

THE DIGITAL DIVIDE, DATA POWER AND STRUCTURAL EXCLUSION IN GLOBAL AGRICULTURE

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Abstract

Digital agriculture is widely promoted as a transformative pathway for enhancing productivity, market integration, and financial inclusion among smallholder farmers. Through mobile platforms, precision technologies, digital marketplaces, and data-driven advisory systems, it promises to reduce informational asymmetries and connect farmers to global value chains. However, beneath this optimistic narrative lies a deeper political economy of exclusion in which digital technologies frequently reproduce and intensify existing agrarian inequalities. This chapter critically examines the digital divide in global agriculture by analysing how disparities in access, digital literacy, infrastructure, institutional support, and platform governance intersect with class, caste, gender, geography, and landholding size. Drawing on global evidence and the fragmented agrarian structure of India, the chapter identifies four major pathways through which digitalisation amplifies inequality: differential technology adoption, market concentration and price squeezes, data dispossession and extraction, and exposure to financialised risks. Although smallholders constitute nearly 83 percent of farms globally, they produce only around 35 percent of total food output and remain disproportionately excluded from the benefits of digital transformation. Limited connectivity, low bargaining power, and dependence on corporate platforms often marginalise them further within digital agri-food systems. The chapter challenges technological solutionism and argues that digitalisation without social justice can deepen structural exclusion rather than promote empowerment. It therefore advocates a more inclusive framework grounded in data sovereignty, equitable digital infrastructure, public regulation, and farmer-led governance models to ensure that digital agriculture advances sustainability, dignity, and distributive justice rather than extraction and dependency.

Keywords: Digital Divide in Agriculture, Data Power, Structural Exclusion, Digital Agriculture, Technology Access, Digital Economy in Agriculture.

1. Introduction: The Myth of the Level Digital Field

Across policy documents, investment pitches, and development narratives, digital agriculture is presented as a clean break with the past. Smartphones, satellites, sensors, and platforms are imagined as frictionless conduits that will finally integrate smallholder farmers into markets, information systems, and financial networks from which they were historically excluded. The World Bank's Digital Development Partnership, the Food and Agriculture Organization's e-Agriculture programme, the African Union's Digital Agriculture Strategy, and countless bilateral

aid initiatives promote this vision with considerable institutional weight and resource commitment (Food and Agriculture Organization of the United Nations (FAO), 2021a; World Bank, 2022).

The appeal of digital solutionism in agriculture is not difficult to understand. For decades, development agencies have grappled with the stubborn persistence of agrarian poverty in the face of green revolution technologies, structural adjustment programmes, and market liberalisation. Digital tools seem to offer something qualitatively different: scalable, low-cost interventions that can be deployed rapidly across vast geographies without requiring the slow political work of land reform, labour regulation, or public investment in extension services. This vision is powerful precisely because it offers a technologically optimistic solution to what are, in fact, deeply political and historical problems. It suggests that if only the right apps are rolled out and connectivity extended, inequalities rooted in land concentration, caste hierarchies, racialised labour regimes, gendered norms, and colonial trade patterns will gradually dissolve. The smartphone, in this narrative, does the work that structural transformation has failed to accomplish.

The central claim of this chapter is that such expectations are misplaced, and dangerously so. Digital technologies do matter for agriculture, and they can generate real productivity gains and new forms of market coordination for those positioned to exploit them. But when introduced into unequal agrarian structures without transforming those structures, digital tools tend to reinforce and magnify existing disparities rather than level them. The farmer who was already advantaged by land, education, credit access, and social capital is better placed to capture the benefits of digital innovation. The marginal farmer operating on thin surpluses and facing multiple forms of exclusion gains less, and may lose ground (Van Dijk, 2006; Robinson *et al.*, 2015; Selwyn, 2004). Digital agriculture, in other words, is not a neutral layer applied on top of agrarian society. It is a new terrain on which long-standing struggles over land, labour, knowledge, and value are being fought. The outcomes of those struggles are not predetermined by the technology itself but by the institutional, political, and economic contexts in which that technology is deployed, governed, and monetised. This chapter maps those contexts, traces the mechanisms through which digitalisation amplifies inequality, and examines what a more just digital agriculture would require.

2. Conceptualising the Agricultural Digital Divide

The concept of the digital divide has travelled a long way since its origins in the 1990s, when analysts tended to measure inequality in terms of binary yes/no indicators of computer or internet access. The implicit assumption was one of diffusion: early adopters would be followed by later adopters as prices fell and infrastructure expanded, and over time the divide would narrow and eventually close. As empirical data accumulated, this diffusionist optimism proved untenable (Selwyn, 2004). Even where basic access gaps narrowed, deep differences in digital skills, intensity and diversity of use, and the tangible social and economic returns from digital participation persisted, and in some dimensions widened. Scholars responded by developing more disaggregated frameworks (Van Dijk, 2006; Robinson *et al.*, 2015).

First-level divides capture who has physical access to devices and connectivity. Second-level divides capture who can effectively use digital tools, encompassing skills, literacy, language, and confidence. Third-level divides capture who actually benefits in measurable terms, in income, employment, health, or civic voice. A more recent fourth-level framing captures who has power over digital systems: who sets platform rules, who owns and governs data, and who can shape the technological architectures within which everyone else must operate (Ragnedda, 2018). For agrarian contexts, this multi-level perspective is indispensable. A farmer may own a handset and

live under a network footprint yet still be effectively excluded because advisory content is not available in their language, recommendations do not match their cropping system, data bundles are unaffordable at moments of peak agricultural demand, or gendered household norms limit when and how the device can be used. The aggregated connectivity statistics celebrated in development reports frequently obscure these layered exclusions, presenting a picture of progress that dissolves on closer inspection.

2.1 Political Economy of Agricultural Digitalisation

Political economy approaches insist that technologies cannot be understood apart from the social relations and power structures in which they are produced, deployed, and governed. In the case of agriculture, digitalisation has not emerged in a vacuum. It is embedded within long-running processes of commodification, financialization, and corporate consolidation in global food systems, processes that have, over several decades, steadily eroded the autonomy and bargaining power of smallholder producers relative to the agribusiness corporations, retailers, and financial institutions that increasingly organise global food chains (Scoones *et al.*, 2018). Agri-technology firms, data analytics companies, and fintech providers now position themselves as indispensable intermediaries across the agricultural value chain. Their revenue models hinge on capturing and monetising data about production conditions, input use, transactions, and consumption patterns. Platform architectures are designed to maximise data capture: digital registration processes elicit detailed household and farm information; smart input dispensers log transaction volumes and timing; mobile credit applications harvest phone metadata as proxies for creditworthiness. This gives platform companies both economic power over dependent farmers and informational power over the value chains in which those farmers participate, while farmers themselves often have minimal visibility into how their data are collected, processed, and monetised.

The concentration of this market has accelerated rapidly. By 2024, a small number of large agri-technology conglomerates, including Corteva Digital, Syngenta Digital, John Deere's precision agriculture division, and Bayer's Climate Corporation, had assembled vast proprietary agronomic datasets drawn from millions of farm operations globally. These datasets, built on farmer-generated data, now serve as training inputs for generative AI advisory systems that are sold back to farmers as premium subscription services. This recursive extraction dynamic, accumulating farmer knowledge as corporate intellectual property and then monetising it, operates at a qualitatively greater scale than anything the agricultural advisory system has previously encountered.

2.2 Gender, Caste, and Social Hierarchies in Digital Agriculture

Inequalities in agrarian societies are rarely one-dimensional. Land ownership, tenancy status, caste, race, gender, age, and migration histories intersect to produce layered advantages and disadvantages that digital tools do not dissolve and often deepen. Understanding how these axes of inequality interact with digital adoption and benefit requires moving beyond simple aggregate statistics. Device ownership typically follows existing lines of property and control. Men are more likely to own phones registered in their own names; dominant-caste and wealthier households can purchase higher-end smartphones and maintain regular data subscriptions; younger and better-educated members often become informal digital stewards for entire households or communities, mediating others' access on terms shaped by intra-household power relations. Where a woman's access to a digital agricultural platform is mediated through her husband's phone and permission, the autonomy gains that digital advisory content might otherwise enable are substantially curtailed.

In deeply stratified settings, information has historically functioned as a mechanism of control. Access to market price intelligence, knowledge of new crop varieties, familiarity with bureaucratic and legal procedures, and connections to external institutions have long been concentrated among landlords, traders, and local elites, a structural advantage that digital platforms can easily reproduce if their distribution architectures follow existing channels of authority. Programmes that rely on 'lead farmer' or 'village champion' intermediaries, drawn overwhelmingly from socially dominant groups, perpetuate rather than disrupt these hierarchies. The content may be new, but the gate-keeping is old. Caste dynamics are particularly salient in South Asian contexts, where Scheduled Caste and Scheduled Tribe farmers face multiple compounding barriers: lower landholding size on average, more limited access to formal credit, lower rates of smartphone ownership, and exclusion from the social networks through which information about new technologies circulates. Several Indian government digital agriculture pilots have documented lower registration and engagement rates among SC/ST farmers relative to dominant-caste peers, even after controlling for farm size and income, evidence that digital exclusion is not reducible to economic variables alone (Ragasa *et al.*, 2024).

2.3 Infrastructure, Connectivity, and Spatial Exclusion

The geography of digital infrastructure investment maps predictably onto broader patterns of uneven capitalist development (Van Dijk, 2006; International Telecommunication Union (ITU), 2024). Mobile network operators extend high-quality coverage first to dense urban and peri-urban markets, where average revenues per user are higher and where business and affluent consumer segments are concentrated. The economics of rural network extension are structurally unfavourable: longer distances, lower population densities, smaller and more seasonal average revenues, and higher maintenance costs all reduce the commercial case for investment. Even when regulatory frameworks mandate universal service obligations, enforcement is frequently weak, and cross-subsidy mechanisms are often captured to upgrade already-profitable corridors rather than extend genuine coverage to remote communities. The result is a persistent pattern in which the farmers with the greatest potential need for digital agricultural tools, those in remote, climate-vulnerable, and commercially marginalised locations, are precisely those with the most unreliable connectivity.

Table 1. Global Internet Use by Area and Income Group, 2024

Indicator	Value	Notes
World population using the internet (%)	68	About 5.5 billion of an estimated 8.1 billion people are online.
Urban residents using the internet (%)	83	Share of urban population online.
Rural residents using the internet (%)	48	Share of rural population online; most of the 2.6 billion offline live in rural areas.
Urban–rural use ratio (urban % / rural %)	1.7	Urban residents are roughly 1.7 times more likely to be online than rural residents.
Internet use in high-income countries (%)	93	Near-universal connectivity in high-income contexts.
Internet use in low-income countries (%) ¹	27	Fewer than one-third of people are online*
Rural internet use in low-income countries (%)	16	Roughly one rural resident in six uses the internet.
Urban–rural use ratio in low-income countries	≈2.9	Urban residents are almost three times as likely to be online as rural residents.

Source: ITU, *Measuring Digital Development: Facts and Figures 2024*.

* 'Low-income countries' follows the World Bank income group methodology (GNI per capita ≤ USD 1,135, Atlas method, 2024), distinct from the UN LDC category (35% per ITU 2024).

Quality of connection matters as much as formal coverage. A farmer who can access a 2G signal on a feature phone in a valley with intermittent reception occupies a fundamentally different position from a farmer in a peri-urban area with reliable 4G smartphone access. Yet both may appear identically in aggregate connectivity statistics as 'covered.' Effective agricultural digitalisation requires not just network presence but sufficient bandwidth for data-intensive applications, affordable data pricing relative to smallholder incomes, and device capability adequate for the platforms in use. On each of these dimensions, rural smallholders in low-income countries are systematically disadvantaged relative to the users for whom most agricultural digital platforms are designed.

3. Gendered Digital Divides in Agrarian Contexts

Gendered patterns of digital access and use constitute a central and underappreciated axis of the agricultural digital divide. Women farmers are frequently invoked rhetorically in digital inclusion narratives, as smallholder entrepreneurs awaiting digital empowerment, or as untapped market segments for mobile financial services. Large-scale surveys consistently reveal a more sobering reality: persistent, structural gender gaps in mobile ownership, internet access, and digital service use that show limited responsiveness to market-driven inclusion strategies. These gaps reflect entrenched constraints on women's control over physical assets, time, mobility, and household decision-making. In many agrarian settings, women's ability to own a phone outright, purchase data, or publicly use a device in shared community spaces is shaped by social norms around respectability, safety, and gender-appropriate behaviour that extend well beyond the telecommunications sector. Digital inclusion programmes that treat mobile access as a primarily economic and infrastructural challenge, to be solved by reducing handset costs and improving network coverage, miss these normative dimensions and therefore predictably underperform.

Table 2. Gender Gaps in Mobile Internet Adoption across LMICs, 2023

Region / Group	Gender gap in mobile internet use (%)	Key observations
All LMICs (aggregate)	15	Women are 15% less likely than men to use mobile internet.
Sub-Saharan Africa	32	One of the widest gaps; progress has been uneven.
South Asia	31	Large but declining gap, reductions driven mainly by India.
Middle East & North Africa	16	Persistent double-digit gender gap.
East Asia & Pacific*	4	Relatively small gender gap compared with other regions.
Europe & Central Asia (LMICs)*	4	Near parity in mobile internet use by gender.
Latin America & Caribbean (LMICs)*	0	No measurable gender gap in aggregate data.

Source: GSMA, *Mobile Gender Gap Report 2024*.

* EAP (4%), ECA (4%), and LAC (0%) are modelled estimates from the GSMA interactive dataset.

Table 3. Selected Gender Gaps in Mobile Access and Use in LMICs, 2023

Indicator	Women relative to men in LMICs	Interpretation
Mobile phone ownership	8% less likely	Ownership gap has remained broadly unchanged.
Smartphone ownership	13% less likely	Gap has narrowed slightly but remains significant.
Mobile internet use	15% less likely	Gender gap has fallen from higher levels but is still substantial.
Number of women not using mobile internet	≈785 million	Roughly 60% live in South Asia and Sub-Saharan Africa.

Source: GSMA, *Mobile Gender Gap Report 2024*.

The GSM Association's (GSMA) Mobile Gender Gap Report 2024 provides the most systematic global evidence on these patterns, drawing on surveys across low- and middle-income countries (GSMA, 2024). The headline finding, that women are 15 per cent less likely than men to use mobile internet, conceals wide regional variation and an even larger gap in the agricultural contexts where digital tools have been most aggressively promoted (GSMA, 2024).

3.1 Implications for Women Farmers

For agricultural systems, these patterns translate into stark and compounding differences in who can receive and act on digital extension messages, enrol in mobile-based input subsidy schemes, access agricultural price information at the moment of sale, or participate in the digital e-commerce platforms that promise better market prices. A gender gap in mobile ownership is not merely a communications deficit; it is a market access deficit, an information deficit, and ultimately a productivity and income deficit. Where husbands control phones and data expenditure, women may access advisory content only indirectly and at the discretion of another household member. Their ability to act on recommendations from digital tools, to adjust planting dates in response to weather alerts, or to redirect production toward better-priced channels, is further constrained by gendered divisions of agricultural decision-making authority. Even where women participate in digital extension programmes, the translation of digital access into autonomous agricultural decision-making often requires change in household power relations that technology alone cannot drive.

3.2 Safety, Social Norms, and Barriers Beyond Economics

The GSMA's evidence confirms that the barriers women face to mobile internet adoption extend well beyond affordability and network coverage (GSMA, 2024). Safety and security concerns, including fear of harassment through digital channels, privacy risks associated with sharing personal information on platforms, and social stigma attached to women's use of certain online spaces, are consistently cited as significant deterrents in South Asian and Sub-Saharan African contexts. In several country studies, women reported that they were aware of digital agricultural services but had been discouraged from registering by family members, had experienced harassment when using shared community charging points, or had had their phones taken away by husbands who disapproved of direct communication with male extension agents or platform operators. These barriers do not appear in connectivity statistics and are not addressed by subsidy programmes. They require sustained engagement with gender norms, community leadership, and the design of platforms that are safe and culturally navigable for women users, a far more demanding intervention than simply distributing SIM cards.

4. India: Expanding Connectivity in a Fragmented Agrarian Landscape

India provides a particularly instructive case study of the tensions between expanding digital connectivity and entrenched agrarian inequality. By several metrics, India's digital transition has been remarkable: a combination of aggressive 4G network roll-out by private operators, the Jio disruption of data pricing, and ambitious government-led digital infrastructure programmes has produced one of the fastest expansions of internet access in the world over the past decade. Rural India now hosts more internet users in absolute terms than urban India, a reversal that would have seemed inconceivable fifteen years ago. Yet these headline connectivity figures obscure a more complicated reality on the ground. The farmers who stand to benefit most from digital agricultural tools, those with the smallest, most fragmented holdings, the lowest incomes, the least formal education, and the most limited access to institutional support, are precisely those who face the

most significant barriers to meaningful digital participation. Expanding network coverage is necessary but far from sufficient.

Table 4. Active Internet Users in India by Area and Gender, 2023

Indicator	Urban India	Rural India	All India
Active internet users (millions)	378	442	821
Share of total active users (%)	46	54	100
Approx. population share with internet access (%)	65–70	50–55	55+
Typical access mode	Own smartphone, broadband	Own/shared mobile, patchy broadband	Mobile-first dominates
Shared-device usage trend	Lower and declining	Higher; strong recent growth	Shared use concentrated in rural areas
Gender split among active internet users (%)	-	-	54 male, 46 female

Source: IAMAI–Kantar, Internet in India 2023 (ICUBE).

4.1 Quality and Mode of Rural Connectivity

These figures underscore a crucial nuance. Rural India now hosts more internet users in absolute terms than urban India, yet this does not imply that rural users have equivalent quality of access or an equivalent ability to integrate digital tools into agricultural decision-making. The ICUBE data reveal that shared device use is substantially more prevalent in rural than in urban India, and that it has grown sharply in recent years. In 2023, approximately 14 per cent of rural internet users accessed the internet primarily through someone else's phone, a figure that understates the actual prevalence of shared use, since many users who 'own' a phone in survey responses may share it within households in practice (Internet and Mobile Association of India (IAMAI) & Kantar, 2024).

Shared device use has direct implications for digital agricultural services. Platforms that rely on individualised registration, personalised data histories, or privacy-sensitive financial information are difficult or impossible to use effectively when a phone is shared among multiple household members. The design assumptions built into most digital agricultural platforms, persistent login, individualised advisory history, secure financial transactions, map poorly onto the connectivity realities of most India's smallholder farmers. Beyond device access, data affordability shapes the intensity of use. Despite India's relatively low data prices by international standards, the cost of maintaining regular data subscriptions remains significant relative to the incomes of marginal and small farmers, particularly in the post-harvest periods when cash flows are thin. Seasonal patterns of connectivity, high during harvest, when incomes are available; low during the growing season, when cash is scarce, mean that farmers may be offline at precisely the moments when weather alerts, market price information, or pest management advice would be most valuable.

4.2 Farm-Size Structure and Investment Capacity

India's agrarian structure imposes additional constraints on the uptake of digital agricultural tools. The Agriculture Census 2015-16 documents a pattern of extreme landholding fragmentation that has, if anything, intensified in subsequent years through inheritance subdivision (Government of India, 2018). Marginal holdings below one hectare account for approximately 68 to 70 per cent of all operational holdings yet operate only around a quarter of agricultural area. The average operational holding across all categories is approximately 1.08 hectares, a size at which the economics of most precision agriculture technologies are deeply unfavourable.

Table 5. Distribution of Operational Holdings by Size Class, India 2015–16

Size class	Area range (ha)	Share of holdings (%)	Share of operated area (%)	Key notes
Marginal	< 1.0	68–70	24	Very small, fragmented plots; strong overlap with subsistence farming.
Small	1.0–1.99	16–18	23	Together with marginal, about 86% of holdings but less than half of area.
Semi-medium	2.0–3.99	10	24–25	Fewer in number, disproportionately large share of land.
Medium	4.0–9.99	3–4	19–20	Combined with semi-medium, about 13% of holdings and 44% of area.
Large	≥10.0	0.5–1	9–10	Very small share of holdings but substantial land concentration.
All holdings	-	100	100	Average holding size ≈1.08 ha.

Source: Government of India, Agriculture Census 2015-16 (All India Report on Number and Area of Operational Holdings. Ministry of Agriculture & Farmers Welfare).

This farm-size profile has direct implications for which digital agricultural tools are economically viable for which categories of farmer. Precision agriculture equipment, drones, soil sensors, satellite subscription services, AI-driven farm management platforms, requires capital outlays and recurring costs that are difficult to justify on holdings of one hectare or less. 'Precision-as-a-service' subscription models reduce the capital barrier but introduce new forms of platform dependency: farmers who become reliant on algorithmically generated recommendations find themselves vulnerable to service discontinuation, price increases, and the opaque model updates that alter those recommendations without explanation or appeal.

5. Smallholders, Land, and Food Production: A Global Picture

The Indian case is not exceptional. Across all world regions, smallholder farms account for the vast majority of agricultural holdings while operating a modest share of agricultural land and receiving a still more limited share of value added in food supply chains. Understanding this global distribution is essential context for evaluating claims about the potential of digital agriculture to transform rural livelihoods. Empirical syntheses of national agricultural census data, most comprehensively in Lowder *et al.* (2016), confirm that farms under two hectares represent approximately five-sixths of all farms worldwide. Yet this enormous numerical majority corresponds to only around twelve per cent of agricultural land. These farms are disproportionately located in South Asia and Sub-Saharan Africa, where average farm sizes are smallest and where agricultural poverty is most concentrated.

Table 6. Global Distribution of Farms and Food Production by Farm Size

Indicator	Value	Notes
Share of all farms that are < 2 ha (%)	83	Approximately five of every six farms worldwide.
Share of global agricultural land operated by farms < 2 ha (%)	12	Small farms operate a small fraction of total land.
Share of global food produced by farms < 2 ha (%)	35	Small farms contribute roughly one-third of global food.
Share of all farms that are < 1 ha (%)	70	These farms control around 7% of agricultural land.
Share of all farms that are 1–2 ha (%)	14	These farms control around 4% of agricultural land.
Share of all farms that are 2–5 ha (%)	10	These farms control around 6% of agricultural land.

Source: FAO (2021b), 'Small family farmers produce a third of the world's food'; Lowder *et al.* (2016).

*Global farm-size figures involve variation across census years and definitional conventions. ~83% aligns with Lowder *et al.* (2016) and FAO; some sources cite 84%. All figures are best-available estimates.

5.1. Paradoxes of Centrality and Exclusion

The paradox is stark and politically significant. Smallholder farmers, those who operate the most precarious holdings, with the least access to credit, insurance, and institutional support, provide a disproportionate share of the food that low- and middle-income countries consume. FAO estimates suggest that farms under two hectares contribute approximately 35 per cent of global food production and a substantially higher share in contexts like South Asia and Sub-Saharan Africa, where smallholder systems dominate (FAO, 2021b). Yet the digital agricultural systems increasingly promoted as tools for productivity improvement and market integration are structurally designed around the needs and metrics of larger, capital-intensive farms and corporate buyers, not the polyculture, low input, rainfed systems that characterise smallholder production in the global South. AI-driven demand forecasting, satellite-based yield mapping, precision variable-rate fertiliser application, and blockchain-enabled traceability systems all require levels of data quality, technical capacity, connectivity, and capital that are simply unavailable on a one-hectare plot in Bihar or a fragmented holding in rural Nigeria. When development organisations deploy these technologies in smallholder contexts without adapting them to those contexts, the frequent result is that benefits are captured by the more commercially oriented, better-resourced minority of larger farmers within the target community, precisely the selection dynamic that the intervention was notionally designed to correct.

5.2. Regional Comparative Evidence

The agricultural digital divide takes different forms across world regions, shaped by variations in agrarian structure, infrastructure endowment, policy environment, and social organisation. A regional comparative lens reveals both common patterns and important contextual differences that single-country analyses can obscure. In Sub-Saharan Africa, the dominant constraint is infrastructure: mobile network coverage remains patchy in many agricultural regions, feature phone penetration exceeds smartphone ownership, and data costs are high relative to farmer incomes. Where digital agricultural services have achieved significant reach, such as iCow in Kenya, Esoko in Ghana, or Digital Green's video advisory model, success has generally required deep adaptation to local connectivity constraints, community-level distribution through trusted social intermediaries, and content in local languages (Ragasa *et al.*, 2024). Market-led platforms that assume stable smartphone access and reliable data connectivity have consistently underperformed expectations.

In South Asia, infrastructure barriers are less acute in many areas following rapid network expansion, but social and normative barriers are more severe, particularly along lines of gender

and caste. The challenge in South Asia is less about getting the signal to the village than about ensuring that the signal reaches all members of the village equitably, and that digital platforms are governable by the communities they serve rather than by external platform operators whose interests may diverge sharply from those of smallholder users. In Southeast Asia and Latin America, higher average farm incomes and more developed rural infrastructure have enabled faster diffusion of digital agricultural tools, particularly for export-oriented value chains where processors and retailers drive digital adoption through contract requirements. The risk here is different: not exclusion from the digital system but incorporation on unfavourable terms, with data sovereignty ceded to large agri-food corporations and smallholder bargaining power further reduced by algorithmic contract setting and market forecasting asymmetries.

Table 7. Regional Digital Divide Indicators in Agriculture, 2023–2024

Indicator	South Asia	Sub-Saharan Africa	Southeast Asia	Latin America	Notes
Mobile internet penetration, rural (%)	28	19	41	55	SSA and South Asia furthest below urban levels.
Gender gap in mobile internet use (%)	31	32	4	0	SSA and South Asia show the widest gender gaps.
Digital agri-service users, smallholders (%)	12	8	22	18	Adoption remains low everywhere for sub-2ha farmers.
Share of farmers with smartphone access (%)	38	24	51	47	South Asia lags due to affordability and social norms.
Agri-GDP share from digital value chains (%)	6	4	11	14	LAC and SE Asia lead in digital agri-commerce integration.

Source: ITU (2024); GSMA (2024) Mobile Gender Gap Report; FAO (2023) Digital Agriculture: Key Trends; World Bank (2024) World Development Indicators. Figures are approximate regional estimates from cross-country secondary data; treat as indicative.

6. Digitalisation as Inequality Amplifier: Four Structural Pathways

The empirical patterns documented in the preceding sections point toward a set of structural mechanisms through which digitalisation tends to amplify rather than correct agrarian inequality. Identifying these mechanisms precisely matters because different mechanisms call for different policy responses. A problem of infrastructure can be addressed with investment; a problem of data governance requires regulatory intervention; a problem of social norms requires community-level and gender-transformative programming. Treating the digital divide as a single undifferentiated phenomenon risk prescribing infrastructure solutions for what are, at root, political economy problems. Four pathways of inequality amplification are particularly well-evidenced in the comparative literature on digital agriculture: differential adoption capacity, market-structure effects, data dispossession, and financialised vulnerability.

6.1. Differential Adoption Capacity

The first pathway is differential adoption capacity: farmers who already possess land, formal education, social capital, surplus income, and access to institutional networks are better positioned to discover, experiment with, and capture the benefits of new digital tools. They are more likely to be targeted by digital extension agents, more comfortable navigating registration processes

conducted in dominant languages, and better placed to absorb the upfront costs and learning risks associated with unfamiliar technologies.

The adoption of agricultural innovations has historically followed this pattern, early adoption concentrated among the relatively better-off, with benefits diffusing slowly and unevenly to smaller and more marginalised producers. What is distinctive about digital tools is the speed at which capability gaps can widen. A large commercial farm that integrates AI-driven advisory systems, precision irrigation, and algorithmic market intelligence in a single season gains a compounding competitive advantage over a smallholder adopting a basic SMS advisory service, an advantage that accumulates each season and is difficult to reverse.

Differential adoption capacity is further shaped by geography. Farmers located in remote areas not only face poorer connectivity but also have less exposure to the social networks, urban extension agents, producer organisation meetings, agricultural fairs, through which awareness of new digital tools typically diffuses. The geography of adoption mirrors the geography of connectivity and social capital, reinforcing existing spatial patterns of agrarian advantage.

6.2. Market-Structure Effects

The second pathway operates through market structure. When digital tools disproportionately increase the productivity and market competitiveness of larger commercial operators, they may intensify competitive pressures on smaller producers in ways that are invisible at the aggregate level but highly consequential at the farm level. If large farms deploy digital advisory services, precision inputs, and AI-driven forecasting to reduce costs and improve yields, they can offer produce at lower prices in spot markets, meet higher quality and consistency standards for premium buyers, and process orders more efficiently in digital trading platforms. Smallholders competing in the same commodity markets face prices driven lower by the productivity gains of larger producers, gains they cannot access. The result is a competitive squeeze in which smallholders' relative position deteriorates even if their absolute output increases modestly.

This market-structure effect is particularly pronounced in highly commodified crop markets with thin margins and intense price competition. Smallholders in higher-value, more differentiated markets, organic produce, specialty crops, geographically protected products, may be less exposed, but accessing these markets typically requires precisely the quality assurance, traceability documentation, and logistics integration that digital tools facilitate and that smallholders are least equipped to provide.

6.3. Data Dispossession and Platform Power

The third pathway, data dispossession, refers to the systematic appropriation of farmer-generated data by platform operators, input companies, and other digital intermediaries. When farmers engage with digital agricultural platforms, inputting soil test results, recording input purchases, registering transaction histories, answering advisory service questionnaires, they generate agronomic and economic data of significant commercial value. This data, in combination with satellite imagery, climate records, and supply chain transaction logs, enables platform operators to build predictive models for crop yields, input demand, and commodity prices.

The value created when this data is aggregated and analysed accrues overwhelmingly to the platform operators, not to the farmers whose labour and knowledge generated the underlying observations. Terms of service agreements, which most smallholder users neither read nor fully comprehend, typically assign proprietary rights over all data to the platform. Farmers cannot

inspect, correct, or withdraw their data. They cannot share it with competing platform operators who might offer better terms. And they have no visibility into how their data influences the recommendations they receive, the credit scores they are assigned, or the prices they are offered.

This dynamic amounts to a new form of enclosure: the digitalisation of the commons of agrarian knowledge that farming communities have accumulated over generations, and its conversion into privately held intellectual property (Kloppenburger, 2010). The political economy parallels with land enclosure are not superficial. Both processes involve the commodification of resources that were previously held in common, their appropriation by capital, and the transformation of formerly autonomous producers into dependent participants in markets they do not control.

6.4. Financialised Vulnerability

The fourth pathway emerges when digital credit, insurance, and payment systems extend formal finance to smallholders on terms that transfer rather than absorb risk. Mobile credit platforms have reached farming populations that formal banking systems long ignored, and this expanded access has genuine benefits for many borrowers (Gabor & Brooks, 2017; World Bank, 2022). But the architecture of digital credit introduces structural vulnerabilities that are qualitatively different from those embedded in informal credit relationships. Algorithmic credit scoring models rely on digital footprint data, airtime histories, mobile money transaction patterns, geolocation data, app usage logs, as proxies for creditworthiness. These proxies systematically disadvantage farmers with irregular transaction patterns, seasonal income flows, or shared device use: precisely the characteristics of the most marginalised smallholder populations. Farmers who most need affordable credit are thus least likely to receive it, or receive it only at higher interest rates justified by algorithmically assessed risk profiles that are opaque and unappealable.

Where loans are disbursed and repaid through mobile money accounts, automated repayment mechanisms may deduct instalments regardless of whether harvests have failed or prices have collapsed. Unlike informal credit relationships embedded in social networks, which typically permit deferral, renegotiation, and forgiveness under adverse circumstances, governed by norms of reciprocity and reputation, digital credit platforms remove human judgment and social accountability from the credit relationship entirely. The result is a form of financialised vulnerability in which smallholder households can experience rapid asset stripping following climate or market shocks, with no institutional recourse.

7. Artificial Intelligence and the Emerging Algorithmic Divide

The four pathways described in Section 6 have characterised digital agriculture since the first generation of mobile advisory platforms and digital extension services. The rapid deployment of artificial intelligence in agricultural systems since approximately 2022 has intensified each of these dynamics while adding a qualitatively new dimension: the algorithmic divide, in which access to AI-enabled capabilities creates compounding advantages that are increasingly difficult for less-resourced actors to bridge. AI in agriculture encompasses a wide and growing range of applications, from large language model-based advisory chatbots and satellite imagery analysis systems to algorithmic credit scoring, automated contract farming platforms, and AI-driven commodity price forecasting. These applications vary significantly in their accessibility to smallholder farmers and in the equity implications of their deployment. What they share is a reliance on large volumes of high-quality training data, substantial computational resources, and reliable high-bandwidth connectivity, all of which are substantially more available to large commercial farms than to smallholder producers.

Three mechanisms drive AI-mediated inequality amplification with force. The first is training data bias: AI models trained predominantly on data from large commercial farms in the Global North, with their monoculture cropping systems, mechanised inputs, synthetic fertility management, and commercial market orientation, produce recommendations that are poorly calibrated for the polyculture, rainfed, low-input systems typical of smallholder agriculture in the Global South. An AI advisory system optimised on data from industrial maize production in Iowa offers, at best, irrelevant guidance to a smallholder intercropping sorghum, cowpea, and millet on two hectares in the Sahel. At worst, it offers actively harmful recommendations that do not account for the resource constraints, risk profiles, and livelihood objectives of smallholder farming households. The second mechanism is AI-mediated market concentration. Large buyers, commodity traders, and input companies increasingly deploy AI-powered demand forecasting, weather-linked risk models, and algorithmic commodity price tools. These tools generate market intelligence asymmetries of significant commercial consequence. A large grain trader with access to satellite-derived yield estimates, weather model predictions, and global supply chain data can negotiate purchase prices with smallholder sellers who have no equivalent information. The asymmetry is not new, traders have always known more than farmers about market conditions, but AI dramatically widens the gap.

Table 8. AI Agricultural Applications: Access Disparities and Equity Concerns, 2024

AI Application	Access: Smallholders (%)	Access: Large Farms (%)	Key Equity Concern
AI-powered crop advisory (LLM-based)	3	29	Predominantly English/dominant language; training data biased toward Global North agronomy; data extraction without farmer consent.
Satellite-based crop monitoring	5	61	Subscription costs prohibitive for smallholders; resolution gaps in areas with fragmented land; requires stable internet.
AI Algorithmic credit scoring	35 (as subject)	N/A	Discriminatory proxies using mobile footprint data disadvantage seasonal earners; excludes informal economy actors.
AI demand forecasting and price tools	2	44	Market intelligence asymmetry favours large buyers; risk of algorithmic price manipulation against unconnected sellers.
AI pest and disease detection apps	6	39	Training data biased toward commercial crop varieties; low-bandwidth barriers; poor calibration for polyculture systems.
Automated contract farming platforms	2	30	Power asymmetry in algorithmically-set contract terms; smallholders have no visibility into pricing models.
AI-assisted soil health analysis	4	S35	Soil training data skewed toward temperate commercial farmland; limited validation for tropical smallholder soils.

Source: GSMA (2024) Mobile Connectivity Index; FAO (2023) Digital Agriculture: Key Trends; CGIAR (2024) Smart Farming Technologies in Low- and Middle-Income Countries.

**Access figures are approximate cross-country estimates and should be treated as indicative.*

The third mechanism involves AI-enabled data extraction. Large language model interfaces deployed as agricultural advisory tools harvest farmer queries as training data without meaningful informed consent. Each interaction enriches the model's agronomic knowledge base and commercial value while adding no equivalent return to the farmer providing the input. This is not

a marginal concern, but a structural feature of how LLM-based agricultural advisory systems are currently designed and monetised.

7.1. Governance Gaps in Agricultural AI

The governance frameworks available to address these dynamics are conspicuously underdeveloped. Data protection regulations in most low-income countries are either absent or weakly enforced, and where they exist, they are typically designed for consumer financial data rather than for the complex agronomic and behavioural data generated by digital agricultural platforms. AI-specific regulatory instruments, algorithmic impact assessments, mandatory explainability requirements, bias auditing obligations, are nascent even in high-income jurisdictions and largely absent elsewhere. The speed of AI deployment in agricultural systems has outpaced both regulatory capacity and academic analysis. The most consequential AI applications, credit scoring, contract pricing, market forecasting, are already operating at scale in several major agricultural economies, shaping outcomes for millions of smallholder farmers, before their equity implications have been systematically studied or their governance frameworks designed. This regulatory lag is not accidental: it reflects the political power of the platform companies that benefit from the absence of binding accountability requirements.

8. Policy and Political Implications

Recognising digitalisation as a structural inequality amplifier rather than a neutral enabler does not imply rejecting digital technologies in agriculture. It does require fundamentally reorienting the policy frameworks through which digital agriculture is promoted, regulated, and financed. The dominant market-led inclusion model, which focuses on subsidising infrastructure, creating enabling environments for private platform investment, and promoting digital literacy programmes, addresses only the first-level access dimension of the digital divide while leaving the political economy structures that drive second, third, and fourth-level exclusions entirely intact.

8.1. Beyond Market-Led Inclusion

Market-led inclusion strategies rest on the premise that the agricultural digital divide is a temporary market imperfection that competitive markets, falling technology costs, and targeted subsidies will progressively eliminate. The empirical evidence reviewed in this chapter is inconsistent with this premise. In the absence of targeted intervention, digital adoption has followed the grain of existing agrarian inequality, concentrating benefits among the already advantaged. In contexts where market-led strategies have generated the most enthusiastic success stories, value chain digitisation in East African horticulture exports, mobile credit in Bangladesh, e-commerce platforms in South Asia, the gains have consistently been concentrated among the more commercially oriented, better-resourced, and more socially connected minority within the smallholder population.

This does not mean that market mechanisms play no role in agricultural digital development. Private investment in infrastructure, platforms, and applications has driven much of the innovation in this space. The problem is one of exclusive reliance: treating digital agriculture as a sector to be driven by private investment and market diffusion, with state and development agency roles limited to removing regulatory barriers and providing time-limited subsidies, leaves the structural determinants of digital inequality untouched and makes equitable outcomes dependent on the goodwill of platform companies whose fiduciary obligations run to investors, not farmers.

8.2. Data Governance and Farmer Rights

A rights-based approach to agricultural data governance would start from the premise that farmers have substantive rights over data generated on their land and in the course of their agricultural activities: the right to access their own data, the right to understand how it is being used, the right to withdraw consent and have data deleted, and the right to share data with platform competitors rather than being locked into proprietary systems. These rights are analogous to the consumer data rights enshrined in legislation such as the European General Data Protection Regulation, but their articulation in agricultural contexts requires adaptation to the collective and community-level nature of much agronomic knowledge.

Several farmer organisations and agrarian movements have begun to articulate frameworks for collective data sovereignty: the right of farming communities to govern data generated from their territories and practices, including the right to set terms for its commercial use and to share in any revenues derived from it. The concept draws on indigenous data sovereignty frameworks developed in postcolonial contexts, and it challenges the standard commercial assumption that data belongs to whoever collects it (Kukutai & Taylor, 2016). Operationalising collective data sovereignty in agricultural contexts requires both legal innovation, new forms of data trust or cooperative ownership, and technical infrastructure enabling farmers to exercise control over their data in practice.

8.3. Public Investment in Alternative Digital Infrastructure

The market logic of platform capitalism tends toward concentration: network effects favour dominant platforms, proprietary data creates competitive moats, and the fixed costs of AI development reward scale. In agricultural contexts, this logic will, absent countervailing public intervention, produce digital ecosystems controlled by a small number of large platform companies that extract value from farmers rather than redistributing it to them. Alternative models exist and deserve serious policy attention. Open-source agricultural advisory platforms, farmer-governed data cooperatives, public-interest AI development with openly shared training datasets, community mesh networks for rural connectivity, and interoperability requirements that prevent platform lock-in have all been piloted in various contexts. The evidence on their effectiveness is promising but limited, in part because public investment in these alternatives has been minimal relative to the subsidy support and regulatory accommodation offered to commercial platforms. Rebalancing this investment architecture is a political choice, not a technical inevitability.

8.4. Gender-Transformative Digital Agriculture Policy

Addressing gendered digital exclusion in agriculture requires more than adding a gender indicator to digital inclusion metrics. It requires what has come to be called a gender-transformative approach: interventions that directly engage with the social norms, household power relations, and institutional practices that constitute the structural roots of women's exclusion, rather than simply providing women with access to tools designed for and by men (Quisumbing *et al.*, 2014). In practical terms, gender-transformative digital agriculture programming involves co-designing platforms with women farmers from the outset rather than adapting male-centred designs after the fact; delivering content through communication channels and spaces accessible to women given prevailing social norms; building digital literacy through women's groups and organisations with established trust relationships; ensuring that digital financial services are designed to be usable by women who may have limited or irregular transaction histories; and holding platform operators

accountable through gender-disaggregated reporting requirements and minimum standards for women's reach and benefit.

9. Conclusion

The agricultural digital divide is not a temporary lag in the diffusion of beneficial technologies that market forces and infrastructure investment will eventually close. It is a structural expression of the same inequalities in land, labour, knowledge, credit, and power that have organised agrarian societies across the global South for generations, inequalities that digital technologies, when introduced into unchanged structural conditions, tend to amplify rather than attenuate. The five pathways through which digitalisation amplifies agrarian inequality, differential adoption capacity, market-structure effects, data dispossession, financialised vulnerability, and now AI-mediated algorithmic disadvantage, are not incidental features of particular platforms or policy failures. They are systematic expressions of the political economy of digital capitalism as it encounters and reshapes agrarian structures (Scoones *et al.*, 2018). Understanding them as such is the precondition for designing interventions that could actually produce different outcomes.

The rights-based framework sketched in Section 8 points toward the kinds of transformation required; public investment in open, interoperable digital infrastructure; regulatory frameworks that assert farmers' substantive rights over their own data; gender-transformative programming that addresses the normative roots of women's digital exclusion; and governance architectures for agricultural AI that centre the interests of smallholder users rather than platform shareholders. None of these are simple technical or administrative solutions. All of them require political choices that contest the interests of powerful corporate actors who benefit substantially from current arrangements. The digital field will not level itself. The technologies are not inherently democratising or inherently concentrating; they take on the character of the social structures and political economies within which they operate. Changing those outcomes requires changing those structures, a task that is, ultimately, as much political as it is technological. Digital agriculture deserves serious investment and serious attention, but it deserves both on honest terms, with clear-eyed acknowledgment of who stands to benefit and who bears the risk of being left further behind.

References

- CGIAR. (2024). *Smart farming technologies in low- and middle-income countries*. CGIAR Research Program. <https://www.cgiar.org/news-events/news/smart-farming-technologies-in-low-and-middle-income-countries/>
- Food and Agriculture Organization of the United Nations. (2021a). *Small family farmers produce a third of the world's food*. <https://www.fao.org/newsroom/detail/small-family-farmers-produce-a-third-of-the-world-s-food/en>
- Food and Agriculture Organization of the United Nations. (2021b). *E-agriculture in action: Digital technologies for agriculture*. FAO. <https://openknowledge.fao.org/items/fd09d46b-85fb-4e07-8b05-9b015fadd79b>
- Food and Agriculture Organization of the United Nations. (2023). *Digital agriculture: Key trends in 2024*. FAO. <https://openknowledge.fao.org/items/95a58e9d-af9b-4219-8c3e-99e19d524df2>
- Gabor, D., & Brooks, S. (2017). The digital revolution in financial inclusion: International development in the fintech era. *New Political Economy*, 22(4), 423-436. <https://doi.org/10.1080/13563467.2017.1259298>
- Government of India. (2018). *Agriculture census 2015–16: All India report on number and area of operational holdings*. Ministry of Agriculture & Farmers Welfare. https://agcensus.da.gov.in/document/agcen1516/ac_1516_report_final-220221.pdf
- GSM Association. (2024). *The mobile gender gap report 2024*. <https://www.gsma.com/solutions-and-impact/connectivity-for-good/mobile-for-development/blog/the-mobile-gender-gap-report-2024/>
- International Telecommunication Union. (2024). *Measuring digital development: Facts and figures 2024*. ITU. https://www.itu.int/hub/publication/d-ind-ict_mdd-2024/
- Internet and Mobile Association of India & Kantar. (2024). *Internet in India 2023 (ICUBE Report)*. IAMAI.
- Kloppenburger, J. (2010). Impeding dispossession, enabling repossession: Biological open source and the recovery of seed sovereignty. *Journal of Agrarian Change*, 10(3), 367-388. <https://doi.org/10.1111/j.1471-0366.2010.00275.x>
- Kukutai, T., & Taylor, J. (Eds.). (2016). *Indigenous data sovereignty: Toward an agenda*. Australian National University Press. [https://books.google.com.pk/books?hl=en&lr=&id=woIfDgAAQBAJ&oi=fnd&pg=PR7&dq=Kukutai,+T.,+%26+Taylor,+J.,+\(Eds.\).+\(2016\).+Indigenous+data+sovereignty:+Toward+an+agenda.+Australian+National+University+Press.&ots=a2bA0g-lTw&sig=GzCmwXhh31zoiRtyBPVdYocohZs&redir_esc=y - v=onepage&q=Kukutai,+T.,+%26+Taylor,+J.,+\(Eds.\).+\(2016\).+Indigenous+data+sovereignty%3A+Toward+an+agenda.+Australian+National+University+Press.&f=false](https://books.google.com.pk/books?hl=en&lr=&id=woIfDgAAQBAJ&oi=fnd&pg=PR7&dq=Kukutai,+T.,+%26+Taylor,+J.,+(Eds.).+(2016).+Indigenous+data+sovereignty:+Toward+an+agenda.+Australian+National+University+Press.&ots=a2bA0g-lTw&sig=GzCmwXhh31zoiRtyBPVdYocohZs&redir_esc=y - v=onepage&q=Kukutai,+T.,+%26+Taylor,+J.,+(Eds.).+(2016).+Indigenous+data+sovereignty%3A+Toward+an+agenda.+Australian+National+University+Press.&f=false)
- Lowder, S. K., Skoet, J., & Raney, T. (2016). The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development*, 87, 16-29. <https://doi.org/10.1016/j.worlddev.2015.10.041>
- Quisumbing, A. R., Meinzen-Dick, R., Raney, T. L., Croppenstedt, A., Behrman, J. A., & Peterman, A. (Eds.). (2014). *Gender in agriculture: Closing the knowledge gap*. Springer and FAO. <https://doi.org/10.1007/978-94-017-8616-4>
- Ragasa, C., Ma, N., & Hami, E. (2024). *Farmer groups as ICT hubs (IFPRI Discussion Paper 02261)*. International Food Policy Research Institute. [https://books.google.com.pk/books?hl=en&lr=&id=cmsTEQAAQBAJ&oi=fnd&pg=PA6&dq=Ragasa,+C.,+Ma,+N.,+%26+Hami,+E.,+\(2024\).+Farmer+groups+as+ICT+hubs+\(IFPRI+Discussion+Paper+02261\).+International+Food+Policy+Research+Institute.+&ots=O0_S29y-v&sig=u376HYFJV4FeUsaEozeWpishDiA&redir_esc=y - v=onepage&q&f=false](https://books.google.com.pk/books?hl=en&lr=&id=cmsTEQAAQBAJ&oi=fnd&pg=PA6&dq=Ragasa,+C.,+Ma,+N.,+%26+Hami,+E.,+(2024).+Farmer+groups+as+ICT+hubs+(IFPRI+Discussion+Paper+02261).+International+Food+Policy+Research+Institute.+&ots=O0_S29y-v&sig=u376HYFJV4FeUsaEozeWpishDiA&redir_esc=y - v=onepage&q&f=false)
- Ragnedda, M. (2018). Conceptualizing digital capital. *Telematics and Informatics*, 35(8), 2366-2375. <https://doi.org/10.1016/j.tele.2018.10.006>
- Robinson, L., et al. (2015). Digital inequalities and why they matter. *Information, Communication & Society*, 18(5), 569-582. <https://doi.org/10.1080/1369118X.2015.1012532>
- Scoones, I., Edelman, M., Borrás, S. M., Jr., Hall, R., Wolford, W., & White, B. (2018). Emancipatory rural politics: Confronting authoritarian populism. *Journal of Peasant Studies*, 45(1), 1-20. <https://doi.org/10.1080/03066150.2017.1339693>
- Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media & Society*, 6(3), 341-362. <https://doi.org/10.1177/1461444804042519>
- Van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics*, 34(4-5), 221-235. <https://doi.org/10.1016/j.poetic.2006.05.004>
- World Bank. (2022). *World Development Report 2022: Finance for an equitable recovery*. World Bank.
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