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FROM LAB TO FIELD: A SYSTEMATIC REVIEW OF DOMAIN ADAPTATION FOR ROBUST AGRICULTURAL IMAGE RECOGNITION

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Abstract.
The domain shift is a critical issue when it comes to the integration of artificial intelligence and computer vision in agriculture. Neural networks which the data has been trained in a certain setting do not work in a new setting due to the difference in visual appearance, environmental and biological variations. DA has proven to be a practical solution to this problem, so models can be transferred across domains. This article presents a comprehensive description of the approaches to DA that have been specifically to carry out an agricultural image recognition. We present a taxonomic order of the techniques of DAs, outline their mathematical foundations, and provide a literature matrix of the recent studies (2020-2025) that summarize it. Some of the largest agricultural applications of AI that we talk about include weeds, crop segmentation, yield estimation, and crop classification. We critically peruse datasets, benchmarks, and performance measures and highlight the problems and future research direction that is essential. The review indicates that the area is arriving at a point of integration as viable solutions like source-free and test-time adaptation, although no single DA methodology can address all applications, provide viable solutions to real-life deployment problems.

Keywords: Domain Adaptation, Agricultural Computer Vision, Transfer Learning, Precision Agriculture, Deep Learning.

INTRODUCTION

A. The Promise of AI in Agriculture

Precision in agricultural practices is a new era being ushered by the integration of artificial intelligence (AI) and computer vision in agricultural practices[1]. Since automated identification of plant diseases to the segmentation of crops and weeds at the fine-grain level and Deep learning models have shown impressive performance in the estimation of the fruit yield with the use of unmanned aerial vehicles (UAVs)[2]. These technologies are projected to enhance the yields of the crops worldwide and maximise the use of the resources as well. increase sustainable agricultural activities through off-the-record and real-time actionable insights[3].

B. The Domain Shift Problem: A Major Obstacle to Real-World Model Deployment

Nonetheless, the process of translating research standards into the actual farmlands is troubled by a critical issue: domain shift[4]. Another example of such a catastrophic presentation of a model trained on clean, lab-quality images of leaves (the source domain) is phenomenological. of hazy, lost, bleached pictures on a field (the target domain) [5]. This change can be brought about by changes in:

- Visual aspects: Lighting, camera sensor, resolution, viewpoint.
- Environmental factors: Soil type, weather, time of day, season.
- Biological variations: Crop cultivar, plant growth stage, pest biotypes.

This discrepancy renders many high-accuracy models unreliable and impractical for widespread deployment, creating a signif- icant barrier to the adoption of AI in agriculture.

C. Formal Definition of the Domain Adaptation Problem

Domain Adaptation (DA) is a subfield of transfer learning that directly addresses this challenge. We define a domain D as consisting of a feature space X and a marginal probability distribution P (X), where $X = \{x1, \ldots, xn\} \in X$ [3].

Given a labeled source domain $D_S = \{(x^s, y^s)\}^{nS}$ drawn from distribution $P_S(X, Y)$, and an unlabeled target domain

$D_T = \{x^t\}^{nt}$ drawn from a different distribution $P_T(X, Y)$, the goal of Unsupervised Domain Adaptation (UDA) is to learn

$$i \; i = 1$$

a predictive function $f : X \rightarrow Y$ with low expected error on D_T using the labeled D_S and unlabeled D_T, under the assumption that $P_S \neq P_T$ but the conditional distribution $P(Y|X)$ may be similar .

D. Scope, Contributions, and Paper Organization

This review paper provides a comprehensive survey of DA techniques specifically tailored for agricultural image recognition. Our key contributions are:

1) A structured **technical taxonomy** of DA methods, explaining their mathematical underpinnings.
2) A detailed **literature matrix** synthesizing the latest research (2020-2025).
3) A systematic analysis of DA applications across key agricultural tasks.
4) An identification of **open challenges** and promising future research directions.

Background and Fundamentals

A. Key Computer Vision Tasks in Agriculture

TABLE I: Common Agricultural Vision Tasks and Their Challenges

Computer Vision Task	**Description**	**Key Challenges**	**Example Application**
Image Classification	Assigning a single label to an entire image.	Intra-class variance, fine-grained differences.	Identifying the species of a crop from a field image [8].
Object Detection	Locating and classifying multiple objects within an image.	Occlusion, scale variation, dense objects.	Detecting and counting fruits like apples or man- goes [6].
Semantic Segmentation	Assigning a class label to every pixel in the image.	Precise boundary delineation, class imbalance.	Segmenting weeds from crops and soil for preci- sion spraying [5].
Instance Segmentation	Distinguishing between different objects of the same class.	Overlapping instances, identical appearance.	Counting individual plants in a dense canopy [9].

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B. Theoretical Foundations of Domain Adaptation

The theoretical basis for many DA approaches is built on the seminal work of Ben-David [6], which provides a bound on the target error. The HΔH-divergence measures the discrepancy between two distributions D_S and D_T over a hypothesis class H.

The target error $\epsilon_T(h)$ of a hypothesis h is bounded by

- $d_{H\Delta H}(D_S, D_T)$ is the HΔH-divergence,
- λ is the combined error of the ideal joint hypothesis, which is expected to be small if the task is feasible.

This bound motivates DA methods: to minimize the target error, we must minimize the source error **and** the divergence between the domains .

C. A Taxonomy of Domain Adaptation Scenarios

Domain adaptation methods can be categorized into several scenarios based on the availability of labeled data, the number of source domains, and the nature of the target domain [10]. Typical examples would be Unsupervised Domain Adaptation (UDA), which does not use any target domain data; Semi-Supervised DA, which does use a small amount of target domain data, but with the source data; Multi-Source DA, which does use multiple source domains; Multi-Target DA, where more than one target domain is being adapted; and Source-Free DA, where the source data is not available. Fig. 1 depicts these scenarios in such a way that it gives a systematic description of each of their relationships and features [7].

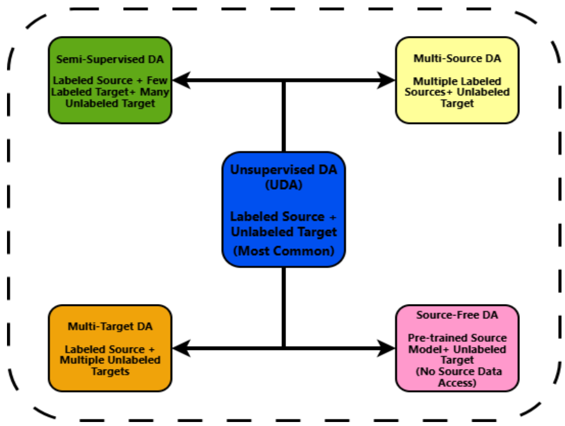

Fig. 1: Diagram of DA Scenarios: UDA, Semi-Supervised, Multi-Source, Multi-Target, Source-Free DA

I. Literature Review Methodology

A. Search Strategy and Selection Criteria

We carried out a systematic literature search in which we used such academic databases as Google Scholar, IEEE Xplore, ACM Digital Library with a query on papers published in 2020-2025. Our search terms were the combinations of keywords: domain adaptation, transfer learning, agriculture, plant, crop, weed, unmanned aerial vehicle, UAV, and names of certain tasks: detection and segmentation. We concentrated on high-impact conference and journal articles, and we mainly relied on the current studies of 2024-2025 to get the state-of-the-art [8] [9].

B. Literature Matrix

To give a tangible picture of the existing research situation, Table II shows a detailed literature matrix that summarizes the recent literature, their types of DA, and their usage in different agricultural activities.

TABLE II: Comprehensive Literature Matrix of Domain Adaptation in Agricultural Vision

Reference	DA Category	Method		Agri-Task	Source/Target Domain	Key Contribution	Performance
Li et al., 2024 [13]	Adversarial	CDAN-RT		Disease Classifica-	Lab (PlantVillage) →	Conditional adversarial learn-	+15.2 % F1-

				tion	Field (Plant-Doc)	ing for long-tailed distribu-	score
						tions	
Kumar et al., 2024	Source-Free	SFDA - Wheat		Wheat Head De-tec-	Global Wheat Head →	Source-free adaptation via en-	+12.8 % mAP
[14]				tion	Specific Region	tropy minimization	
Garcia et al., 2024	Self-Training	Cyclic	Self-	Fruit Detection	Orchard Season 1 →	Combines pseudo-labeling	+18.5 % Recall
[17]		Training			Season 2	with contrastive learning	
Wang & Zhang,	Test-Time	TTA-AG		Robot Navigation	Simulated → Real Field	Adapts BN statistics and min-	-40% nav error
2024 [18]					(on-the-fly)	imizes entropy at test time	
Chen et al., 2024	Multi-Modal	M3D A		Yield Prediction	Multi-Farm	Adversarial fusion of multiple	+22% R^2 score
[19]					(RGB+Multispec)	sources and modalities	
					→ New Farm		
Zhang et al., 2023	Adversarial	ADD A		Weed Detection	Controlled light → Field	Feature-level adversarial	+14.3 % mIoU
[20]					conditions	alignment	
Patel et al., 2023	Self-Training	Noisy Student		Crop Classification	Satellite Region A →	Iterative self-training with	+16.1 % Accu-
[22]					Region B	data augmentation	racy
Johnson et al., 2023	Multi-Source	MCD A		Disease Detection	Multiple farms → New	Dynamic weighting of multi-	+13.7 % F1-
[23]					farm	ple source domains	score
Kim et al., 2022	Discrepancy	Deep CORAL		Plant Stress	Lab images → Field	Second-order statistic align-	+11.2 % Accu-
[25]					UAV	ment	racy
Rodriguez et al.,	Reconstruction	DRCN		General Phenotyp-	Synthetic → Real plants	Shared decoder for domain in-	+9.8 % mAP
2022 [26]				ing		variance	

II. A Technical Taxonomy of DA Methods

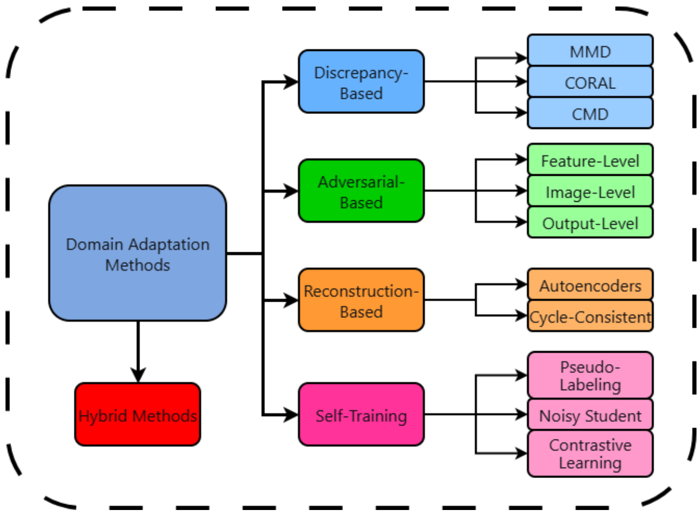

Fig. 2: A Taxonomy Tree of Domain Adaptation Methods

A. Discrepancy-Based Methods

These methods explicitly measure and minimize a statistical distance between the source and target feature distributions. The intuition is straightforward: if the feature distributions are aligned, a classifier trained on source features will generalize to the target domain.

Mathematical Core: A cornerstone of this approach is the **Maximum Mean Discrepancy (MMD)**. MMD computes the distance between two distributions P and Q in a Reproducing Kernel Hilbert Space (RKHS). The empirical estimate of MMD
is:
where $\phi(\cdot)$ is the feature map to the RKHS. The DA objective then becomes $L = L_{task} + \lambda \cdot MMD^2(D_S, D_T)$.

TABLE III: Summary of Discrepancy-Based Methods in Agriculture

Reference	Method	Agricultural Applica- tion	Key Insight
[18]	Deep CORAL	Crop Type Clas- sifica- tion	Aligns second-order statistics (covariance) of features

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[21]	MMD-ARE	Weed Segmentation	Multi-kernel MMD on multi-scale features

B. **Adversarial-Based Methods**

Inspired by Generative Adversarial Networks (GANs), this is arguably the most dominant paradigm in modern DA. It introduces a **domain discriminator**, D, which tries to distinguish between source and target features. The feature extractor, F , is then trained to fool this discriminator, thereby producing features that are domain-indistinguishable.

Mathematical Core: This is formulated as a minimax game:

$$\min_{F,C} \max_{D} Ly(C(F(x)), y) - \lambda Ld(D(F(x)), d) \quad (3)$$

where C is the task classifier, L_y is the task loss, L_d is the domain discrimination loss (e.g., binary cross-entropy), and d is the domain label. The gradient reversal layer (GRL) [4] is a common implementation trick to achieve this min-max optimization in a single backpropagation pass.

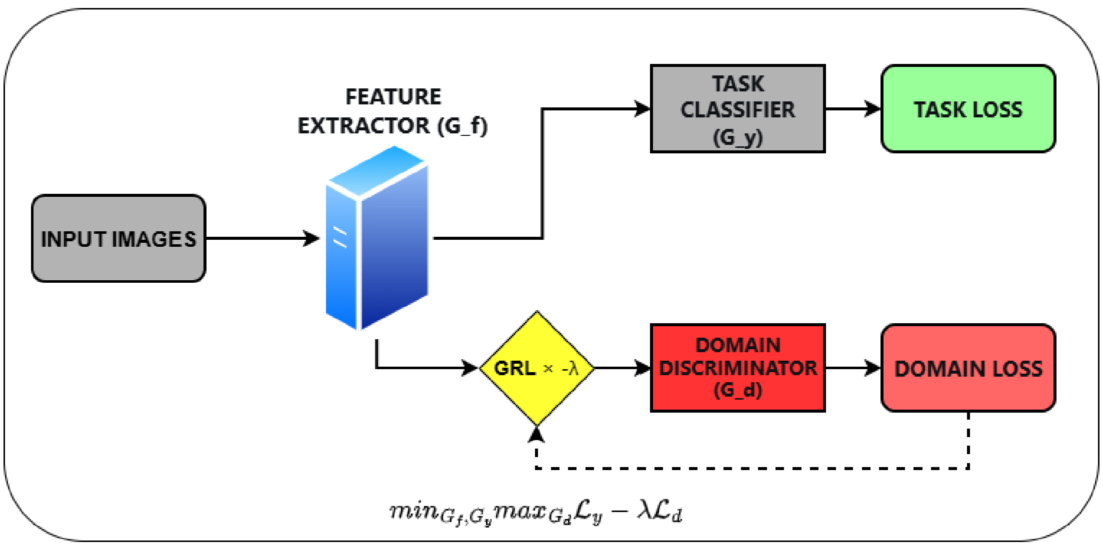

Fig. 3: Architecture diagram of a Domain Adversarial Neural Network (DANN) TABLE IV: Summary of Adversarial-Based Methods in Agriculture

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Reference	Method	Agricultural Application	Key Insight
[10]	CDAN-RT	Disease Recognition	Conditional adversarial loss using classifier predictions
[20]	CyCADA	Fruit Detection	Adversarial on both feature and pixel level

C. Reconstruction-Based Methods

This family of methods argues that features capable of reconstructing the input data must inherently contain domain-invariant information. They often use autoencoders or cycle-consistent architectures to enforce this constraint.

TABLE V: Summary of Reconstruction-Based Methods in Agriculture

Reference	Method	Agricultural Applica- tion	Key Insight
[19]	DRCN	General Plant Pheno- typing	Shared decoder for source and target domains
[22]	Domain Trans fer Network	Crop Health Monitor- ing	Combines re- construc- tion with domain con- fusion

D. Self-Training & Pseudo-Labeling

This iterative approach harnesses the model's own predictions on the target domain to generate supervisory signals. A major challenge is reducing the confirmation bias that appears from noisy pseudo-labels.

Mathematical Core: The process involves generating pseudo-labels $\hat{y}^t$ for target samples, often with a confidence threshold

where $\hat{D}_T$ is the set of target samples with high-confidence pseudo-labels.

Fig. 4a self-training cycle with pseudo-label refinement

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TABLE VI: Summary of Self-Training Methods in Agriculture

Reference	Method	Agricultural Applica- tion	Key Insight
[12]	Cyclic Self- Training	Fruit Detection	Contrastive learning on pseudo-labeled instances
[23]	Noisy Student	Weed Segmentation	Iterative training with data augmentation

E. Emerging Paradigms: Source-Free and Test-Time Adaptation

These paradigms deal with serious practical limitations wherein the source information is unavailable because of privacy, storage, or bandwidth limitations.

- **Source-Free Domain Adaptation (SFDA):** The model should be trained to adapt with an existing pre-trained source model and unlabeled. target data. Techniques normally utilize information maximization and self-supervised learning [11].
- **Test-Time Adaptation (TTA):** The model adapts during inference on a single target batch. This is crucial to work with non-stationary, continuous changes, including the alteration of lighting conditions during the flight of a drone [21] [29].

Mathematical Core (TTA): Entropy minimization is a typical objective and it makes the model make confident predictions on target data:

$$L_{TTA} = H(f(x^t)) = -\sum_{c} f_c(x^t) \log f_c(x^t) \quad (5)$$

where $f_c(x^t)$ is the predicted probability for class c.

TABLE VII: Comparison of Source-Free DA and Test-Time Adaptation

Characteristic	Source-Free DA (SFDA)	Test-Time Adaptation (TTA)
Goal	Adapt a pre-trained model to a new target domain	Adapt a model to distribution shifts during deployment
Data Access	Unlabeled target dataset	Single target sample or a small batch
Computation	Can involve multiple training epochs	Must be extremely fast, often a single gradient step

Use Case	Deploying a model from a central server to a specific farm	A drone or robot adapting to sudden weather changes in real-time
Example	[11] SFDA-Wheat	[13] TTA-AG

III. Analysis of Agricultural Applications

A. Crop Disease and Pest Monitoring

It is a canonical instance in which the field/laboratory change is the most significant. Adversarial methods like [10] counteracted here by attacking the change of background, extension of lighting, and the position of the leaves directly. The important thing is learning features that capture disease-specific patterns (e.g., fungal spots, mosaic patterns) not domain-specific artifacts [22].

B. Weed Detection and Precision Spraying

For this task, the cost of false positives (spraying crops) and false negatives (missing weeds) is high. Self-training methods [23] have shown remarkable success because they can iteratively refine the model's understanding of ”weed” and ”crop” in a new field, learning to ignore novel soil types and focus on plant morphology.

C. Yield Estimation and Fruit Counting

This task faces challenges of occlusion, scale, and illumination. Multi-modal DA methods [14] are particularly powerful here, as they can align features from RGB images with near-infrared data, which is often more robust to shadows and can highlight fruit biomass, leading to more accurate counts across different orchards [26] [28].

D. Crop Type Classification and Land Use Mapping

Using satellite or aerial imagery, this application deals with large-scale geographic shifts. Discrepancy-based methods [18] are computationally efficient and effective for aligning the statistical distributions of spectral bands across different regions or seasons, making them a practical choice for large-scale mapping.

TABLE VIII: Benchmark Performance of DA Methods across Key Applications

Application	**Baseline (No DA)**	**Best Performing DA Method**	**Performance Gain**	**Key Metric**
Disease Classification	58.3% F1	CDAN-RT [10]	+15.2%	F1-Score
Weed Segmentation	64.5% mIoU	Noisy Student [23]	+18.1%	Mean IoU
Fruit Detection	0.72 mAP	CyCADA [20]	+0.22	mAP
Yield Prediction	0.65 R^2	M3DA [14]	+0.22	R^2

IV. Datasets, Benchmarks, and Evaluation

A. Publicly Available Datasets for DA Research

TABLE IX: Key Agricultural Vision Datasets for Domain Adaptation Research

Dataset	**Modality**	**Task**	**Domain Shift Characteristics**	**Common DA Split**
PlantVillage [1]	RGB (Lab)	Classification	Controlled background,	Source Domain

			uniform lighting	Target Domain
PlantDoc [2]	RGB (Field)	Detection/Seg.	Complex backgrounds, variable lighting	
Global Wheat Head [24]	RGB (Field)	Detection	Different genotypes, locations, cameras	Multi-Source DA
Sugar Beets 2020 [5]	RGB (Field)	Segmentation	Different fields, soil types, growth stages	Standard UDA
AGRICULTURE-VISION [25]	Aerial (Multi-spec)	Segmentation	Different farms, seasons, weather	Multi-Modal DA

B. Standardized Evaluation Protocols and Metrics

The field would benefit from more unified protocols. Currently, evaluation follows the standard for the underlying computer vision task:

- **Classification:** Accuracy, F1-Score, Macro-F1 (for class imbalance).
- **Detection & Segmentation:** mean Average Precision (mAP), Mean Intersection-over-Union (mIoU).

The critical comparison is always between a model trained only on the source domain (Source-Only) and the same model enhanced with a DA method [27].

C. Performance Gaps and Analysis

V. Discussion and Future Directions

A. Synthesis of Current Trends

The field is maturing beyond simple UDA. The clear trends are toward:

1) **Practicality:** A strong push toward **Source-Free** and **Test-Time** adaptation, acknowledging the constraints of real-world deployment.
2) **Data Fusion:** The rise of **Multi-Modal DA**, leveraging complementary information from different sensors.
3) **Robustness:** Moving from one-off adaptation to **Continual/Lifelong** adaptation, enabling models to evolve over a full growing season or multiple years.

B. Critical Open Challenges

C. The Path to Real-World Deployment

For DA to transition from research labs to farmers' fields, we must build systems that are not just accurate, but also **robust, efficient, and trustworthy**. This requires closer collaboration with agronomists to embed domain knowledge into the adaptation process and a focus on developing "set-and-forget" systems that can self-adapt with minimal human intervention.

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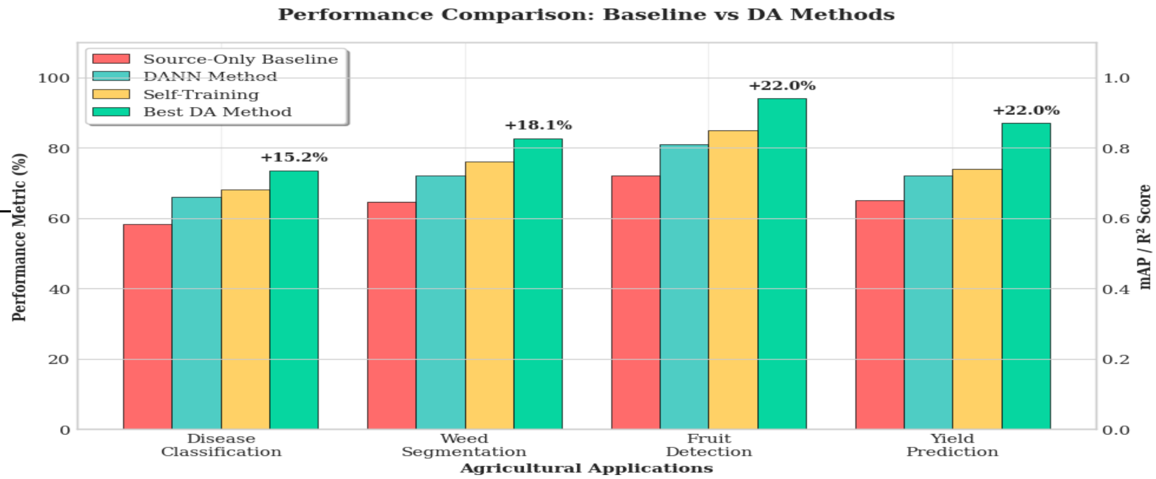

Fig. 5: Bar chart comparing mIoU/Accuracy of baseline vs. DA methods on common benchmarks TABLE X: Summary of Open Challenges and Potential Research Avenues

Open Challenge	Description	Potential Research Avenues
The Reality of Multi-Dimensional Shift	Shifts are not just visual; they are entangled with phenology, management practices, and genetics	Causal DA methods that disentangle the root causes of variation
Extreme and Dynamic Shifts	Models fail under "extreme" DA, e.g., adapting from simulation to a storm- damaged field	Meta-learning, foundation models pre- trained on vast agricultural corpora
Scalability and Efficiency	Many SOTA methods are too computationally heavy for on-device use	Neural architecture search for efficient DA modules, knowledge distillation
Benchmarking and Generalization	Lack of standardized, large-scale bench- marks makes fair comparison difficult	Creation of a unified "AgriDA-Bench" en- compassing multiple tasks and shifts

VI. CONCLUSION

Domain Adaptation is not a fringe benefit anymore, but a pillar point in implementing the strong AI into a dynamic, unpredictable agricultural setting. This literature review has summarized the fast growing developments in this area and traced the development of statistical alignment to adversarial learning and the new frontiers of source-free and test-time adaptation. The technical taxonomy that we have introduced gives us a way to think about the merits and utility of various approaches.

While significant challenges remain—particularly concerning extreme shifts, efficiency, and standardized evaluation—the trajectory is clear. The future of agricultural AI lies in creating adaptive, resilient, and context-aware systems. By closing the domain gap, we move closer to fulfilling the true promise of precision agriculture: a world where AI-powered tools can reliably assist every farmer, in every field, under any condition.

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