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;