomes compared with uniform practices (Xing and Wang, 2024). Decision-support frameworks based on the Internet of Things and optimization models further show that coordinated, long-term irrigation and fertilization planning can simultaneously increase economic returns and environmental benefits compared with empirical management, indicating that regional eggplant yield prediction models can be directly embedded in smart fertigation and farm-planning systems (Lin et al., 2020).

8 Strategies for Sustainable Eggplant Production Under Climate Variability

Sustainable eggplant production under climate variability requires fertilizer strategies that enhance yield while maintaining soil health. A four-year eggplant field study showed that combining the full recommended NPK dose with farmyard manure increased yield by 47% over mineral fertilizer alone and substantially raised soil organic carbon and available N, P, and K, improving agronomic efficiency and nutrient recovery. At the broader vegetable level, a global meta-analysis found that enhanced-efficiency fertilizers (EEFs), such as nitrification inhibitors and polymer-coated urea, increased vegetable yield by about 7.5%-8.1% and improved quality while markedly reducing nitrous oxide emissions and nitrate leaching, especially when matched to soil pH and organic carbon conditions.

Optimizing nitrogen remains central, because excessive N is common in high-value vegetables and is associated with low recovery and high leaching risk. A review of nitrogen management in field vegetables emphasizes that aligning N supply with crop demand, improving synchronization via split applications, sensor-based diagnostics, and better irrigation management can simultaneously maintain yields and reduce nitrate losses below the root zone.

For eggplant in arid oasis conditions, a two-year drip-irrigation trial identified mild water deficit combined with medium N rate as the optimal strategy, significantly increasing yield, fruit quality, and water productivity compared with both higher and lower N and water levels, illustrating how fertilizer optimization must be co-designed with water management under variable climates.

Climate-smart agriculture (CSA) offers a framework to adapt eggplant systems to temperature and rainfall instability while reducing environmental impacts. A recent review highlights precision nutrient management, integrated soil fertility strategies, and regenerative practices (e.g., organic amendments, biochar, agroforestry) as key CSA options that improve soil health, raise nitrogen use efficiency, and increase carbon sequestration, thereby buffering crops against climate stress. Another synthesis of climate-change impacts on agroecosystems stresses that adaptation must address multiple risks-yield decline, water scarcity, pests, and product quality-through measures such as improved water and soil management, agronomic practices, and smart technologies tailored to local conditions.

At farm level in drought-prone regions, smallholders already employ practical adaptive strategies that are highly relevant for eggplant, including optimal water resource use, soil and water conservation, and nutrient management techniques to stabilize production under rainfall variability (Mpala & Simatele, 2024). A global scoping review of agricultural adaptation strategies further identifies crop and land-use adjustment, water and soil management, farmer training, agro-meteorological services, and early warning systems as central adaptation pillars; it emphasizes that biodiversity-based and climate-smart agriculture can simultaneously enhance resilience and productivity if supported by suitable policies and knowledge transfer.

Intelligent yield prediction systems can support sustainable eggplant production by integrating fertilization regimes, climate variables, and real-time field data to guide adaptive management. A comprehensive review of AI-based crop-yield prediction shows that machine and deep learning models using temperature, rainfall, humidity, soil type, and vegetation indices (e.g., NDVI, EVI, LAI) alongside management variables (such as irrigation and cultivation practices) substantially improve estimation accuracy and offer powerful tools for planning under environmental variability. Building on these insights, a crop yield prediction algorithm (CYPA) that combines climate, weather, yield, and chemical (including fertilizer) data demonstrated very high performance with ensemble models such as Random Forest and Extra Trees, and further enhanced efficiency via active learning to reduce labeled data needs.

For climate-resilient farming, future systems must be lightweight, deployable on edge devices, and tightly coupled with sensing infrastructures. An on-device AI framework using Random Forest on smart agricultural devices showed that integrating environmental sensor data with ML can achieve over 90% accuracy in detecting yield suitability and optimize irrigation scheduling to enhance water-use efficiency and support climate-resilient production without reliance on cloud computing. Reviews of IoT-enabled smart sensors in precision agriculture underscore that networks of soil, plant, and climate sensors, linked with AI/ML on IoT platforms, enable real-time monitoring, predictive analytics, and automated control of irrigation and fertilization, though challenges in cost, data management, and connectivity must be overcome for large-scale application in eggplant systems.

References

Abbas F., Al-Naemi S., and Al-Otoom A., 2025, Effects of controlled environment agriculture and nutrient sources on the production of eggplants (*Solanum melongena var. esculenta* L.), HortScience, 60(6): 970-980.
https://doi.org/10.21273/hortsci18550-25

Abdel-Salam M., Kumar N., and Mahajan S., 2024, A proposed framework for crop yield prediction using hybrid feature selection approach and optimized machine learning, Neural Computing and Applications, 36(33): 20723-20750.
https://doi.org/10.1007/s00521-024-10226-x

Badshah A., Alkazemi B., Din F., Zamli K., and Haris M., 2024, Crop classification and yield prediction using robust machine learning models for agricultural sustainability, IEEE Access, 12: 162799-162813.
https://doi.org/10.1109/access.2024.3486653

Bana R.S., Jat G.S., Grover M., Bamboriya S.D., Singh D., Bansal R., Choudhary A.K., Kumar V., Laing A.M., Godara S., Bana R.C., Kumar H., Kuri B.R., Yadav A., and Singh T., 2022, Foliar nutrient supplementation with micronutrient-embedded fertilizer increases biofortification, soil biological activity and productivity of eggplant, Scientific Reports, 12(1): 5146.
https://doi.org/10.1038/s41598-022-09247-0

Başay S., Dorak S., and Asik B.B., 2025, The effects of organic fertilizer applications on the nutrient elements content of eggplant seeds, Agronomy, 15(2): 439.
https://doi.org/10.3390/agronomy15020439

Burdett H., and Wellen C., 2022, Statistical and machine learning methods for crop yield prediction in the context of precision agriculture, Precision Agriculture, 23(5): 1553-1574.
https://doi.org/10.1007/s11119-022-09897-0

Cai S., Zhao X., and Yan X., 2022, Effects of climate and soil properties on regional differences in nitrogen use efficiency and reactive nitrogen losses in rice, Environmental Research Letters, 17(5): 054039.
https://doi.org/10.1088/1748-9326/ac6a6b

Chandio A.A., Ozdemir D., and Tang X., 2025, Modelling the impacts of climate change on horticultural crop production: evidence from Turkiye, Food and Energy Security, 14(1): e70040.
https://doi.org/10.1002/fes3.70040

Chioti V., Zeliou K., Bakogianni A., Papaioannou C., Biskinis A., Petropoulos C., Lamari F.N., and Papasotiropoulos V., 2022, Nutritional value of eggplant cultivars and association with sequence variation in genes coding for major phenolics, Plants: 11(17), 2267.
https://doi.org/10.3390/plants11172267

Cui J., Mak-Mensah E., Wang J.W., Li Q., Huang L., Song S., Zhi K.K., and Zhang J., 2024, Interactive effects of drip irrigation and nitrogen fertilization on wheat and maize yield: a meta-analysis, Journal of Soil Science and Plant Nutrition, 24(2): 1547-1559.
https://doi.org/10.1007/s42729-024-01650-y

Dey B., Ferdous J., and Ahmed R., 2024, Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables, Heliyon, 10(3): e25112.
https://doi.org/10.1016/j.heliyon.2024.e25112

Dollison M., and Tapas M.O., 2024, Yield components and nutritional analysis of Eggplant (*Solanum melongena* L.) under varying rates of Vermicast fertilizer, Diversitas Journal, 9(1): 316-331.
https://doi.org/10.48017/dj.v9i1.2952

Gao X.Q., Zhang L.C., An Y.L., Wang S.J., Feng G.Z., Lv J.Y., Li X.Y., and Gao Q., 2025, Synergistic effects of fertilization on maize yield and quality in northeast China: a meta-analysis, Agriculture, 15(13): 1371.
https://doi.org/10.3390/agriculture15131371

Gupta S., Geetha A., Sankaran K.S., Zamani A.S., Ritonga M., Raj R., Ray S., and Mohammed H.S., 2022, Machine learning-and feature selection-enabled framework for accurate crop yield prediction, Journal of Food Quality, 2022(1): 6293985.
https://doi.org/10.1155/2022/6293985

Hoque M.J., Islam M.S., Uddin J., Samad M.A., De Abajo B.S., Vargas D.L.R., and Ashraf I., 2024, Incorporating meteorological data and pesticide information to forecast crop yields using machine learning, IEEe Access, 12: 47768-47786.
https://doi.org/10.1109/access.2024.3383309

Huang N., Lin X., Lun F., Zeng R., Sassenrath G.F., and Pan Z., 2024, Nitrogen fertilizer use and climate interactions: Implications for maize yields in Kansas, Agricultural Systems, 220: 104079.
https://doi.org/10.1016/j.agsy.2024.104079

Iniyan S., Varma V.A., and Naidu C.T., 2023, Crop yield prediction using machine learning techniques, Advances in Engineering Software, 175: 103326.
https://doi.org/10.1016/j.advengsoft.2022.103326

Islam A., Shanto M.N.I., Rabby M.S.M., Sikder A.R., Uddin M.S., Arefin M.N., and Patwary M.J., 2023, Eggplant yield prediction utilizing 130 locally collected genotypes and machine learning model, In 2023 26th International Conference on Computer and Information Technology (ICCIT), IEEE, pp.1-6.
https://doi.org/10.1109/iccit60459.2023.10441036

Jabed M.A., and Murad M.A.A., 2024, Crop yield prediction in agriculture: A comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability, Heliyon, 10(24): e40836.
https://doi.org/10.1016/j.heliyon.2024.e40836

Kaniyassery A., Thorat S.A., Kiran K.R., Murali T.S., and Muthusamy A., 2023, Fungal diseases of eggplant (*Solanum melongena* L.) and components of the disease triangle: a review, Journal of Crop Improvement, 37(4): 543-594.
https://doi.org/10.1080/15427528.2022.2120145

Krishnadoss N., and Ramasamy, L.K., 2024, Crop yield prediction with environmental and chemical variables using optimized ensemble predictive model in machine learning, Environmental Research Communications, 6(10): 101001.
https://doi.org/10.1088/2515-7620/ad7e81

Kiran Kumar V., Ramesh K.V., and Rakesh V., 2023, Optimizing LSTM and Bi-LSTM models for crop yield prediction and comparison of their performance with traditional machine learning techniques: V. Kiran Kumar et al, Applied Intelligence, 53(23): 28291-28309.
https://doi.org/10.1007/s10489-023-05005-5

Kuradusenge M., Hitimana E., Hanyurwimfura D., Rukundo P., Mtonga K., Mukasine A., Uwitonze C., Ngabonziza J., and Uwamahoro A., 2023, Crop yield prediction using machine learning models: Case of Irish potato and maize, Agriculture, 13(1): 225.
https://doi.org/10.3390/agriculture13010225

Li H., Mei X., Wang J., Huang F., Hao W., and Li B., 2021, Drip fertigation significantly increased crop yield, water productivity and nitrogen use efficiency with respect to traditional irrigation and fertilization practices: a meta-analysis in China, Agricultural Water Management, 244: 106534.
https://doi.org/10.1016/j.agwat.2020.106534

Li J., Zhang H., Zhou C., Teng A., Lei L., Ba Y., Yu J., and Li F., 2025, Integrated effects of water and nitrogen coupling on eggplant productivity, fruit quality, and resource use efficiency in a cold and arid environment, Plants, 14(2): 210.
https://doi.org/10.3390/plants14020210

Lin N., Wang X., Zhang Y., Hu X., and Ruan J., 2020, Fertigation management for sustainable precision agriculture based on Internet of Things, Journal of Cleaner Production, 277: 124119.
https://doi.org/10.1016/j.jclepro.2020.124119

Liu D., Mishra A., and Ray D., 2020, Sensitivity of global major crop yields to climate variables: a non-parametric elasticity analysis, Science of the Total Environment, 748: 141431.
https://doi.org/10.1016/j.scitotenv.2020.141431

Mahesh P., and Soundrapandiyan R., 2024, Yield prediction for crops by gradient-based algorithms. Plos one, 19(8): e0291928.
https://doi.org/10.1371/journal.pone.0291928

Meng L., Liu H., L. Ustin S., and Zhang X., 2021, Predicting maize yield at the plot scale of different fertilizer systems by multi-source data and machine learning methods, Remote Sensing, 13(18): 3760.
https://doi.org/10.3390/rs13183760

Mohan R.N.V., Rayanoothala P.S., and Sree R.P., 2025, Next-gen agriculture: integrating AI and XAI for precision crop yield predictions, Frontiers in Plant Science, 15: 1451607.
https://doi.org/10.3389/fpls.2024.1451607

Morales A., and Villalobos F.J., 2023, Using machine learning for crop yield prediction in the past or the future, Frontiers in Plant Science, 14: 1128388.
https://doi.org/10.3389/fpls.2023.1128388

Nguyen G.N., Lantzke N., and van Burgel A., 2022, Effects of shade nets on microclimatic conditions, growth, fruit yield, and quality of eggplant (*Solanum melongena* L.): a case study in Carnarvon, Western Australia. Horticulturae, 8(8): 696.
https://doi.org/10.3390/horticulturae8080696

Oladosu Y., Rafii M.Y., Arolu F., Chukwu S.C., Salisu M.A., Olaniyan B.A., Fagbohun L.K., and Muftaudeen T.K., 2021, Genetic diversity and utilization of cultivated eggplant germplasm in varietal improvement, Plants, 10(8): 1714.
https://doi.org/10.3390/plants10081714

Osman M.A., Onono J.O., Olaka L.A., Elhag M.M., and Abdel-Rahman E.M., 2021, Climate variability and change affect crops yield under rainfed conditions: a case study in Gedaref State, Sudan, Agronomy, 11(9): 1680.
https://doi.org/10.3390/agronomy11091680

Parent L.E., 2024, Vegetable response to added nitrogen and phosphorus using machine learning decryption and the N/P ratio, Horticulturae, 10(4): 356.
https://doi.org/10.3390/horticulturae10040356

Paudel D., Boogaard H., De Wit A., Janssen S., Osinga S., Pylianidis C., and Athanasiadis I.N., 2021, Machine learning for large-scale crop yield forecasting, Agricultural Systems, 187: 103016.
https://doi.org/10.1016/j.agsy.2020.103016

Saeed F., Chaudhry U.K., Raza A., Charagh S., Bakhsh A., Bohra A., Ali S., Chitikineni A., Saeed Y., Visser R.G.F., Siddique K.H.M., and Varshney R.K., 2023, Developing future heat-resilient vegetable crops, Functional and integrative genomics, 23(1): 47.
https://doi.org/10.1007/s10142-023-00967-8

Sharma P., Dadheech P., Aneja N., and Aneja S., 2023, Predicting agriculture yields based on machine learning using regression and deep learning, IEEe Access, 11: 111255-111264.
https://doi.org/10.1109/access.2023.3321861

Taşan S., Cemek B., Taşan M., and Cantürk A., 2022, Estimation of eggplant yield with machine learning methods using spectral vegetation indices, Computers and electronics in agriculture, 202: 107367.
https://doi.org/10.1016/j.compag.2022.107367

Thingujam U., Bhattacharyya K., Ray K., Phonglosa A., Pari A., Banerjee H., Dutta S., and Majumdar K., 2020, Integrated nutrient management for eggplant: yield and quality models through artificial neural network, Communications in Soil Science and Plant Analysis, 51(1): 70-85.
https://doi.org/10.1080/00103624.2019.1695824

Xing Y., and Wang X., 2024, Precise application of water and fertilizer to crops: challenges and opportunities, Frontiers in Plant Science, 15: 1444560.
https://doi.org/10.3389/fpls.2024.1444560

Xing Y., Zhang X., and Wang X., 2024, Enhancing soil health and crop yields through water-fertilizer coupling technology, Frontiers in Sustainable Food Systems, 8: 1494819.
https://doi.org/10.3389/fsufs.2024.1494819

Zhou C., Zhang H., Yu S., Chen X., Li F., Wang Y., and Liu L., 2023, Optimizing water and nitrogen management strategies to improve their use efficiency, eggplant yield and fruit quality, Frontiers in Plant Science, 14: 1211122.
https://doi.org/10.3389/fpls.2023.1211122