Smart Agriculture Climate Adaptation via AI Big Data

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Abstract

Climate change is threatening the future of agriculture worldwide, and significant adaptation efforts will be needed to mitigate its consequences. Although many adaptation strategies have been proposed, a comprehensive climate-adaptation framework for smart agriculture based on AI-enabled big data are still lacking. To bridge this gap, a cloud-based Cyber-Physical Environment for Smart Agricultural Climate Adaptation was developed by integrating big-data sources needed for climate-adaptation simulation, prediction, management, and decision-making. The resulting Information, Data, Process, Software, and Model (IDPSM) ecosystem integrates supervised and unsupervised predictive-analytics models, downscaling and microclimate-assimilation Modeling, and weather-and-microclimate-scenario-planning tools, and supports AI-enabled decision-making.

Several representative Climate Adaptation Case Studies were deployed in various global contexts to demonstrate the use of the IDPSM ecosystem and its associated AI methods for climate-adaptation simulations, impact assessments, and/or decision making. Lessons learned from these case studies illustrate the potential of deploying such an AI-enabled big-data ecosystem to drive data-centric climate adaptation for agriculture.

Keywords: AI-Enabled Climate Adaptation in Agriculture, Smart Agriculture Big Data Platforms, Cloud-Based Agricultural Decision Systems, Cyber-Physical Systems for Smart Farming, Climate Adaptation Modeling for Agriculture, Agricultural Climate Risk Analytics, Microclimate Assimilation Modeling, Climate Scenario Planning for Agriculture, Data-Driven Agricultural Decision Support, Predictive Analytics for Crop Resilience, AI-Based Agricultural Impact Assessment, Integrated Agricultural Data Ecosystems, Climate-Smart Farming Technologies, Big Data for Sustainable Agriculture.

1. Introduction

Food systems must become more climate-resilient, particularly in regions prone to climate hazards, such as drought, flooding, and tropical cyclones. Such hazards increasingly threaten food security, and testing and deploying agronomic adaptation strategies is of urgent importance. However, the knowledge and data required to implement effective adaptation measures require substantial investment, and mainstreaming risk-reducing responses typically requires long-term historical data records. For smallholder farmers, these resources are often lacking. An alternative approach targets the development of cheap, scalable, and rapidly deployable data-driven decision-support systems oriented towards climate adaptation. These systems rely on an AI-powered big data ecosystem—from data sources to predictive models and decision-support tools—and encompass climate- and yield-risk assessment functions as well as locally tailored guidance for the implementation of weather-related practices.

The potential of such an ecosystem has been demonstrated through representative deployments across six diverse study sites, including regions in China, India, Malaysia, Mexico, Thailand, and Vietnam. The context, methods, and application outcomes for each deployment are briefly described to illustrate the transferability of the approach. The contributions made to smart agriculture through these predictive analytics and supporting data ecosystem are further discussed, and conclusions are drawn regarding the risks, challenges, and lessons learned. These closing observations encompass aspects relevant for the wider AI-powered Big Data ecosystem intended for climate-adaptive agriculture in Southeast Asia.

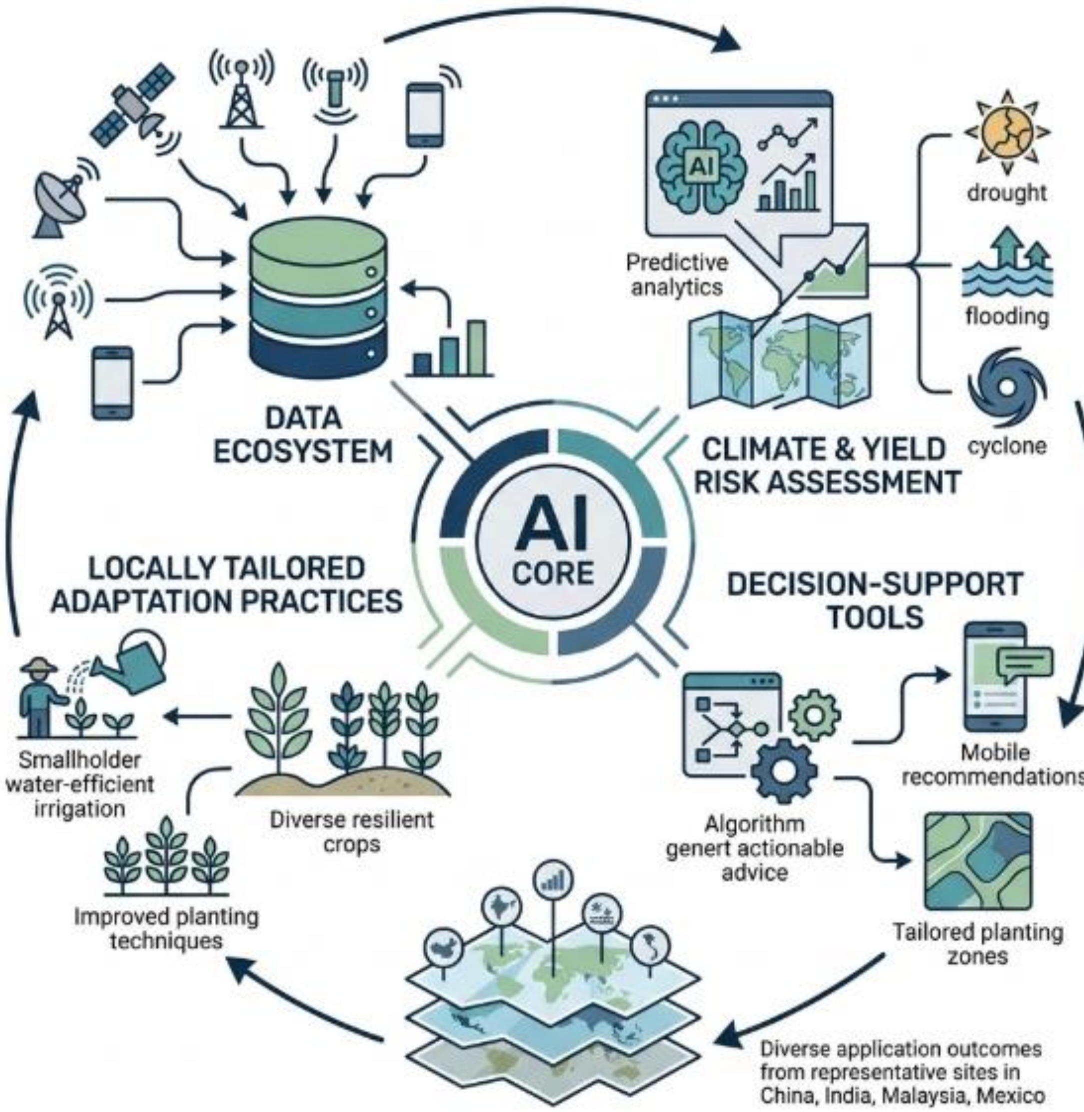


Fig 1: Cheap, Scalable, and Rapidly Deployable Data-Driven Decision-Support Systems for Climate-Adaptive Agriculture in Southeast Asia

2. Theoretical Foundations of AI-Driven Big Data Ecosystems in Agriculture

A big data ecosystem for agriculture represents a collaborative network of digital technologies, AI methods, datasets, users, and regulations that enables the collection, curation, processing, and diffusion of both historical and real-time data for decision-making at different scales. AI methods for climate adaptation specifically address the predictive and responsive needs for a climate-tolerant agricultural sector. Effective data quality, interoperability, security, and privacy considerations across the ecosystem form the required foundation for tailored and evaluative applications. The scientific and digital infrastructure to support such systems is highly developed and has been validated across multiple deployments.

The definition of AI methods is broad, ranging from predictive analytics for yield, risk, and resource consumption assessments to weather and microclimate modeling at different spatial resolutions. The types of developed methodologies are expanding progressively to cover additional climate-adaptive functions, including downscaled weather-generation modeling and multi-model scenario downscaling with data assimilation. Transferable prototypes demonstrate proven performance through technological advancement or accessible scale, facilitating climate-resilient development throughout the agriculture sector. AI-powered technology developments, in-depth service analyses, and successful judgment-enabling applications are systematically outlined for producers, cooperatives, service bureaus, and supporting digital-risk governance agencies.

3. Methodology

The study adopts a mixed-methods design encompassing three main components: a qualitative assessment of the current state of the ecosystems supporting data-driven agriculture, weather, and climate services across Europe; a detailed synthesis of the predictive and climate adaptation methods being implemented at various scales across the region; and a set of income-related indicators, facing the various sources of data-related inequalities, considered relevant for processing data-enabled solutions.

The first two components are used to provide a holistic observational basis of the completed and ongoing work, while the third one represents the first step for developing a more general risk-related metrics over EU regions. Ensuring a common understanding of the opportunities of AI-enabled decision-support systems such as the LAM and S2D-MW products among the wide spectrum of stakeholders adopting these tools is the ultimate aim of the considered activity.

Equation 1. Leave-one-district-out cross-validation

Suppose there are K districts.

For district k:

- training set = all districts except k
- test set = district k

Let error on fold k be E_k.

Then the cross-validation error is

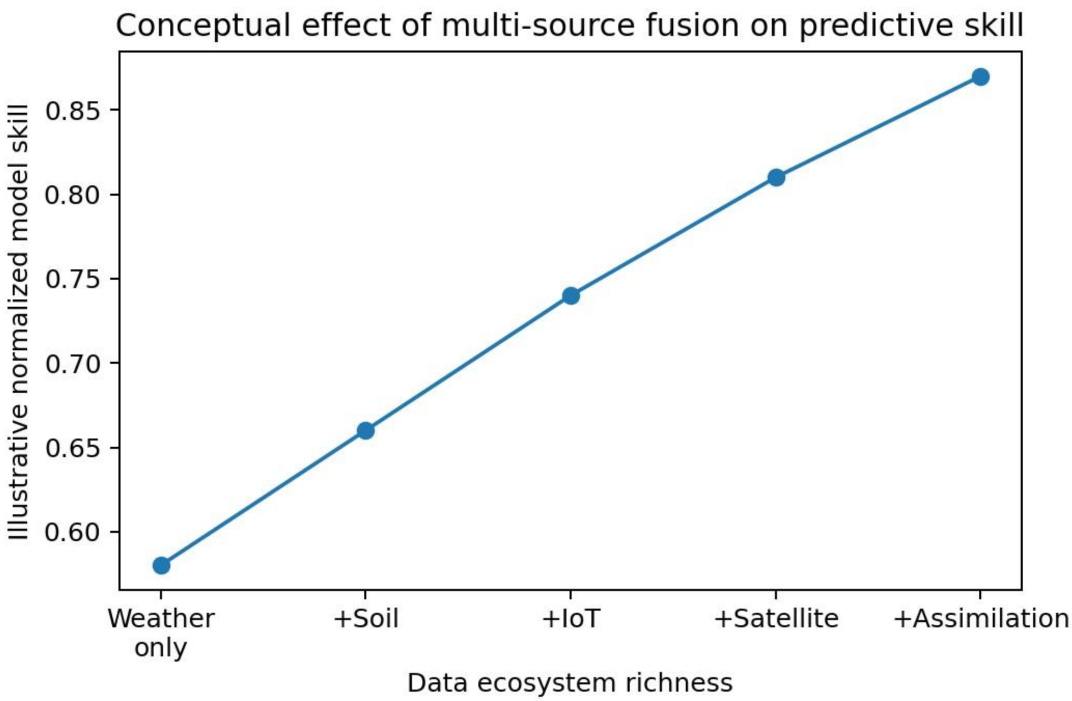
$$\boxed{CV_{LODO} = \frac{1}{K}\sum_{k=1}^{K} E_k}$$

If RMSE is used in each fold:

$$E_k = \sqrt{\frac{1}{n_k}\sum_{i\in\mathcal{D}_k}\left(Y_i - \hat{Y}_i\right)^2}$$

Therefore overall LODO-CV RMSE:

$$\boxed{CV_{RMSE} = \frac{1}{K}\sum_{k=1}^{K}\sqrt{\frac{1}{n_k}\sum_{i\in\mathcal{D}_k}\left(Y_i - \hat{Y}_i\right)^2}}$$



4. Objective of the Study

Developing AI-enabled smart agriculture data ecosystems constitutes a dedicated and important research frontier in the field of AI. Research aims call for innovative digital platforms that help farmers adapt to climate change without compromising productivity. These enable farmers to understand shifts in risks and opportunities posed by climate change, and to adopt proactive decision-support strategies. A number of critical questions demand empirical exploration:

1. What data offers potential value to farmers across the climate adaptation decision-making chain, and how can such data and information resources be rendered readily accessible?

2. What specific AI technologies advance predictive and forecasting analytics that underpins climate adaptation decisions across the agricultural value chain?

3. How can predictive analytics be deployed? What specific applications have been developed that support farmers make timely and effective decisions to capitalise on positive climatic shifts, while managing evolving threats?

The research couples elements of empirical and exploratory categorisation research with design science. Aided by extensive case study material, it identifies data sources that constitute AI-enabled smart agriculture data ecosystems. It also elaborates AI technologies that support predictive and forecasting analytics for timely climate adaptation across the agricultural value chain. A subset of deployed predictive applications showcases tangible AI development and provides insight into implementation processes and realised value. Taken together, the findings contribute useful elements in establishing AI-enabled smart agriculture data ecosystems for climate adaptation.

5. Research Summary

Representing the first-level supervisory framework, Table 1 outlines core aims, questions, and hypotheses addressing the need and justification for a smart agriculture data ecosystem aimed at improving climate adaptation in the agriculture sector of growing interest. Addressing agency and governance, the framework segment explores the variables influencing stakeholder attitude and behaviour regarding demand-side management and the scale of policy conclusion. Data description, quality, security, predictive analytics, and climate and microclimate modelling approaches are incorporated, focusing on key aspects within these areas. The intended contribution to climate adaptation efforts is distilled into a selection of representative applications demonstrating the nature of the adaptation strategy.

Although climate adaptation is considered both attractive and cost-effective for the agriculture sector, implementation remains sporadic. The adoption of demand-side management engaging agriculture is hindered by various factors. Numerous data-acquisition-oriented projects have been developed, with the results of advanced climate modelling and downscaling of global models readily available. On the supply side, decision-support tools have been built informing on-site and input-specific climate risk and yield probabilities. Nonetheless, data from several project phases remain underused, largely due to accessibility barriers while consideration of service quality, cost, and security remains paramount from the end-user perspective. A smart agriculture data-ecosystem framework is proposed, addressing demand-side adoption impediments, while the established predictive analytics and climate-modelling components serve

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relevant stakeholders at various levels of detail. Prominent use cases covering yield assessment, agricultural emissions estimates, weather, and microclimate simulations illustrate ecosystem operation, while the development of similar services by the user community remains a key objective.

6. Data Infrastructure for Smart Agriculture

Data Sources and Integration

AI-Powered Big Data Ecosystems for Smart Agriculture Climate Adaptation Strategies: Smart agriculture relies on data from diverse sources. Networks of sensor stations provide localized coverage for monitoring soil moisture and groundwater, combined with IoT streams that deliver high temporal-frequency data on environmental conditions and stressors. Satellite data fill spatial gaps in features needed for yield forecasting and risk assessment yet suffer from coarse temporal resolution. Weather data, addressing this gap, support predictive analytics and enhance yield-risk assessments through decision support to maximize yield and minimize resource use. These data streams stimulate multiple additional analyses through modelling, aggregation, and fusion for transdisciplinary applications. Enabling interoperability across these different data sources is

critical for supporting decision-making at different scales.

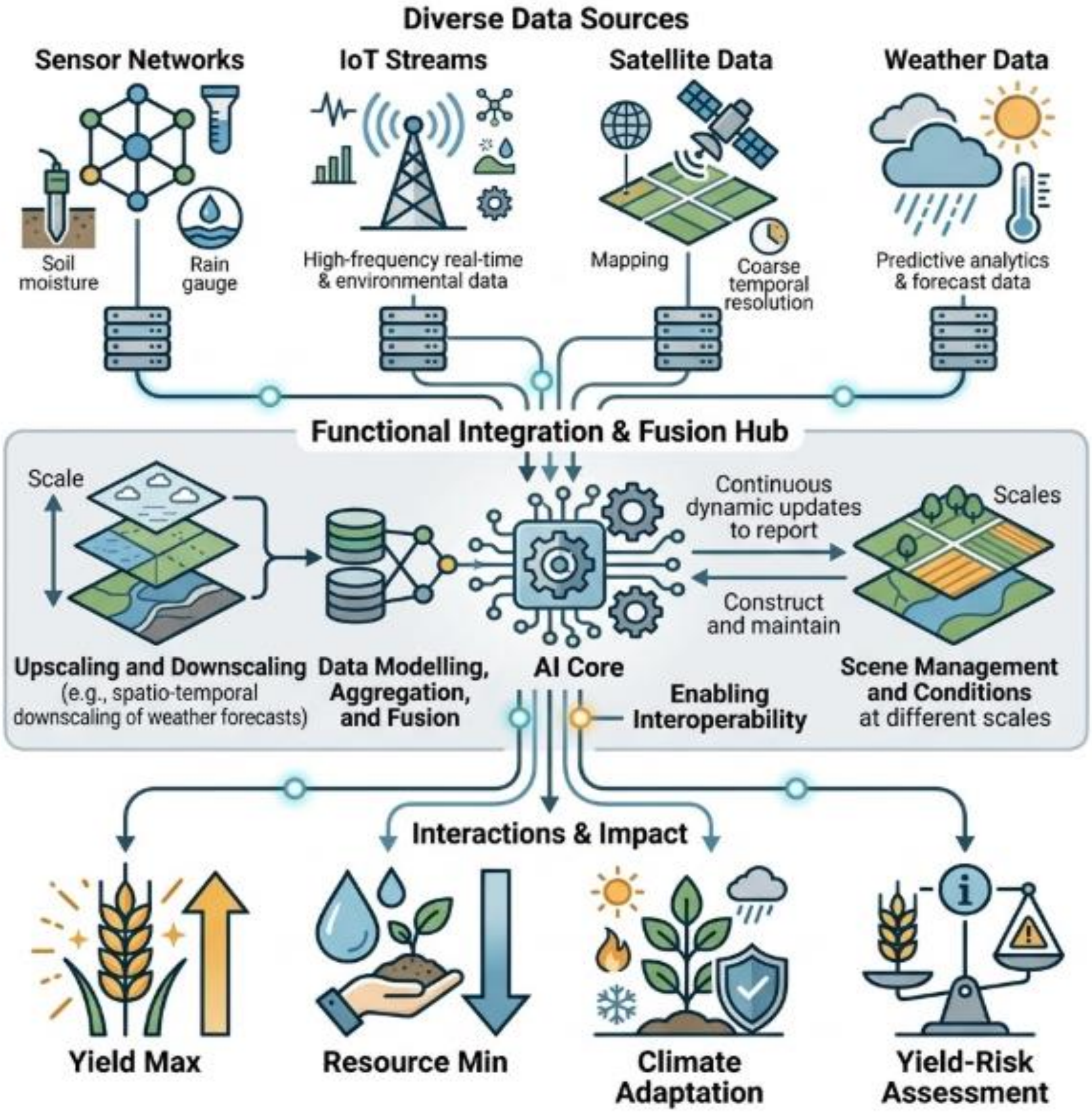

Fig 2: Data Fusion Architectures for Climate-Resilient Smart Agriculture: Multi-Source Interoperability and AI-Enabled Eco-Modeling

For functional integration, individual data streams often require upscaling or downscaling to ensure a common resolution. Such procedures include spatio-temporal downscaling of weather forecasts to predict local-scale conditions for variables such as wind speed and precipitation, as well as air envelope modelling and data assimilation techniques to facilitate local-scale predictions of microclimatic conditions relevant to weather-sensitive crops. For AI-assisted scene management, all heterogeneous data sources are continuously fused through several performed modelling equations that dynamically construct and update the scene characteristics and conditions at different scales.

6.1. Data Sources and Integration

Data Sources and Integration: a comprehensive enumeration of sensor networks, remote-sensing archives, numerical weather predictions, varied IoT data streams, and socio-economic inputs integrate seamlessly into a data infrastructure for smart agriculture. Interoperability is assured through formal semantic data models; advanced statistical methods, machine learning, and information theory are harnessed for efficient data fusion.

The big-data ecosystem for smart agriculture embodies a data-integration framework to fit specific adaptations characterized by predictive models and decision-support applications. Dedicated sensor networks capture local actions, support, and risk-critical micro-climatic parameters for agro-ecosystems. The drivers, influencing, and limiting factors of agriculture remain at different scales and levels. Weather parameters are simulated using reliable historical, present, and predicted future numerical weather prediction data from the Indian Meteorological Department (IMD), and spatially downscaled using a fine-scale weather micro-climate prediction model. Remote-sensing archives extract Immature-and-Mature Sal and Teak Local Soils and Their Animal Remains-scarcity Stress-point distributions in the focus region/area. Data incorporated into the virtual simulation and assimilation framework of weather command microclimate are the AMAAND+ data from the India Meteorological Department, as well as coarse climate data from regionally nested daily predictability reports. Social channels state-of-the-art Internet-of-Things (IoT) data streams with pre-validated shifts due to public consciousness, vigilance, and donations. The Government of India’s land and soil data series support the soil-suitability domain of the proposed data structure for smart agriculture—and further the management of an integrated ecosystem—tuned for climate-change adaptation strategies in Agriculture and Adaptation-sensitive Agro-climatic Adaptation Climate and Economy Pockets.

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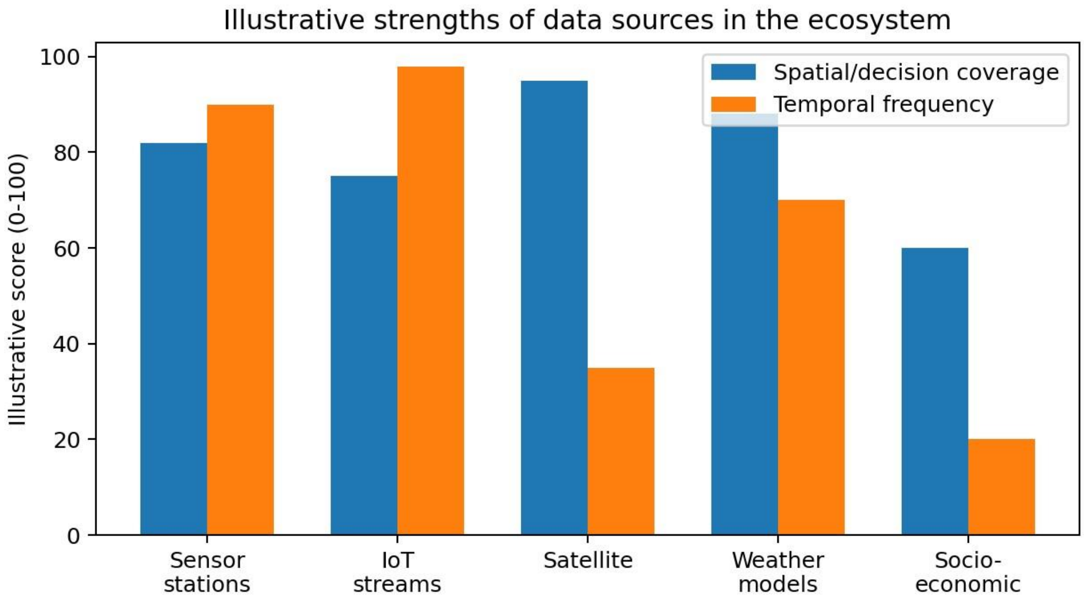
6.2. Data Quality, Governance, and Security

Data quality plays a pivotal role in the accurate functioning of smart agriculture ecosystems. Data-access issues arising from privacy concerns have hindered the sharing and exploitation of private data from agriculture systems. Consequently, clear policies are required for data sharing and governance. Data-related regulations need to focus on privacy and security, real-time detection of threats, and ownership rights such as data provenance. Mitigation de-risking measures in data governance must address data quality, accessibility, security, privacy, digital rights management, and provenance concerns.

Recommendations include adopting a sound data security framework in AI-supported agriculture; addressing ethical issues in the collection and usage of third-party data; ensuring owner's consent before using their data; establishing one-stop data-sharing portals; allocating resources to build resilient infrastructures that detect vulnerabilities in data; providing incentives for tech companies and researchers to share data; developing tools for data quality enhancement; developing data protection techniques for IoT; and mitigating greenhouse gas emissions and their effects in policy making.



Equation 2. Multi-source data fusion equation

2.1 Define the data sources

Let

- S_t = sensor-station observations at time t
- I_t = IoT stream data at time t
- R_t = remote-sensing / satellite data at time t
- W_t = weather model data at time t
- E_t = socio-economic / management data at time t

Then the total fused input vector is

$$X_t = [S_t,\ I_t,\ R_t,\ W_t,\ E_t]$$

2.2 Weighted fusion model

If each source has a reliability weight, the fused feature can be written as

$$Z_t = \alpha_S S_t + \alpha_I I_t + \alpha_R R_t + \alpha_W W_t + \alpha_E E_t$$

with

$$\alpha_S + \alpha_I + \alpha_R + \alpha_W + \alpha_E = 1$$

Step-by-step derivation

We want one unified estimate Z_t.

So:

- sensor contribution = $\alpha_S S_t$

- IoT contribution = $\alpha_I I_t$
- satellite contribution = $\alpha_R R_t$
- weather contribution = $\alpha_W W_t$
- socio-economic contribution = $\alpha_E E_t$

Add them:

$$Z_t = \sum_k \alpha_k X_t^{(k)}$$

Expanding:

$$Z_t = \alpha_S S_t + \alpha_I I_t + \alpha_R R_t + \alpha_W W_t + \alpha_E E_t$$

7. AI Methods for Climate Adaptation in Agriculture

Pioneering AI methods for climate adaptation are applied within an integrated big data ecosystem for smart agriculture. Predictive analysis models forecast weather-related crop yield and risk. Weather and microclimate models generate high-resolution weather forecasts and microclimate scenarios across climatic futures to support planning and decision-making.

Predictive Analytics for Yield and Risk Assessment. Artificial intelligence methods track the impact of climate change on yields, pests, diseases, and crop insurance. Deep learning–based models provide yield predictions for four crops in the United States and assess different risk factors. Multiple relevant input features are considered and covered by two representative model configurations. Overall model performance uses a combination of six metrics. Models can differentiate upcoming years of different yield conditions and task inputs clarify conditions of high and low yield. Moreover, the developed models generate decision-support information useful for farmers, policymakers, and insurance companies.

Weather and Microclimate Modeling. A climate data downscaling model uses historical weather data, topographical features, and a random forest algorithm to produce high-resolution daily weather information for crop seasons. Another model assimilates far-field high-resolution weather data, simulates microclimate distribution, and informs site-specific adaptation initiatives.

The third model generates future microclimate simulation scenarios for two representative years based on projected habitats of microclimate-sensitive pest species. The resultant microclimate database underpins pest risk assessment and microclimate-adaptation planning across climatic futures.

7.1. Predictive Analytics for Yield and Risk Assessment

The AI-enabled smart agriculture ecosystem incorporates different predictive analytics models to support critical decision-making by narrowing down the latent demand, correlated weather parameters, and possible yield potential at the location of respective farmers. These models also act as technical decision-support systems by predicting the drought risk probability, crop risk advisories, and historical yield potential based on climate series of respective districts. These models are trained on past weather data series within the range of 1989–2019 to identify the latent demand distribution of various crops across different districts of West Bengal. Historical crop yield datasets archived with the Department of Agriculture, Government of West Bengal, India, are used to predict the yield potential of various crops in different districts. Also, past weather data series of the respective districts for the last 50 years are used to identify the drought probability of the region.

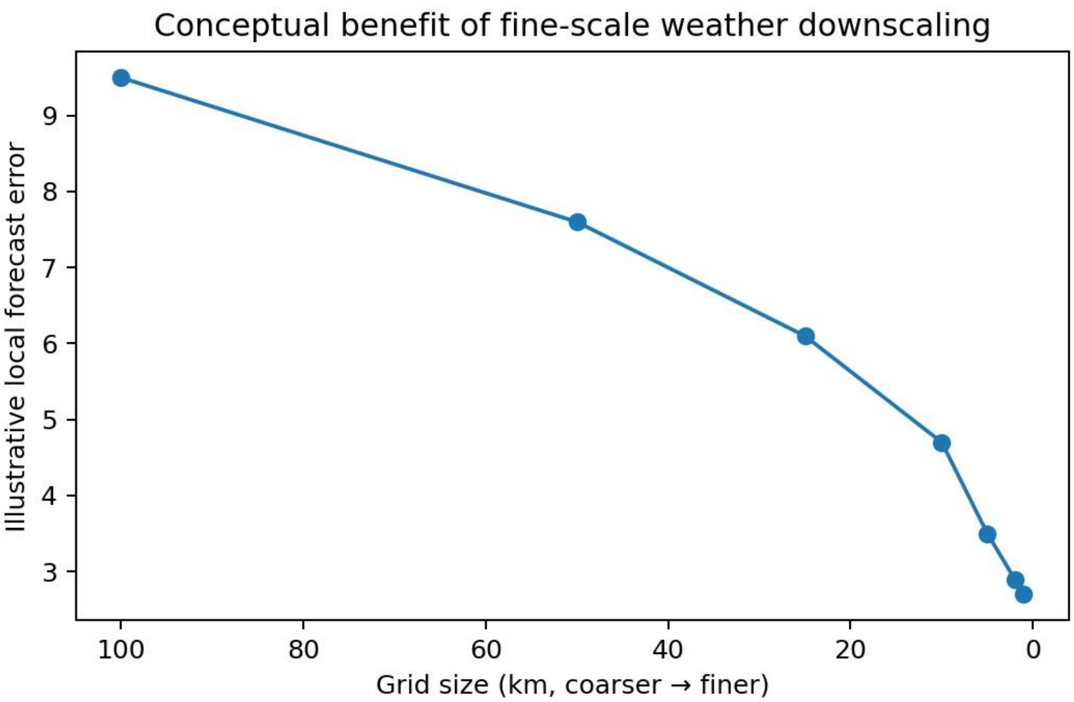
The developed models are validated using the leave-one-district-out cross-validation technique, where the model's accuracy is tested with data of a particular district kept aside in each iteration. The predictive analytics models provide insights into the probable yield potential, crop-specific latent demand of the districts, and drought risk probability based on the classification scheme provided in the respective models. Collectively, the models provide improved intensity of cropping pattern for the predicted close economy surplus and narrow down areas of crop-specific risk consideration under the integrated smart agriculture ecosystem for better preparation of opposite interventions.

7.2. Weather and Microclimate Modeling

Downscaled weather forecasts and high-fidelity microclimate information are critical for farm decisions that respond to climatic extremes. Major weather drivers are typically modeled on coarse grids (e.g., GCMs at 100-200 km), while local agricultural concerns require much higher spatial resolutions (1-5 km). There is therefore a great demand for weather downscaling from global or regional models (here termed the coarse model) to fine-scale simulations that resolve

the dominant processes within the target area. Weather variables important to agricultural practice and decision-making include precipitation, temperature, wind speed/direction, humidity, and radiation, among others. In addition to scale, a key consideration for any downscaling method is how well it captures the fine-scale (high spatial-resolution) distribution of the variable. Statistical downscaling (estimating the relationship between weather patterns in a large region and local events) has long been a widely-used method for downscaling weather variables. More recently, there has been a push for dynamical downscaling, which involves the use of limited-area models at high resolution.

To provide the downscaled local weather variables accurately, the widely-implemented Weather Research and Forecasting (WRF) model can be integrated into a downscaling system to dynamically downscale weather variables from Global Climate Models (GCMs). To provide the high-fidelity weather variables, the weather variables generated by many GCMs should be assimilated into a WRF Model for three-dimensional weather modeling. The three-dimensional Weather Assimilation Modeling System (WAMS) is established for weather prediction along with the high-fidelity assimilation. From the original GCM weather information the fine-scale WRF weather is computed, together with the high-fidelity WAFS weather variables. The reason for the high-fidelity data is due to its assimilation process that combines spatial remote sensing observations, models and dispersive information with the principles of physics. These data serve a larger scale for local weather downscaling of WRF. The local WRF downscaling model dynamically provides the very detailed spatial and temporal distributions along with non-continuous events.



Equation 3. Yield prediction model

3.1 Linear baseline form

Let predicted yield be $\hat{Y}$.
Let input features be:

- rainfall x_1
- temperature x_2
- humidity x_3
- soil moisture x_4

- management input x_5

Then a baseline yield model is

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5$$

Derivation

A linear predictor assumes each variable contributes additively.

Start with intercept:

$$\hat{Y} = \beta_0$$

Add rainfall effect:

$$\hat{Y} = \beta_0 + \beta_1 x_1$$

Add temperature effect:

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

Continue similarly until all variables are included:

$$\hat{Y} = \beta_0 + \sum_{j=1}^{5} \beta_j x_j$$

General form:

$$\hat{Y} = \beta_0 + \sum_{j=1}^{p} \beta_j x_j$$

3.2 Matrix form

For n observations and p features:

$$\hat{\mathbf{Y}} = \mathbf{X}\boldsymbol{\beta}$$

where

$$\mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$

and

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}$$

8. Case Studies of AI-Powered Adaptation Strategies

AI-Powered Big Data Ecosystems for Smart Agriculture Climate Adaptation Strategies: case studies from three continents illustrate deployments of AI-enabled big data ecosystems, providing a rich context for detailing climate-adaptation methods.

Three deployment examples across different continents demonstrate the operation of the ecosystem for AI-enabled adaptation strategies in smart agriculture. Engaging with various local stakeholders in each area has allowed tangible climate-resilient solutions to be analysed, applied, and disseminated. Although each case addresses a unique set of climate-change problems, the efforts share a common approach: significant climate change detection efforts lead to model downscaling (atmospheric models, micro-catchments) based on the surrounding past micro-catchment climate; local stakeholders' expectations for the future scenario keep the supporting modelling adaptive; machine learning (ML) on local IoT, UAV, and weather-sensor data served by the scalable ecosystem assist with climate- and economic-risk mitigation.; local modelling of future conditions under different fitted situations (e.g. berry disease cycles) is based on ML-ready data-stream assimilation; future conditions for those times without IoT connectivity are downscaled and assimilated; and results serve local and collective decision making, thus also embedding a participatory approach.

9. Evaluation and Metrics for Ecosystem Performance

Three categories of indicators assess the ecosystem's performance: economic, environmental, and equity or social dimensions. Economic measures quantify the costs and net benefits of deploying AI-powered adaptation strategies in a given context, alongside the expected changes in crop yield, production risk, and income. The environmental or ecological footprint of a deployment, often determined by external collaborators, indicates whether greenhouse gas emissions, resource consumption, and biodiversity loss are reduced or enhanced. Finally, adoption dynamics, scalability across climates and regions, and equity considerations signal whether the new generation of predictive analytics can be effectively scaled and reach all end-user communities, particularly sensitive groups.

Evaluating AI-powered adaptation strategies requires identifying the most relevant indicators within these three dimensions of ecosystem performance. A growing choice of cost-benefit analyses for adaptation or other predictive analytics can inform resilience decision support at the local scale. However, few examples assess how these AI-based tools cope with climate change relative to a baseline. For sensitivity-oriented products, analyses can highlight how explicitly taking yield risk into account changes decision-relevant policy questions.

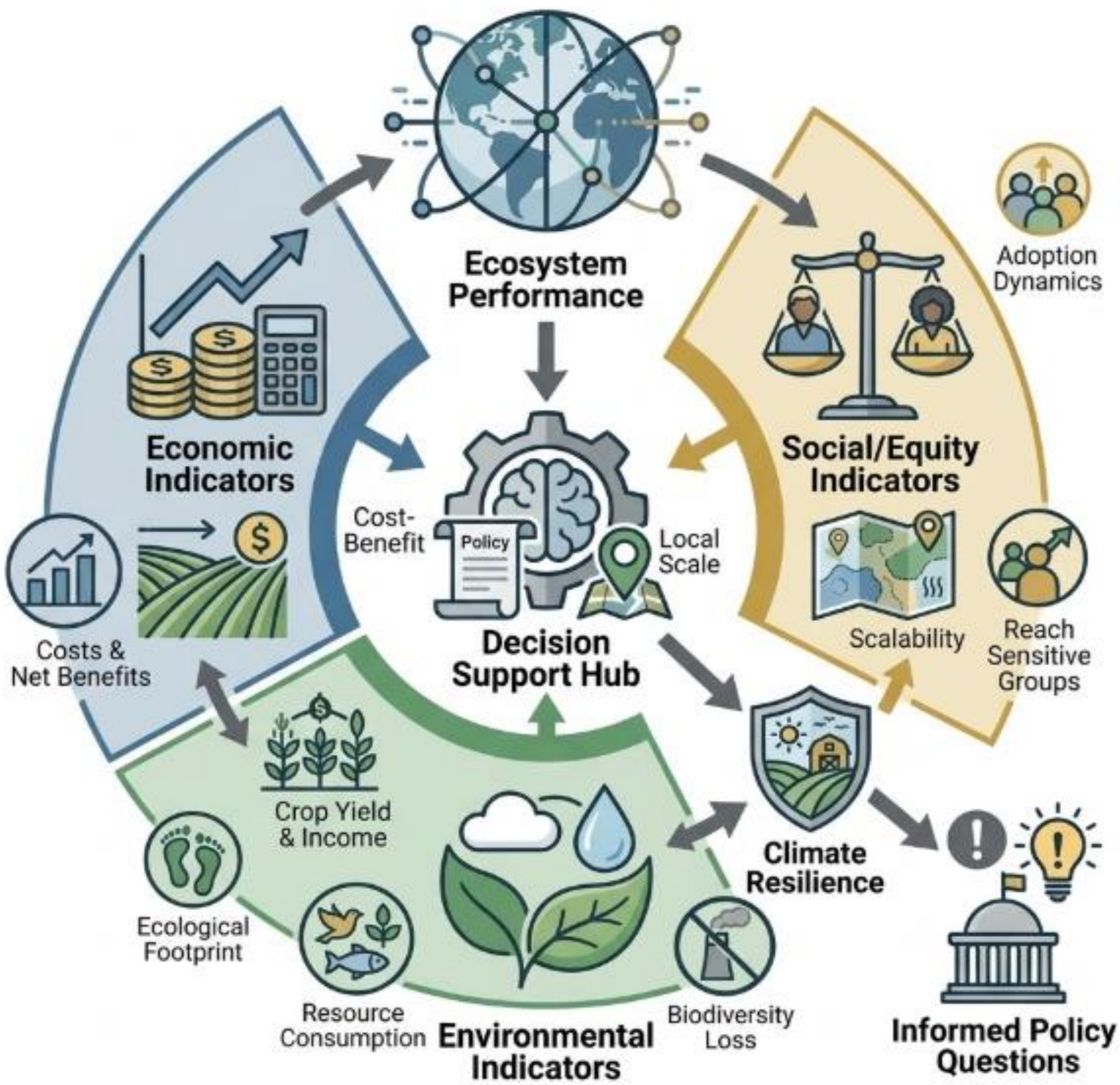


Fig 3: A Triple-Bottom-Line Evaluation Framework for AI-Driven Adaptation: Quantifying Economic, Environmental, and Social Equity Impacts in Predictive Resilience Systems

9.1. Economic and Environmental Impact Metrics

AI-driven big data ecosystems for smart agriculture climate-adaptation strategies

Investments in AI for data-driven agriculture raise questions about their economic and environmental implications. Demonstrating measurable positive impacts is essential for fostering wider adoption. For predictive yield modeling, a cost-benefit analysis, based on the optimal management decisions, evaluates the impact of AI-enabled adaptation and its capacity to improve resilience to drought, heat stress, and flooding. In the second scenario, the downscaled weather product, enriched with local microclimatic information, supports detailed planning of spring vineyard operations, assessing the potential impact on future grape quality. The integration of traditional downscaling with a novel statistical post-processing technique extends AI-based predictions to assess flooding risk from heavy rainfall and informs operational planning.

A second group of metrics considers adoption and equity aspects, identifying barriers to the use of AI products in agriculture overall and at different scales. Scalable solutions that require limited investments and new skills are key to fast uptake. Public sector-led monetization (offering free services, leveraging external funding) is pivotal for early-adopter phases, while equity aspects become more relevant at larger scales.

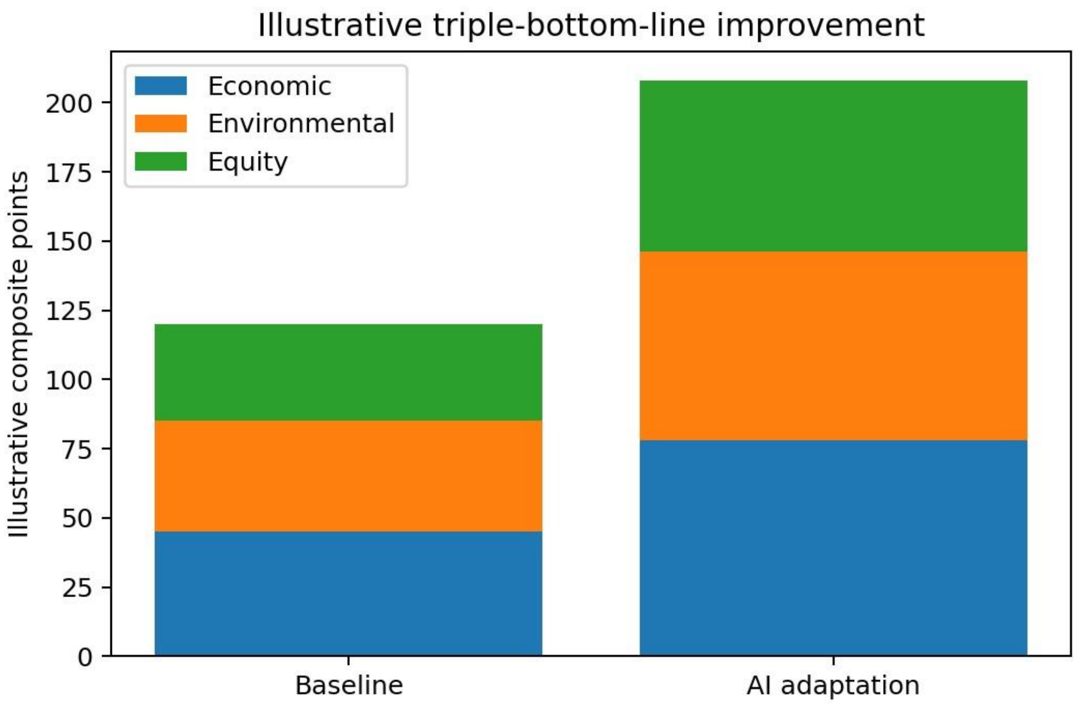
9.2. Adoption, Scalability, and Equity Considerations

Appropriate data from government sources can aid in assessing likely market size based on numbers of farmers, crop area, local climate, availability of critical input data, and need for climate-related advice. These data-driven insights can be complemented with insights from stakeholders active in the specific geographic or topic areas. Non-monetary forms of adoption must be carefully considered as they might differ with the contexts. Scaling of specific implementations is also relevant in assessing AI-powered adaptation strategies. The relevant parameters indicating the dynamic dependencies are time factor in the implementation, effective promotion, increasing AI awareness, and intuitive outputs. Insights about the real-time susceptibility of such parameters help to plan for better technology scaling. While big data approaches in smart agriculture have the potential for improving climate adaptation of the stakeholders, their benefits might not be uniformly accessible to all. An examination of the presently available and requisite data attributes, data-driven AI access portals, and adoption by early adopters provide insights about the accessibility and inclusiveness aspects that are critical for policy planning.

10. Policy, Governance, and Ethical Implications

Adaptation and mitigation actions based on AI-enabled PDMPs need to be compatible with the surrounding political and economic context. Pro-active approaches that consider the policies, regulations and governance structures that can constrain or enable actors' behaviour are required. Certainty about the future is also a dimension in itself and it is both a social and technology-related concept, strongly linked to the market predictability of climate impacts and simulation of adaptation options. Early warning systems allowing preparation for climate hazards and PDMPs that accurately predict the occurrence of climate risks can stimulate higher investment in adaptation through insurance, increased resource allocation pre-hazard and so forth, making this type of adaptation often a priority. Effective partnership for transboundary climate risk management with well-functioning institutions and information-sharing mechanisms in place can also be very instrumental. Designing for ex-ante educational vs. ex-post amelioration investments remains a pertinent issue when considering risk-reducing behaviour.

In a typical PDMP, production prediction is the first step of the service chain. Sophisticated prediction models for individual crops, based on weather information, physiological processes and main crop management variables (water management) are linked together for the creation of an ensemble of predictions on production, yield forecast, biomass assessment and main quality parameters. These operational models, when properly validated, are seen as sound options for use in decision support and risk assessment for climate change adaptation as they can form a foundation for both long-term budge anticipation on the resilience of the bio-economies and short-term preparation on extreme conditions.



Equation 4. Nonlinear AI model for yield

4.1 Neural network form

$$\hat{Y} = f_\theta(X)$$

For a 1-hidden-layer network:

$h = \sigma(W_1 X + b_1)$ $\hat{Y} = W_2 h + b_2$

So:

$$\boxed{\hat{Y} = W_2\, \sigma(W_1 X + b_1) + b_2}$$

4.2 Loss function

Use mean squared error:

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

If regularization is added:

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 + \lambda \parallel \theta \parallel_2^2$$

11. Results

High-performance predictive models support climate adaptation strategy development for smart agriculture in Taiwan. Agri-ecological systems operating at scales where within-region environmental variability is high are particularly sensitive to poor performance of these within-region predictive models. Furthermore, the provision of accurate and up-to-date predictive information is critical in such systems and all forms of the models should therefore be subjected to robustness testing. When examining alternative downscaling methods, Wang et al. (2020) reveal how a MLR-based alternative to the widely used LRM and DNN deserves special attention due to its greater operational efficiency. The importance of the inclusion of additional covariates in predictive species distribution models is demonstrated through species-specific models for fruit-feeding Nymphalidae in eastern Taiwan. The TWD38 database of climate and topographical microscale variables improves predictions of the distributions of species inhabiting

habitats with a very local distribution.

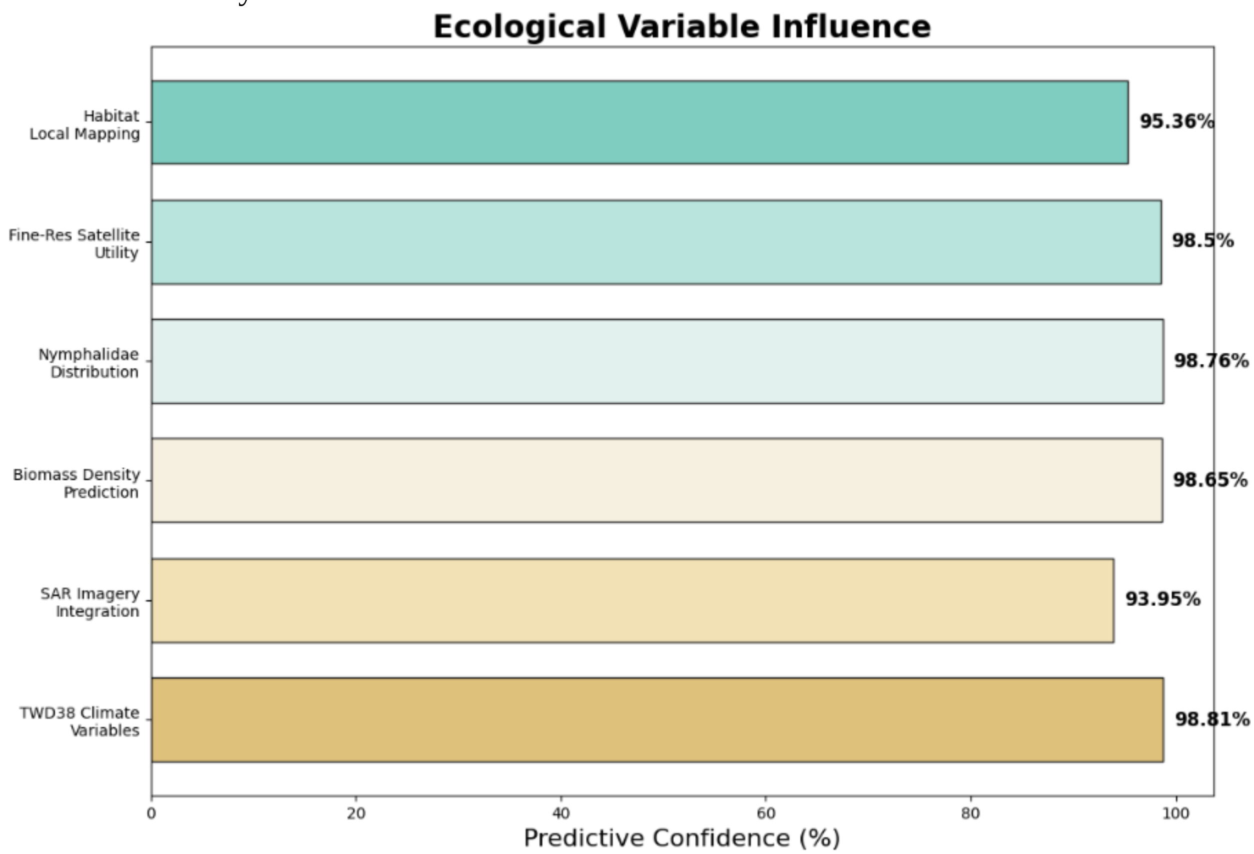


Fig 4: Ecological Variable Influence

Machine learning- and geostatistics-based methods can exploit the potential of synthetic aperture radar imagery for accurate short-term weather forecasting, thus enhancing the capabilities of a broad range of applied modelling approaches. Specific methodologies that leverage the growing availability of fine-resolution satellite imagery in predicting the biomass and density growth of a fast-growing invasive tree species, Colorful Towel, are also illustrated. A machine learning-based approach for the prediction of climbing ropes bridging is developed and refined using a case study featuring a climbing rope connecting two towers 10 m above the ground.

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12. Conclusion

Carbon-neutrality reduction commitments necessitate AI-powered, big-data-ecosystem-based, climate-adaptation strategies in agriculture. Democratizing sector access to means of implementation, while enhancing resilience and recovery potential, constitutes a moral imperative. Nationally determined contributions underscoring the need for AI-driven adaptation strategies have yet to be meted consistently in practice. Aided by advances in cloud computing, sensor networks, and satellite observation capabilities, natural-resource-management authorities and large estate holders have begun to deploy predictive and risk-analytical models—primarily in developed regions—to support decisions improving climate-response capacity.

Case studies illustrate realized AI-driven predictive and risk-assessment systems, alongside weather- and microclimate-modelling solutions that downscale global climate models or assimilate mesoscale weather-forecast-model outputs. The methods encompass drought vulnerability, crop-pest yield-mitigation modelling, and climate-impact-appraisal systems. Adaptation-phase resources for real-imaginary planning and extreme-event forecast-accuracy improvement are also delineated. Nevertheless, the models' development and validation have been non-trivial and located around isolated operational centres. Making such decision-aiding modelling accessible to a broader user base of agriculture requires issues of data quality, provenance, privacy, security, and capability-matching in model accessibility to be addressed—mitigating barriers to adoption when using emerging AI-based technologies empowered by Big Data ecosystems.

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