Article
ISDI 2026/46

معهد التنمية المستدامة والإبتكار
INSTITUTE FOR SUSTAINABLE DEVELOPMENT & INNOVATION

Why AI in Agriculture Is Harder Than It Looks

The Economic, Technical, and Human Challenges of Localising AI in Jordanian Agriculture


Picture by Omar Dajani, a Watermill on the Zarqa River

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EXECUTIVE SUMMARY

Artificial intelligence holds real promise for Jordanian agriculture — smarter irrigation, earlier disease detection, better yield forecasting, and more efficient resource use. But the gap between what AI can do and what Jordanian farms can actually use is wide, and it isn't a technology problem so much as a structural one.

Three barriers dominate. First, Jordan's farms are small, so the fixed costs of sensors, controllers, and software fall on producers who lack the volume to spread them out — meaning even a technically sound system can fail to pay for itself. Second, reliable local agricultural data is scarce: irrigation, soil, pest, and yield records often don't exist in usable digital form, and models built on European, North American, or Chinese datasets don't transfer cleanly to Jordanian crops, soils, and climate without local retraining. Third, every new layer of technology brings a new layer of upkeep — installation, calibration, connectivity, monitoring — that small and mid-sized farms typically can't staff internally, pushing them toward costly outside support.

These problems compound each other: thin margins limit investment in data infrastructure, weak data limits localisation, and localisation demands more technical support than most farms can absorb.

None of this is a dead end. The piece argues for spreading fixed costs through cooperatives and shared infrastructure (regional weather networks, shared sensors, public satellite data); closing the data gap by fine-tuning existing models with smaller local datasets rather than building from scratch, backed by ministry- and university-led data collection; adopting technology incrementally to limit risk and build trust; and closing the skills gap through extension services and local technicians who turn maintenance into a nearby service rather than an imported speciality.

The bottom line: AI's success in Jordanian agriculture won't be decided by model accuracy alone. It depends on building an affordable, locally adapted technical ecosystem around the model — one that delivers real economic value and puts these tools within reach of the small farms that make up most of the sector.

Computer science and artificial intelligence (AI) offer clear opportunities for agriculture. They support better irrigation, disease detection, yield prediction, farm planning and resource management. Yet integrating these systems into everyday farming is difficult, especially in countries such as Jordan. The main barriers are often economic and operational.

One of the biggest problems is farm size. Jordanian agriculture is dominated by small holdings, with a large share of farms covering less than one hectare. Technologies such as sensors, cameras, automated irrigation controllers and AI software often involve fixed costs. A large farm spreads these costs across a high volume of production. A small farmer does not have the same advantage. Even when a system improves efficiency, the financial return might not justify the initial investment, software fees, maintenance, and replacement costs.

A second problem is data. Modern AI systems depend on large amounts of reliable information, yet many farms have limited historical records on irrigation, fertiliser use, pests, disease, soil conditions, and yield. In many cases, the problem starts before the AI model itself. The required data does not exist in digital form.

Collecting new data creates another expense. A useful agricultural AI system might need soil sensors, local weather stations, water-flow meters, cameras, satellite imagery, or regular field measurements. These devices need installation, calibration, connectivity, and maintenance. A failed sensor or a poorly calibrated camera produces poor data, which reduces the value of the software built on top of it.

Localisation creates a further challenge. Many agricultural AI models are developed using datasets collected in Europe, North America, China, or other large agricultural markets, and their performance does not automatically transfer to Jordan. Local crops, varieties, soils, temperatures, water quality, pests, and farming practices differ. Even an accurate disease-recognition or irrigation model might perform poorly when applied to conditions it was never trained on. Building a useful local system therefore requires Jordanian agricultural data and testing under local conditions.

The human cost of integration is also easy to underestimate. Each new layer of technology introduces new technical responsibilities. Sensors need someone to install and troubleshoot them. Networks and data systems need maintenance. Software needs configuration and updates. AI systems need monitoring to ensure their recommendations remain reliable.

For a large agricultural company, these tasks might be handled by an internal technical team. For a small or medium-sized farm, they often require outside specialists or additional employees. This increases operating costs and creates dependence on skills that are not traditionally part of farm management. A system designed to reduce labour or improve efficiency might therefore introduce a new category of technical labour.

These barriers are closely connected. Small farms struggle to justify investment in data infrastructure. Weak data makes localisation difficult. Localised systems require more testing and technical support. More technology increases maintenance costs. As a result, the main challenge is rarely developing the AI model itself. The harder problem is building an affordable technical system around the farm, from data collection to maintenance, while still producing enough economic value for the farmer to keep using it. None of these barriers is permanent. The first response is to spread the cost. Cooperatives let many small farms share the same sensors, weather stations, and software. A single irrigation controller covering several neighbouring plots lowers the fixed cost per farmer. Government programmes and agricultural universities reduce the burden further by funding shared infrastructure, such as regional weather networks and public satellite data. A small farmer then gains access to good inputs without needing to purchase each device separately.

The data problem has a similar path. Building a local model from zero is expensive, but fine-tuning an existing one is cheaper. Developers take a model trained abroad and adjust it with a smaller set of Jordanian samples. This lowers the volume of local data needed to reach useful accuracy. Public sources help here too. Satellite imagery and open weather records give reliable inputs without new hardware on every farm. Ministries and research centres lead structured data collection, so records exist in digital form for the whole sector rather than one holding at a time.

Adoption also works best in stages. A farmer starts with one low-cost tool, proves its value, then expands. This limits risk and builds trust before larger spending. The skills gap narrows the same way. Extension services, vocational training and local technicians turn maintenance into a service farmers buy nearby rather than a specialist they import from outside. The core point stands. The hard problem is not the AI model. The system around the model matters more. Once the system is shared, funded and built for local conditions, the technology reaches the small farms Jordan needs to support.