Culturally Attuned and Resource-Aware Foundation Models for East African Agriculture: A Theoretical Framework and Research Agenda

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Abstract

East African agriculture supports more than 175 million people but faces mounting challenges from climate change, resource constraints, and information access barriers. Current foundation models fail to address the region's computational limitations (devices with 1-4GB RAM), linguistic diversity (200+ languages), and knowledge system differences. This paper presents CARA-FM (Culturally Attuned and Resource-Aware Foundation Models), a theoretical framework comprising four pillars: Community-Driven Data Architecture, Indigenous Knowledge Systems, Edge-First Model Design, and Participatory Governance. We propose evaluation metrics that span the technical (computational efficiency), agricultural (yield improvement), and cultural (community acceptance) dimensions. Although empirically unvalidated, this framework provides a research agenda for developing agricultural AI systems that operate within severe resource constraints and respect local contexts. Our contribution is theoretical and offers a blueprint for future empirical work rather than implemented solutions.

Keywords: Foundation Models, Agricultural AI, Theoretical Framework, East Africa, Resource-Constrained Computing, Indigenous Knowledge

1 Introduction

Agriculture remains the main livelihood of approximately 175 million people in East Africa, including Kenya, Tanzania, Uganda, Rwanda, and Ethiopia (FAO, 2023). The sector contributes between 25% and 35% of the regional GDP while employing 65% to 75% of the workforce (World Bank, 2023). Despite its economic importance, agricultural productivity is severely constrained, with yields at only 30–40% of their potential, owing to limited access to timely and relevant information in local languages (AGRA, 2019).

Foundation Models (FMs) have transformative potential in agriculture through image recognition (Awais et al., 2025), natural language processing (Paaß and Giesselbach, 2023), and multimodal reasoning (Wang et al., 2024). However, applying these models to East African agricultural contexts reveals fundamental challenges that current approaches fail to address adequately.

1.1 The Research Problem

AI models trained primarily on Global North data experience significant performance degradation when applied to African contexts (Hassan, 2023), which is attributed to the systematic exclusion of African data (Mehrabi et al., 2021). Infrastructure constraints compound these challenges: only 27% internet penetration, 13% of the population unreached by mobile networks (GSMA, 2024), intermittent electricity, and devices with limited computational capabilities.

This paper addresses four research questions: (1) How can foundation models operate effectively within East African agricultural contexts, given severe resource constraints? (2) What theoretical frameworks can guide the integration of Indigenous knowledge with modern AI? (3) How should evaluation metrics assess AI systems across the technical, agricultural, and cultural dimensions? (4) Which governance structures ensure equitable benefit distribution?

1.2 CARA-FM Framework

We propose Culturally Attuned and Resource-Aware Foundation Models (CARA-FM), a theoretical framework for envisioning AI systems designed from the ground up for East African realities. The framework comprises four pillars that address specific aspects of contextual AI development.

2 Foundation Model Challenges in East African Agriculture

Understanding the specific challenges facing foundation model deployment in East African contexts is essential for developing appropriate solutions to address them. This section synthesizes the available evidence while acknowledging the gaps in the empirical data.

2.1 Computational Resource Constraints

The computational requirements of current foundation models present significant barriers to their deployment in East African agricultural contexts. Standard vision transformers require hundreds of millions of parameters and gigabytes of memory (Dosovitskiy et al., 2020). Large language models demand even greater resources, with models such as GPT-3 requiring specialized hardware for inference (Brown et al., 2020).

In contrast, the technological infrastructure available to most farmers in East Africa is limited and outdated. While comprehensive surveys are needed, the available data suggest that rural areas face severe constraints. Electricity access remains intermittent in many regions, with rural electrification rates varying significantly across countries and regions. Internet connectivity, where available, often provides speeds measured in kilobits rather than megabits, as assumed by the cloud-based AI systems.

Device capabilities present additional limitations. Smartphones accessible to farmers typically have limited memory, modest processors, and limited storage capacity. Although these devices are increasingly prevalent, they cannot run models designed for high-performance hardware. This mismatch between model requirements and available infrastructure necessitates a fundamental rethinking of the deployment approaches.

Table 1: East African Agricultural Context: Challenges and Implications for Foundation Model Deployment

Challenge Category	Current State	Impact on FM Deployment
Infrastructure	27% internet penetration; 13% unreached by mobile; intermittent electricity	Requires extreme edge computing and offline capabilities
Computational	Devices with limited RAM (1-4GB), modest processors, no GPU access	Need models under 500MB with CPU-only inference
Linguistic	200+ indigenous languages; minimal NLP resources; code-mixing prevalent	Demands multilingual models with local language support
Data	Limited labeled data; missing indigenous crops and practices	Requires community-driven data collection
Economic	0.5-2 hectare farms; limited cash income	Solutions must be extremely affordable or free
Knowledge Systems	Rich indigenous knowledge; different epistemologies	Needs hybrid knowledge representation
Cultural	Community-based decision making; oral traditions	Requires participatory design and voice interfaces

2.2 Data Representation and Availability

The effectiveness of foundation models depends critically on the quality and representativeness of the training data (Bommasani et al., 2021). Current models, primarily trained on data from high-resource contexts, may not capture the diversity of East African agriculture.

East African farming systems exhibit remarkable diversity. Farmers cultivate numerous indigenous crop varieties adapted to local conditions. Traditional intercropping practices, in which multiple crops grow together, differ fundamentally from monoculture systems that are commonly used in training datasets. Local pest species, disease variants, and soil types may be absent from the global datasets.

This data gap extends beyond simple underrepresentation. The knowledge systems, practices, and contexts of East African agriculture may differ qualitatively from those in existing datasets. Creating appropriate training data requires not only collection but also careful consideration of the knowledge to be represented and how to encode it in the data.

2.3 Linguistic and Communication Barriers

Language presents a multifaceted challenge in the implementation of agricultural AI. East Africa's linguistic diversity, with over 200 living Indigenous languages across the five countries, means that most farmers communicate in languages with minimal digital resources (Joshi et al., 2020).

This challenge extends beyond simple translation. Agricultural communication involves specialized terminology, metaphorical expressions and culturally embedded concepts. Code mixing, in which speakers combine multiple languages, is common in multilingual communities and has not been addressed by the existing models. Voice-based communication predominates in areas with limited literacy.

Current multilingual models show significant performance degradation in low-resource languages. Even when basic language support exists, the specialized vocabulary of agriculture is often not addressed in AI models. The complexities of human communication must be addressed to develop effective communication systems.

2.4 Cultural and Knowledge System Considerations

East African agricultural practices are embedded with deep cultural knowledge that has accumulated over generations. Farmers rely on indigenous indicators for weather prediction, traditional practices for soil management, and community-based systems for knowledge sharing (Orlove et al., 2010; Pretty and Bharucha, 2015). While these knowledge systems are highly effective in local contexts, they differ fundamentally from the scientific frameworks encoded in foundation models.

The integration of indigenous knowledge with AI systems presents both technical and ethical challenges. Technical challenges include the representation of qualitative and context-dependent knowledge in AI frameworks. Ethical challenges include ensuring respectful representation, preventing knowledge appropriation, and maintaining community control of traditional knowledge.

2.5 Economic and Sustainability Constraints

The economic realities of smallholder farming impose additional constraints on AI deployment. With average farm sizes of 0.5 to 2 hectares and limited cash income, farmers cannot afford expensive technological solutions. Any proposed system must demonstrate clear value while remaining financially accessible to the public.

Sustainability considerations extend beyond an individual's affordability. The long-term viability of AI systems depends on sustainable funding models, local capacity for maintenance and improvement, and alignment with existing agricultural-support systems. Without addressing these economic realities, technically sophisticated solutions may not have a significant impact.

3 The CARA-FM Theoretical Framework

The Culturally Attuned and Resource-Aware Foundation Model (CARA-FM) framework proposes an approach for developing agricultural AI systems that are specifically designed for East African contexts. This section presents the theoretical foundations and key components of this framework.

3.1 Design Principles

CARA-FM is built on several core principles that differentiate it from standard foundation model approaches:

1. *Context-First Design:* Rather than adapting existing models, CARA-FM proposes the development of systems from the ground up for East African realities. This includes

considering infrastructure constraints, linguistic diversity, and cultural practices as primary design requirements rather than obstacles to be overcome.

2. *Community Ownership*: The framework emphasizes community control over data, models, and benefits. This principle extends beyond consultation to encompass genuine ownership structures that ensure local benefits from artificial intelligence (AI) development.

3. *Knowledge Pluralism*: CARA-FM recognizes multiple valid knowledge systems, including scientific and indigenous approaches. The framework seeks to create representations that respect and integrate diverse forms of knowledge.

4. *Radical Efficiency*: Given the infrastructure constraints, the framework prioritizes extreme computational efficiency. This involves not only model compression but also a fundamental rethinking of the architectures for resource-constrained deployments.

3.2 Pillar 1: Community-Driven Data Architecture

The first pillar addresses data collection, curation, and governance using community-centered approaches.

This pillar draws on participatory research methodologies, citizen science approaches, and data sovereignty movements. The goal is to create data collection systems that respect local governance structures, while generating high-quality training data.

Distributed data collection could leverage existing agricultural extension networks. Extension officers present in most rural communities could coordinate data collection efforts. Farmers could contribute images, voice recordings, and textual descriptions of their practices and challenges.

Quality assurance may involve multi-tiered validations. The initial data collected by farmers could be reviewed by extension officers with expert validation for subset sampling. This hierarchical approach balances quality and scalability.

Data governance requires careful consideration. We propose exploring data trust models in which communities collectively own and control agricultural data. These trusts could establish usage policies, benefit-sharing mechanisms and ensure that data serve the community's interests.

Key questions include how to incentivize participation, ensure data quality, represent diverse agricultural practices, and create sustainable governance. Technical challenges involve developing collection tools for low-resource devices and creating efficient data-synchronization protocols.

3.3 Pillar 2: Indigenous Knowledge Systems

The second pillar focuses on integrating traditional agricultural knowledge into artificial intelligence (AI) systems.

This pillar is based on knowledge representation, ethnographic computing, and Indigenous data sovereignty. The challenge involves creating representations of knowledge systems that may operate on epistemological foundations that differ from those of Western sciences.

Knowledge representation could employ hybrid approaches that combine symbolic and neural methods. Graph-based representations may capture the relationships between crops, practices, indicators, and outcomes. These graphs could incorporate uncertainty and regional variation.

The integration of scientific knowledge requires careful design. Rather than privileging one knowledge system, the framework proposes creating translation layers that allow different knowledge forms to inform agricultural decision-making. This may involve probabilistic reasoning systems that can work with both quantitative and qualitative data.

Ethical considerations require careful attention. Any system must ensure proper attribution, prevent appropriation, and maintain community control over traditional knowledge. This may involve access controls, usage monitoring, and benefit-sharing protocols.

Critical questions include how to represent context-dependent knowledge, integrate qualitative insights with quantitative models, ensure cultural appropriateness, and prevent the misuse of traditional knowledge.

3.4 Pillar 3: Edge-First Model Design

The third pillar addresses the technical architecture of resource-constrained deployments.

This pillar draws on research on model compression, edge computing and federated learning. The goal is to create AI systems that can operate effectively on devices with limited memory, processing power, and connectivity.

The model architecture could employ hierarchical designs. Small models running on farm-level devices could handle routine tasks, with more complex queries escalated to district-level servers when connectivity permits. This hierarchical approach balances capabilities with resource constraints.

Compression techniques offer several potential solutions. Knowledge distillation could create small student models from larger teachers. Quantization could reduce memory requirements. Pruning could eliminate unnecessary parameters. The combination of these techniques might achieve the extreme compression ratios required.

Federated learning could enable collaborative improvement without centralizing data. The devices could train on local data and share only model updates. This approach addresses both connectivity constraints and data sovereignty issues.

Key questions include determining acceptable accuracy-efficiency trade-offs, developing compression techniques for multilingual models, creating robust federated learning protocols for intermittent connectivity, and designing adaptive systems that adjust to available resources.

3.5 Pillar 4: Participatory Governance

The fourth pillar establishes a framework for community control and benefit distribution.

This pillar draws on participatory design, democratic governance theory and cooperative economics. The goal is to ensure that AI systems serve the interests of the community rather than extracting value from it.

Governance structures could adapt cooperative models. Farmer-majority boards could oversee system development and deployment. Clear decision-making processes could ensure transparency. Regular community consultations could guide system evolution. The distribution of benefits requires careful consideration. Revenue from data or services could flow back to communities through pre-determined formulas. Investing in local capacity building could ensure sustainable impact. Transparent accounting could maintain trust.

Accountability mechanisms may include regular audits, community feedback systems, and grievance procedures. These mechanisms could ensure that the systems remain aligned with the needs and values of the community.

Critical questions include how to design effective governance structures, ensure meaningful participation, distribute benefits equitably, and maintain accountability.

4 Evaluation Framework

Table 2: CARA-FM Evaluation Metrics

Dimension	Metric	Description
Technical	CEI	Computational Efficiency Index
	DFS	Deployment Feasibility Score
	MPP	Multilingual Performance Parity
Agricultural	YIP	Yield Improvement Potential
	IOE	Input Optimization Efficiency
	IAE	Information Access Enhancement
Cultural	CAI	Cultural Alignment Index
	CAS	Community Acceptance Score
	KPV	Knowledge Preservation Value

CARA-FM evaluation requires metrics beyond standard AI performance measures, spanning technical, agricultural, and cultural dimensions, with specific indices measuring computational efficiency, deployment feasibility, yield improvement potential, and cultural alignment.

5 Lessons from African Agricultural AI Initiatives

African agricultural AI demonstrates remarkable innovation. Notable successes include Farmerline's Darli AI, which operates in 27 languages and serves over 1 million farmers with 2.5x yield increases (Senyo, 2018), Apollo Agriculture's ML credit assessment, which achieved 2.6x production increases (van Tuijl et al., 2022), and Aerobotics' disease detection, which reduced crop losses by 20-40% across 18 countries (Ndhlovu, 2025).

Table 3: Selected African Agricultural AI Success Stories

Initiative	Country	Innovation	Impact
Farmerline	Ghana	27-language chatbot	2.5x yield increase; 1M+ farmers
Apollo Ag	Kenya	ML credit + satellite	2.6x production increase
Aerobotics	S. Africa	AI disease detection	20-40% loss reduction

Community initiatives, such as Masakhane, have produced machine translation benchmarks for 52 African languages (Nekoto et al., 2020). The African Union's Continental AI

Strategy provides a unified framework for the 2025-2030 implementation (African Union, 2024).

Key lessons include: language-first approaches demonstrate fundamental importance for adoption; complex partnerships involving the government, private sector, NGOs, and academia are essential; sustainability requires hybrid models that balance commercial viability with social impact; and genuine community engagement through existing structures builds critical trust and ownership.

6 Research Agenda and Future Work

CARA-FM validation requires comprehensive research in multiple domains.

6.1 Foundation Model Evaluation and Dataset Creation

Future research should systematically evaluate the LLaMA-2 family models (Touvron et al., 2023), multilingual models (mT5, XLM-R, BLOOM) (Xue et al., 2020), and vision transformers for East African agricultural tasks. Critical datasets include East African Agricultural Language Corpus covering 20+ regional languages, comprehensive visual datasets of indigenous crops and practices, and multimodal knowledge bases integrating text, speech, and visual data.

6.2 Technical Development and Implementation

The priorities include extreme model compression beyond the current limits, robust federated learning protocols for intermittent connectivity, and edge-cloud orchestration. Pilot studies should span diverse agroecological zones across Kenya, Ethiopia, Uganda, Tanzania, and Rwanda, employing randomized controlled trial designs where feasible, with strong partnerships involving national research institutes, extension services, and farmer cooperatives.

7 Risks and Ethical Considerations

The development of agricultural AI carries significant risks that require proactive mitigation. Technical risks include model bias, which may disadvantage marginalized groups, performance degradation under real-world conditions, and technical dependence, which may lead to the loss of traditional knowledge. Social risks encompass knowledge appropriation, representing digital colonialism, cultural disruption conflicting with traditional practices, and elite capture benefiting only well-resourced farmers. Economic risks involve unsustainable costs, creating system dependencies, market disruption causing price collapse, and value extraction, leaving farmers with minimal benefits despite providing data.

Mitigation strategies include regular bias auditing and continuous model updating for technical risks; strong governance structures and gradual implementation for social risks; and diverse funding sources with cooperative ownership models for economic risks.

8 Discussion and Implications

CARA-FM challenges dominant AI development paradigms by proposing a ground-up design that considers local constraints, knowledge systems, and priorities rather than adapting high-resource solutions. This contributes to discussions on technological sovereignty, positioning African countries as AI innovators rather than passive adopters.

Although designed for East African contexts, CARA-FM principles may be broadly applicable to regions facing similar challenges of linguistic diversity, resource constraints, and cultural specificity. The framework's emphasis on efficiency and cultural attunement could inform global AI development as environmental and cultural concerns grow.

This research agenda requires unprecedented interdisciplinary collaboration across AI, agriculture, anthropology, economics, and community engagement, challenging traditional boundaries while advancing both practical deployment and theoretical understanding.

We acknowledge significant limitations: CARA-FM remains unvalidated, technical feasibility is unclear, and the economic viability of developing entirely new systems for resource-constrained contexts is questionable. The integration of indigenous knowledge with AI systems may be fundamentally incompatible, potentially resulting in knowledge loss rather than preservation.

9 Conclusion

This paper presents CARA-FM as a theoretical framework for developing culturally attuned and resource-aware foundation models for East African agriculture. The framework comprises four foundational pillars: Community-Driven Data Architecture, Indigenous Knowledge Systems, Edge-First Model Design, and Participatory Governance, collectively addressing the core AI deployment challenges in East Africa.

Although CARA-FM faces significant technical and economic feasibility challenges, the potential benefits justify pursuing this research agenda. Foundation models offer significant agricultural potential through pre-training on extensive datasets, potentially addressing food security challenges, supporting climate adaptation, and improving farmer livelihoods, while demonstrating alternative paths for community-controlled AI development.

The detailed research agenda provides concrete steps for empirical validation, including evaluating existing foundation models, creating appropriate datasets, developing technical solutions, and conducting pilot studies. Success requires unprecedented collaboration across disciplines, sectors, and borders, with governments, NGOs, research institutions, and communities working toward shared goals.

As East Africa navigates agricultural challenges amid rapid technological change, CARA-FM offers a vision in which AI serves local needs, respects cultural knowledge, and ensures community benefits. Through rigorous research, respectful collaboration, and commitment to community benefit, East Africa can demonstrate how AI serves human development while respecting local contexts and ensuring equitable benefits for all.

Future work should prioritize empirical validation through pilot studies, dataset development, and technical feasibility assessments. The research community must address the ethical implications of integrating Indigenous knowledge into AI systems and develop appropriate governance mechanisms. Ultimately, CARA-FM represents a vision of technological development that prioritizes human agency, cultural preservation, and equitable benefit distribution.

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