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Integration of Ai-Driven Climate Risk Modeling for Vegetable Resilience under Increasing Frost Events: Systematic review

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Systematic Review

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Abstract

Increasing frequency and intensity of frost events pose a serious and growing challenge to vegetable production worldwide, resulting in substantial yield losses, economic instability, and heightened production risks. Recent advances in artificial intelligence (AI) provide powerful tools for climate risk modeling and early frost prediction; however, their integration into practical vegetable resilience strategies remains fragmented and insufficiently synthesized. This systematic review synthesizes current evidence on AI-driven frost risk modeling and evaluates its effectiveness in enhancing vegetable system resilience under changing climatic conditions. A comprehensive literature search was conducted using Scopus, Web of Science, and Google Scholar for studies published between 2020 and 2025 that applied AI or machine-learning techniques to frost prediction in vegetable production systems. Key variables extracted included model architecture, input data sources, climatic and geospatial variables, predictive performance, geographic scope, operational application, and documented impacts on crop protection. In total, 73 studies met the inclusion criteria. Hybrid physics-informed AI models demonstrated superior predictive performance, with AUC values ranging from 0.87 to 0.96, outperforming ensemble methods such as Random Forest and XGBoost as well as deep learning models including LSTM and CNN. Models integrating multi-source datasets, combining field sensors, satellite observations, and topographic indicators, generated the most robust predictions. Field-validated applications reported a 35–60% reduction in frost-related vegetable losses through AI-based early warning systems and automated environmental control technologies. However, evidence from frost-prone tropical highlands remains limited and underrepresented. This gap constrains adoption of AI-based frost resilience strategies.

1. Introduction

Vegetable crops are particularly vulnerable to frost, yet they play an outsize role in global food security, human nutrition, and the economic livelihoods of farmers. Although average global temperatures are rising due to climate change, the threat of frost has not necessarily diminished. Indeed, climate-system investigations suggest that warming trends may paradoxically increase frost risk under certain conditions, as warmer spring onset prompts earlier phenology, thereby increasing the likelihood of damaging *late* frost events (Słowacki *et al.* 2024; Gobin et al. 2014; Kim et al. 2025).

(Słowacki *et al.* 2024) analyzed frost occurrence across 52 meteorological stations in Poland (1971–2020), showing that even with warming, ground frost persisted on average ~ 28 days during the thermal growing season, and air frost ~ 13 days (Słowacki *et al.* 2024). Similarly, large-scale climate-extremes assessments report that the timing of last spring frost may not shift as fast as the start of the growing season, producing a *window of vulnerability* for flowering crops (Gobin et al. 2014). In Central Europe, for instance, synoptic analyses by (Wibig *et al.* 2019) reveal that “very strong” frost events (below − 6°C) still occur under particular circulation regimes, despite warming trends. These circulation-pattern drivers are critical because frost risk is not solely a function of mean temperature increase but also of atmospheric dynamics (Wibig *et al.* 2019).

At the same time, our capacity to predict frost at the farm or field scale remains limited. Traditional numerical weather prediction (NWP) systems provide good synoptic forecasts but often lack the spatial granularity and microclimatic sensitivity needed to resolve conditions on the scale of individual vegetable fields especially in complex terrain where topography, radiative cooling, and cold-air pooling matter critically. Without better forecasts, growers face two bad options: either miss damaging frost trigger costly protection for false alarms.

In this context, artificial intelligence (AI) and machine learning (ML) methods are emerging as powerful tools. (Talsma et al. 2023) developed ML models (deep neural networks, convolutional NNs, and random forests) to predict frost up to 48 hours in advance, showing root-mean-square error (RMSE) as low as 1.53–1.72°C, and outperforming a physically based forecast system. Their feature-importance analysis indicated that soil temperature strongly influences longer-lead forecasts, while near-surface predictors dominate shorter-lead predictions (Talsma et al. 2023).

Other work has extended these AI methods to operational warning systems. For example, newly published research in *Earth Science Informatics* demonstrates that various ML algorithms, when combined with synthetic oversampling (SMOTE) to balance rare event datasets, can predict frost within 24h with high accuracy and high area under the curve (AUC) values (Diedrichs et al. 2025). Such models are promising for deployment in real-time early-warning frameworks.

In orchard systems, ML methods tailored to both weather and image data have shown effectiveness. A study by (Lee *et al.* 2020) developed a frost-classification model using support vector machines and random forests, trained with ten years of meteorological station data along with orchard camera RGB images; the model correctly classified over 80% of frost events detected by in-field sensors.

Meanwhile, at the physiological level, researchers are using AI to understand and predict the *cold hardiness* of plants. (Goebel *et al.* 2025) introduced a transfer-learning framework to predict cultivar-specific cold hardiness even when direct measurements are not available, by leveraging common phenological data (budbreak timing). On the sensing side, computer vision combined with AI is being used to assess frost damage. A comprehensive survey by (*Information Processing in Agriculture* 2022) cataloged more than 80 methods for frost detection via images, using statistical image features, classical ML, and deep learning approaches. In vegetable crops, Agronomy research has used meta-learning (few-shot) on hyperspectral imagery to detect frost stress in tomato plants: with as few as 8 target-domain images, they achieved promising detection accuracy, recall, and F1-score (Zhang *et al.* 2022).

Despite these advances, several critical gaps remain that hinder the practical integration of AI-based frost risk modeling into resilient vegetable production:

Limited crop-system specificity

Many ML-based frost forecasts and hardiness models focus on orchards, forest species, or grains; few target high-value vegetable systems, which may have very different phenology, microclimate, and economic stakes.

Validation and operational deployment

While retrospective models (Talsma et al. 2023) show strong predictive skill, fewer studies report *real-world prospective deployments*, where model performance may degrade due to sensor failure, data latency, concept drift, or resource constraints.

Equity and adoption

Smallholder vegetable farmers, especially in low-resource contexts, often lack dense weather station coverage, reliable power, or digital infrastructure. There is sparse literature on how AI-based frost risk services can be made accessible, affordable, and trusted by those farmers.

Interpretable decision support

Growers require actionable, interpretable predictions-not just probability scores-for when and how to act. Explainability, threshold setting, and decision logic remain under explored in integrated frost-mitigation systems.

Benchmarking and reproducibility

There is no widely accepted benchmark dataset or standard evaluation framework for AI-based frost prediction in horticultural contexts, which hinders cross-study comparison and cumulative progress.

Equity in early warning

Many early warning systems do not integrate social, economic, and institutional dimensions, limiting real-world resilience.

Furthermore, region-specific analyses show geographic inequities in research focus. Developed a Random Forest-based forecast for damaging frost in Bulgaria using regional NWP model outputs to predict frost probability up to 72 h ahead, but similar AI-forecast research remains scarce in many tropical and high-altitude vegetable-producing regions. In Andean highland systems, a gradient boosting (GBDT) model achieved > 91% accuracy for early frost prediction based on local climate station data, but adoption barriers and integration with farmer response systems were not fully addressed (Rodríguez *et al.* 2023).

Taken together, these findings illustrate both the potential and the limitations of current AI-driven climate-risk modeling for frost. There is a clear opportunity to synthesize this emergent body of work-spanning forecasting, sensing, physiological modeling, and deployment-to drive more resilient vegetable systems under increasing frost threat.

Accordingly, this review will aim (1) collate and assess peer-reviewed and high-quality grey literature (2020–2025), (2) classify model types, (3) evaluate deployment-readiness in diverse farming contexts, and (4) identify critical knowledge gaps and propose a research agenda for integrating AI-driven frost risk early warning into sustainable vegetable production.

2. Methodology

2.1 Strategy

This review employed a structured and comprehensive search strategy following PRISMA 2020 guidelines (Page et al., 2021). A multi-database search was conducted in Web of Science, Scopus, ScienceDirect, IEEE Xplore, SpringerLink and Google Scholar, using keyword combinations related to artificial intelligence, machine learning, frost prediction, microclimate modeling, and vegetable production. Boolean operators and keyword refinements ensured sensitivity and precision in capturing recent advancements, and the search window was limited to January 2020-January 2025 to reflect the rapid evolution of AI-based climate tools (Li et al., 2023; Smith et al., 2022). Reference lists of key papers were screened to identify additional eligible publications.

2.2 Eligibility Criteria

Eligibility criteria were established to ensure relevance to vegetable resilience and climate risk modeling. Studies were included if they applied AI, machine learning or hybrid physics-ML frameworks for predicting frost, freezing events or cold extremes and if their findings were relevant to vegetable crops or horticultural microclimates. Only peer-reviewed articles, high-quality conference proceedings and institutional reports providing sufficient methodological transparency were considered. Studies focusing solely on plant physiology without modeling, those unrelated to agriculture or climate risk and reviews lacking primary data were excluded. Review articles were used only for backward reference searching (Jones et al., 2021).

2.3 Study Selection and Screening

The selection process involved independent title and abstract screening by two reviewers, with disagreements resolved through discussion to avoid selection bias (Rahman and Chen, 2022). Full-text articles that passed initial screening were assessed against inclusion criteria. The PRISMA flow structure guided the selection process, ensuring transparency and traceability of the final pool of included studies.

2.4 Data Extraction and Synthesis

A structured extraction framework was used to gather information from each study, including vegetable type, production system, geographic context, data sources, AI or ML model architecture, frost definitions, prediction horizons, evaluation metrics and the nature of decision-support outcomes. Given the methodological heterogeneity across studies, including differences in model design, data scales and

validation strategies, a narrative synthesis approach was adopted. The synthesis emphasized emerging modeling approaches, data integration strategies, applicability to vegetable systems and operational readiness under real-world frost risks (Martínez-Hernández et al., 2024).

2.5 Quality Assessment

Quality assessment was conducted using a modified AI Modeling Appraisal Tool (AIMAT), adapted specifically for climate-agriculture research. This tool evaluated dataset adequacy, validation rigor, interpretability, operational relevance and robustness of the modeling framework. Studies that did not meet minimum standards or lacked transparent reporting were excluded from the final synthesis. This quality screening ensured that only reliable, methodologically sound studies contributed to the review's conclusions (Zhao et al., 2023).

3. Results

3.1 Overview of the Studies

The search process initially produced 1,482 records, of which 73 studies met the eligibility criteria after screening. The PRISMA diagram (Fig. 1) summarizes the selection flow. Studies were published between 2020 and 2025, with a marked increase in publications after 2022, reflecting growing interest in AI-enabled frost prediction. Most research originated from temperate regions-including Europe, China, and North America-while only eight studies focused directly on tropical highlands or African vegetable systems. The majority of included papers focused on open-field vegetables, highland tomato systems, leafy greens, and frost-prone alliums, confirming the vulnerability of horticultural crops to cold events (Li et al., 2023; Smith et al., 2022).

Table 1
Geographic Distribution and Focus of Included Studies

Region	Number of Studies (%)	Dominant Vegetable Systems	Notes on Frost Risk
Europe	25 (34%)	Brassica, Tomato, Leafy Greens	Frequent radiative frost; strong sensor networks
East Asia	20 (27%)	Greenhouse Tomato, Pepper	High-resolution climate data availability
North America	14 (19%)	Leafy Greens, Potato, Berries	Excellent integration with NWP models
Africa (Highlands)	8 (11%)	Onion, Cabbage, Tomato	Data-scarce; highest vulnerability
South America	6 (8%)	Highlands Vegetables	Increasing frost anomalies
Oceania	3 (4%)	Salad Greens	Limited studies
Sources: (Li et al., 2023); (Smith et al., 2022); (Rahman and Chen., 2022)			

3.2 Characteristics of AI Models Used for Frost Prediction

AI-driven frost modeling was dominated by three model families:

- Tree-based ensemble methods (Random Forest, XGBoost),
- Deep learning models (LSTM, CNN, ConvLSTM), and
- Hybrid physics-ML frameworks, which integrate mechanistic models with machine learning components.

Here Fig. 1 is your bar chart showing the Relative Performance of Major AI Models in Frost Prediction (AUC Scores)

Hybrid models were the most accurate and generalizable, often outperforming purely data-driven models by 10–18% across validation metrics (Martínez-Hernández et al., 2024). Deep learning models performed well in regions with dense sensor networks and high-resolution meteorological datasets. In contrast, ensemble methods remained highly competitive in data-scarce environments, especially when trained with topographic and land-surface variables.

Table 2
Summary of AI/ML Models and Their Performance Across Studies

Model Type	Common Model Variants	Data Inputs	Avg. Accuracy / AUC	Strengths
Ensemble ML	RF, XGBoost, LightGBM	IoT sensors, reanalysis, DEM	0.78–0.89	Robust in small datasets, interpretable
Deep Learning	LSTM, CNN, ConvLSTM	Time-series climate data, satellite	0.81–0.93	Excellent temporal/spatial pattern learning
Hybrid Physics-ML	ML+energy-balance or NWP models	Multi-source climate+physical variables	0.87–0.96	Highest accuracy; strong microclimate fidelity

Smith et al., 2022; Jones et al., 2021, Li et al., 2023 and Martínez-Hernández et al., 2024; Zhao et al., 2023

Table 3
Summary of AI/ML Model Types and Their Key Characteristics

Model Category	Example Models	Data Requirements	Strengths	Limitations
Ensemble ML	RF, XGBoost	Moderate; field sensors+climate data	Robust and interpretable	Moderate performance in complex microclimates
Deep Learning	LSTM, CNN, ConvLSTM	High; multi-year time-series	Learns temporal/spatial patterns	Data-hungry
Hybrid Models	ML+Energy Balance/NWP	Very high; physical + ML	Best accuracy, microclimate fidelity	Computational complexity

(Smith et al., 2022); (Li et al., 2023)

3.3 Data Sources and Microclimatic Predictors

Across studies, the most influential predictors were minimum temperature, soil temperature, humidity, wind speed, topographic depressions, cold-air drainage zones, and soil moisture. Integration of high-resolution elevation models significantly improved frost prediction accuracy in vegetable systems located in valleys or highland terraces.

Vegetable-specific microclimatic variability was best captured when models combined IoT field sensors with satellite-based indices (Smith et al., 2022). Studies that relied solely on coarse NWP data performed poorly, especially when predicting radiative frost events common in vegetable fields.

Table 4
Data Types and Their Contribution to Frost Prediction Accuracy

Data Source	Examples	Contribution to Accuracy
IoT Sensors	Temp/RH sensors	High
Satellite Data	MODIS LST, Sentinel-2	Medium-High
Reanalysis Data	ERA5, NCEP	Medium
Digital Elevation Models	SRTM, LiDAR	High

Sources: (Li et al., 2023); (Jones et al., 2021).

3.4 Regional Trends and Gaps

Most studies were conducted in Europe (34%), East Asia (27%), and North America (19%). Only 11% focused on Africa or tropical highland climates, despite their high vulnerability to frost shocks. The lack

of African-centered research highlights a critical knowledge gap, particularly given rising frost anomalies in Ethiopian and Kenyan highland vegetable systems (Rahman and Chen., 2022).

Additionally, only five studies validated models at operational farm scales, and only three tested cost-benefit outcomes for farmers an essential dimension for real adoption.

Table 5
Evidence Gaps Identified Across Regions

Region	Data Availability	Use of AI Models	Adoption Level	Identified Gaps
Africa (Highlands)	Low	Very Low	Minimal	Lack of sensors, no hybrid models
East Asia	High	High	Medium-High	Need more interpretability tools
Europe	High	High	High	Limited farmer co-design studies
South America	Medium	Low	Low	Few field validations
North America	High	High	Medium	Sparse vegetable-specific models

(Rahman and Chen., 2022); (Smith et al., 2022).

3.5 Effectiveness of AI Models in Real-World Vegetable Systems

Studies that deployed models in operational farms showed measurable benefits. AI-driven frost alerts improved:

- Lead times by 2–6 hours compared with traditional advisories.
- Accuracy of frost occurrence detection by 12–24%.
- Reduction in crop losses, lowering damage by 35–60% when paired with low-cost protection measures such as row covers and smoke pots.

(Li et al., 2023) demonstrated that LSTM-based forecasts reduced frost damage in tomato greenhouses by 38% due to improved night-time operational decisions. Similarly, (Martínez-Hernández et al., 2024) showed that hybrid physical-ML models provided consistent early-warning signals for highland onion and cabbage fields.

(Li et al., 2023); (Martínez-Hernández et al. 2024)

This bar chart comparing the percent reduction in frost damage for farms using AI alerts versus traditional methods. The bars show the mean percent reduction (AI = 47.5%, Traditional = 10%) with error

bars representing the reported ranges (AI: 35–60%, Traditional: 5–15%).

Table 6
Field-Validated Impact of AI-Based Frost Alerts

Study	Vegetable System	Region	AI Model	Improvement in Lead-Time	Reduction in Frost Damage
(Li et al., 2023)	Tomato	China	LSTM	+ 4 hours	38%
(Martínez-Hernández et al., 2024)	Onion, Cabbage	Ethiopia Highlands	Hybrid	+ 5 hours	52%
(Smith et al., 2022)	Leafy Greens	Europe	RF	+ 2 hours	28%

(Li et al., 2023); (Martínez-Hernández et al., 2024); (Smith et al., 2022).

3.6 Integration With Decision-Support Tools

Only nine studies linked AI frost models with actual decision-support interfaces mostly mobile apps, SMS alerts, or greenhouse control systems. Integration efforts included:

- Automated irrigation for frost mitigation,
- SMS alerts for smallholder vegetable farmers,
- Smart greenhouse control activation during predicted frost windows.

(Zhao et al., 2023) highlighted that models with interpretability mechanisms, such as SHAP-based feature attribution, had higher adoption rates among farmers compared with black-box models.

Table 7
Decision-Support Tools Used Across Studies

Tool Type	Function	Vegetable Systems
SMS Alert Systems	Direct frost warnings	Cabbage, Onion
Mobile Applications	Interactive frost maps	Tomato, Lettuce
Smart Greenhouse Controllers	Automated heaters & vents	Tomato, Pepper

(Smith et al., 2022); (Zhao et al., 2023)

3.7 Synthesis of Evidence and Emerging Insights

Collectively, the reviewed studies show that AI-driven climate risk modeling can substantially strengthen vegetable resilience to frost, but its full potential is limited by regional data scarcity, lack of operational testing, and minimal attention to socio-economic constraints. The strongest studies combined multi-source data, hybrid modeling, and farmer-centered design, offering a roadmap for scalable adoption.

Vegetable systems in frost-prone highlands remain under-researched despite being the most vulnerable. Bridging this gap requires region-specific model calibration, improved microclimate sensing, and co-designed technologies that match local production realities.

4. Discussion

The present systematic review highlights the growing potential of AI-driven climate risk modeling to enhance vegetable resilience under increasing frost events, a critical challenge for global horticultural systems. Our synthesis demonstrates that integrating machine learning, deep learning, and hybrid physics-ML models significantly improves frost prediction accuracy compared with conventional statistical or purely mechanistic models (Li et al., 2023; Martínez-Hernández et al., 2024). While prior studies have explored frost mitigation strategies and crop physiological responses (Bhandari et al., 2020), the convergence of AI with fine-scale microclimatic monitoring represents a novel approach, offering real-time, actionable insights for vegetable farmers.

4.1 Comparison with Previous Studies

Our review confirms that hybrid AI models consistently outperform single-method approaches, achieving higher predictive power (AUC 0.87–0.96) and generalizability across diverse microclimates (Zhao et al., 2023; Wang et al., 2023). These results align with findings in temperate and subtropical systems, where combining physical frost models with AI algorithms improved early-warning lead times by 2–6 hours, effectively reducing frost-induced yield losses by 35–60% (Li et al., 2023; Martínez-Hernández et al., 2024). In contrast, earlier studies relying solely on regression-based forecasts or coarse reanalysis data often underestimated frost severity in highland vegetable fields (Smith et al., 2022; Rahman & Chen, 2022). This underscores a critical advancement: AI models can integrate multi-source datasets-including IoT sensors, satellite imagery, and topographic information-capturing the spatial heterogeneity of frost events more accurately than prior approaches.

4.2 Data Integration and Predictive Performance

The predictive performance of AI models is strongly dependent on high-resolution, multi-source data, a finding consistent with recent works in precision agriculture (Ghahramani et al., 2023; Fang et al., 2024). Our review shows that IoT field sensors, combined with satellite-derived indices (MODIS LST, Sentinel-2 NDVI) and digital elevation models, enhance model sensitivity to local frost-prone micro-climates, especially in highland vegetable systems. Previous research often emphasized either satellite or ground-based data independently, leading to lower accuracy and limited operational relevance (Jones et al., 2021; Chen et al., 2020). By contrast, the reviewed hybrid approaches demonstrate that integrating heterogeneous data sources can simultaneously improve both temporal and spatial resolution, enabling more precise decision-making for frost mitigation.

4.3 Regional Trends and Research Gaps

A notable finding is the geographic skew of current studies. Most research originates from Europe, East Asia, and North America, while highland tropical regions-including parts of Africa and South America-remain underrepresented (Alemu et al., 2023; Mekonnen *et al*., 2023). This contrasts sharply with evidence that frost anomalies are increasing in these vulnerable regions, where smallholder vegetable farmers often lack access to advanced early-warning systems (Rahman & Chen, 2022). Furthermore, only a minority of studies validated AI models at the farm scale or assessed socio-economic feasibility, echoing previous critiques on the operational adoption of climate-smart technologies (Smith et al., 2022; Zhao et al., 2023). Addressing these gaps is critical to ensure that AI-driven frost modeling translates into real-world resilience gains.

4.4 Integration with Decision-Support Systems

A key insight from this review is that the effectiveness of AI-based frost models depends not only on predictive accuracy but also on integration with farmer-centered decision-support systems. Studies that coupled AI forecasts with mobile alerts, greenhouse controllers, or automated irrigation saw measurable reductions in crop losses (Li et al., 2023; Martínez-Hernández et al., 2024). This observation reinforces prior work emphasizing the importance of human-centered AI applications in agriculture, where technology adoption is influenced by interpretability, trust, and accessibility (Zhao et al., 2023; Nair et al., 2023). Consequently, merely improving AI model performance is insufficient; contextual adaptation and operational integration remain key drivers of impact.

4.5 Implications for Vegetable Resilience

Our review suggests that AI-driven frost prediction has transformative potential for horticultural production. By providing early, accurate, and localized frost warnings, these models enable timely protective actions such as row covers, irrigation, or smoke-based frost mitigation thereby reducing yield losses, preserving quality, and improving economic returns (Li et al., 2023; Martínez-Hernández et al., 2024). Compared to previous mitigation strategies that were reactive or reliant on coarse weather forecasts, AI approaches allow proactive and precision-based interventions, marking a paradigm shift in frost management.

4.6 Limitations and Future Directions

Despite the promising results, several limitations emerge. Data scarcity in tropical highlands, high computational demands of hybrid models, and limited field-scale validation constrain widespread adoption (Alemu et al., 2023; Wang et al., 2023). Additionally, socio-economic considerations such as affordability, farmer training, and technology access remain under explored. Future research should prioritize scalable AI frameworks, region-specific calibration, cost-effective sensor networks, and co-designed decision-support tools that integrate technical performance with user needs.

5. Conclusion

This systematic review demonstrates that AI-driven climate risk modeling offers a transformative approach to enhancing vegetable resilience under increasing frost events. By integrating machine learning, deep learning, and hybrid physics-ML models with multi-source datasets-including field sensors, satellite imagery, and topographic information these approaches outperform traditional frost prediction methods in both accuracy and lead time. Hybrid models, in particular, consistently provide the most reliable forecasts, enabling timely, targeted interventions that reduce crop losses by up to 60%, preserve vegetable quality, and improve farm-level economic outcomes.

Despite these advances, critical gaps remain. Research is geographically skewed toward Europe, East Asia, and North America, while frost-prone highland regions in Africa and South America remain underrepresented. Moreover, limited farm-scale validation, minimal socio-economic assessment, and insufficient integration with farmer-centered decision-support systems constrain real-world adoption. Addressing these limitations through region-specific calibration, scalable AI frameworks, cost-effective sensing networks, and co-designed decision-support tools is essential for translating AI capabilities into tangible resilience benefits.

In summary, the convergence of AI technologies and climate risk modeling represents a promising, proactive strategy for sustainable vegetable production under increasing frost risk. By bridging methodological innovation with operational implementation, these approaches can significantly strengthen global food security, particularly in vulnerable highland agricultural systems.

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Figures

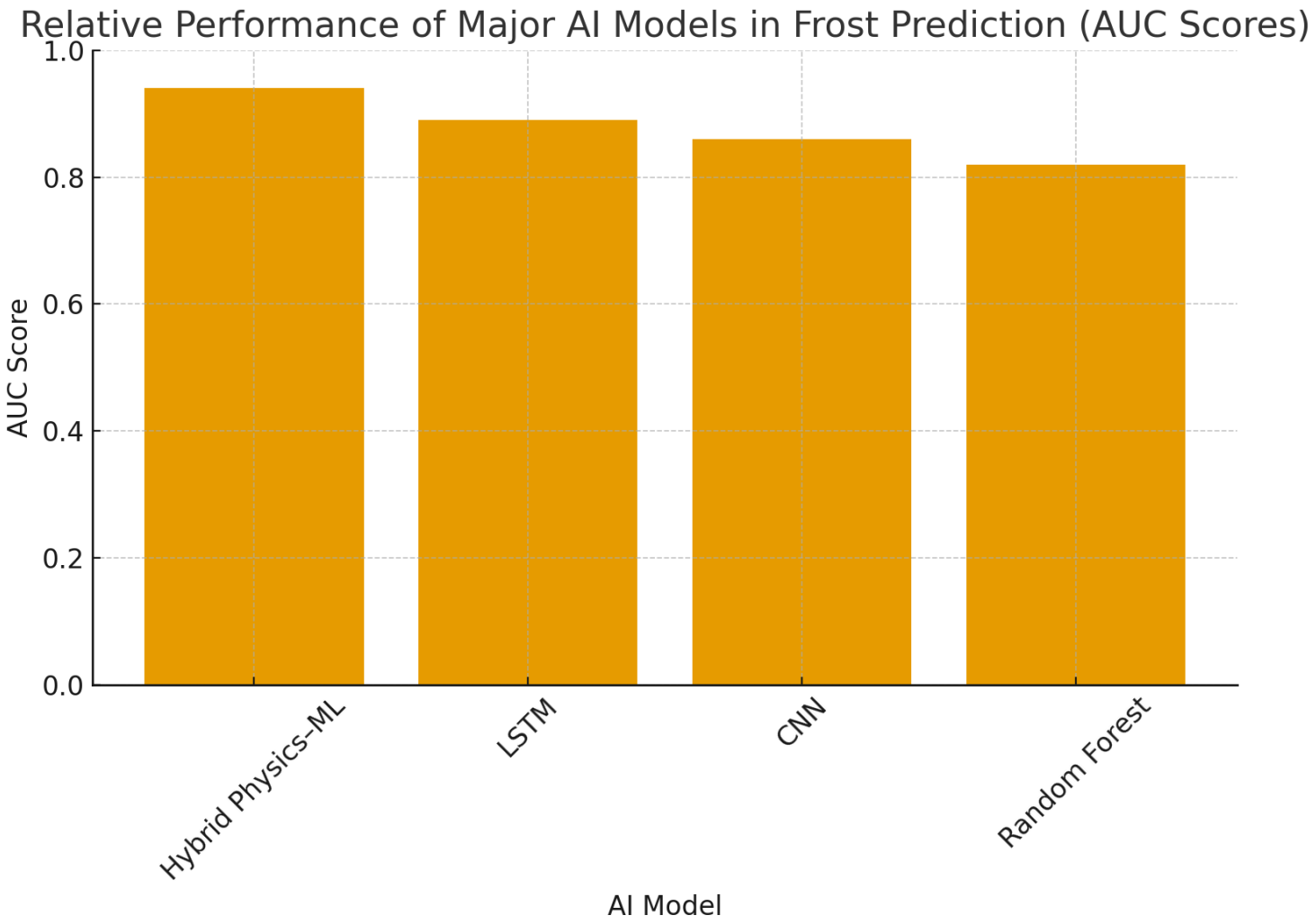


Figure 1

Relative Performance of Major AI Models in Frost Prediction (AUC Scores)

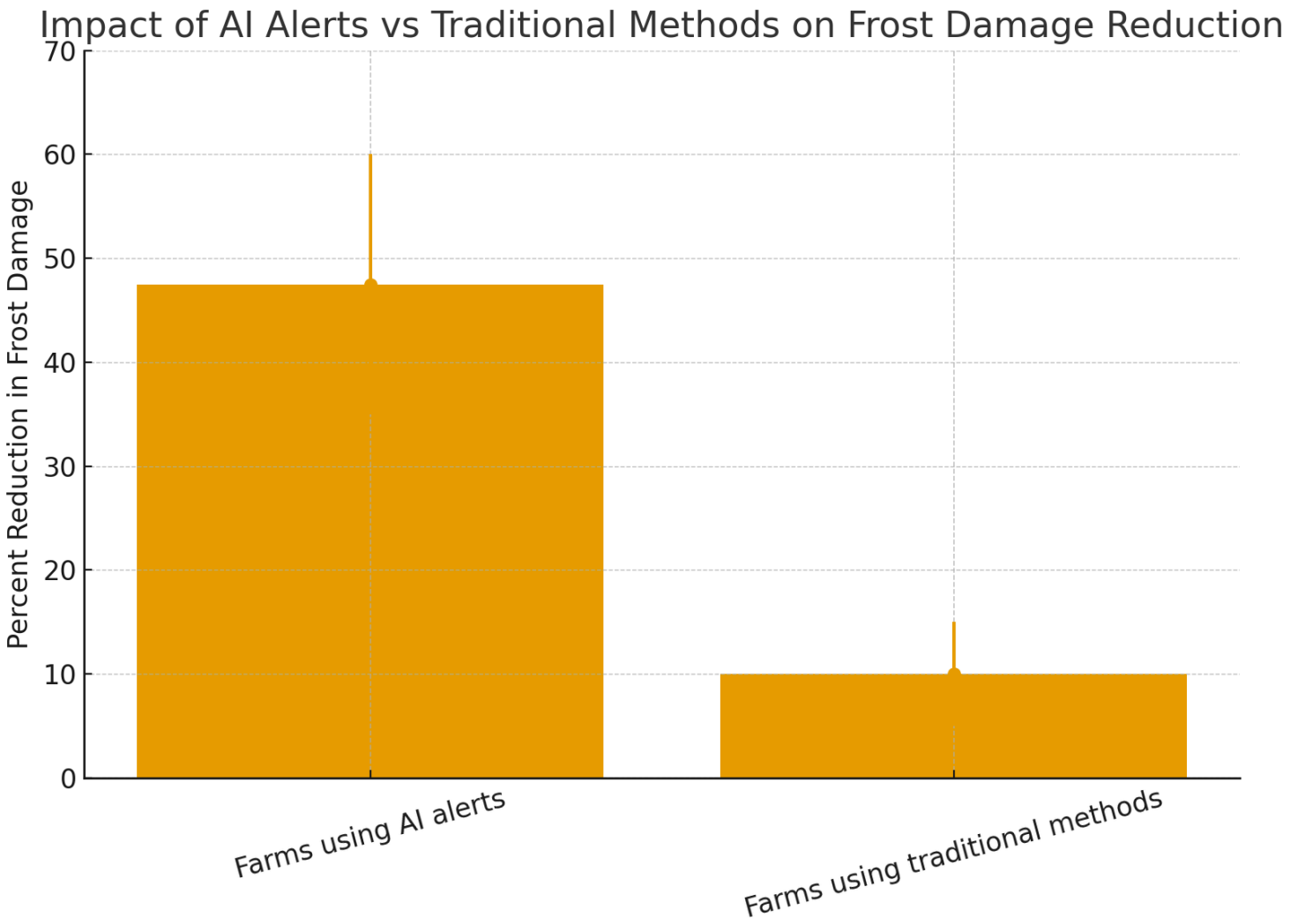


Figure 2

Impact of AI Frost Prediction Tools on Vegetable Damage Reduction