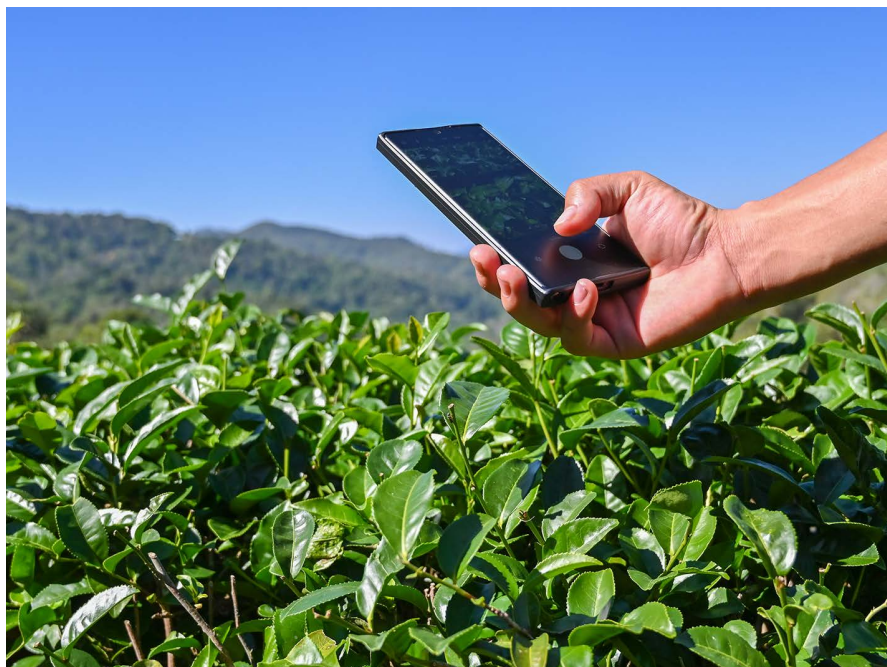


UNDERSTANDING DIGITAL AGRICULTURE

Ten Years of Interdisciplinary Research
at the #DigitAg Institute

Edited by Véronique Bellon-Maurel, Karine Gauche,
Martha-Lucia Enriquez, Nathalie Lyon-Caen

Prefaced by Vincent Martin



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Preface

Over the past ten years, I have seen first-hand how digital technology can inform our decisions without ever being a substitute for those who practice agriculture from day to day. This conviction—forged through field experience and diverse collaborations with farmers, researchers, engineers, and public policymakers worldwide—forms the basis of my perspective on the role that digital technology can play in service of a more resilient, sustainable, and fair agriculture.

The promises of innovation are many, but one observation stands out: a gap remains between what we are capable of designing and what stakeholders actually adopt in the field. The challenge is not merely to innovate, but to create the conditions for use: trust, support, perceived value, simplicity, governance, and training. An innovation only has impact when it is adopted, adapted, and sustainably integrated into practices and decisions. This is where the transition from potential to impact truly takes place.

This requires responsible research and innovation, mindful of social, environmental, and economic consequences. Responsible, because it is accountable to society and the living world: they must anticipate, protect, and remain answerable. Responsible, because technological progress that weakens, excludes, or obscures is not progress—even when it leverages tools as powerful as artificial intelligence.

Digital technology can be a factor for inclusion, but it can also widen inequalities faster than it bridges them if access, skills, and equity are not designed in from the start. Reducing the digital divide is not a secondary objective; it is a condition for sustainability, efficiency, and fairness. We do not build the future with only a portion of the stakeholders, nor by assuming that technology will impose itself.

This is where the humanities and social sciences come in. They remind us that no technology changes practices by its presence alone. Understanding usage, barriers, perceptions, incentives, stakeholder logic, and power dynamics is necessary to transform potential into actual adoption. Without them, data is deaf, models are blind, and solutions are flawed. Taking usage into account is even more vital in the Global South, where smallholder family farms are in the majority and sit at the heart of food security and territorial resilience. Digital tools will only be relevant there if they adapt to the diversity of farms, socio-economic contexts, and local knowledge.

This is where #DigitAg has made a unique contribution: by creating a common language between disciplines, linking sensors with behaviours, algorithms with usage, and models with territories. Ten years of work have produced not only tools and knowledge but have also structured a community that learns, shares, adjusts and cooperates. This interdisciplinarity is the prerequisite for useful, appropriate and adopted innovation.

It is also with this vision that open innovation initiatives like OccitANum were born within #DigitAg, bringing together researchers, farmers, companies, public actors,

and citizens to co-construct digital solutions for the agroecological transition. These experiments prove that open, frugal and regional innovation can be a driver of inclusion, trust and uptake.

This book recounts the ten-year journey of #DigitAg, which began at a time when precision agriculture was the most advanced form of agricultural digitalisation. This path continued with the democratisation of the Internet of Things (IoT) and dedicated applications for agriculture and value chains, stimulated by entrepreneurial fervour and the creation of numerous startups. It continues today with the rise of artificial intelligence (AI), revitalised by the promises of generative AI. Artificial intelligence can offer considerable advances, such as those described in this book (facilitating large-scale phenotyping, early detection of water stress, or analysing satellite imagery time series), but its value depends on the context, the quality of the data, and how it is used. It is neither a shortcut nor a guarantee of results; it is a powerful force, but one at the service of a human, scientific and societal project.

As artificial intelligence further accelerates technological cycles, this book reminds us that no solution will replace listening, cooperation, responsibility and discernment. This is the guiding principle of the roadmap on digitalisation and AI innovation led by the FAO, which in April 2025 brought together a hundred experts and aims precisely to transform intentions into tangible results by creating the conditions for a responsible, inclusive, and useful AI for all.

The success of this transformation also relies on enlightened public policies capable of framing digitalisation to guarantee equity, transparency and sustainability. Our challenge is therefore not to innovate faster, but to innovate with meaning, with method, and with everyone.

I hope these pages inspire, through the use of real-life practical examples, those who want to close the gap between intentions and results and make digital technology and AI a lever for autonomy, resilience and trust. The task is immense, but the course is clear: to put innovation at the service of the living world, local areas and communities, and not the other way around. The path lies ahead of us, and it can only be travelled together.

Vincent Martin
Head of the Office of Innovation
Food and Agriculture Organisation of the United Nations (FAO)

General introduction

Karine Gauche, Véronique Bellon-Maurel

» Digital Agriculture: a strategic lever at the heart of the Agriculture Innovation 2025 report...

Published in 2015, the Agriculture Innovation 2025¹ report presents thirty proposals for building a more sustainable and innovative French agriculture. Coordinated by a team including Jean-Marc Bournigal (President of Irstea), François Houllier (CEO of Inra), Philippe Lecouvey (Director of Acta), and Pierre Pringuet (Chair of the Board of AgroParisTech), it advocates for a systemic approach to innovation: mobilizing research, disseminating results to the field, adapting training and developing public policies or, more broadly, regulations.

To address intense food and environmental pressures, the report emphasizes the urgency of rethinking agricultural models by leveraging innovation, particularly digital technology. Agricultural digitalisation is presented as a major lever for developing more resilient agriculture that integrates competitiveness, sustainability, and societal expectations.

The structuring of interdisciplinary research dedicated to digital agriculture is highlighted to address challenges particularly related to data: its collection (smart sensors), its modelling (voluminous and heterogeneous data, otherwise known as ‘big data’), and its use for decision support.

» ...to which #DigitAg, an interdisciplinary Convergences Institute, responds...

Created in 2017 as part of the *Investissements d'Avenir* programmes (PIA), the convergences institute #DigitAg embodies the organisation of a community. Led by INRAE, it brings together sixteen public and private partners with the goal of structuring research for sustainable, competitive, and inclusive digital agriculture in France, Europe and the Global South.

Research is organised around six complementary research axes covering the major issues linked to digital agriculture. Axis 1 examines the transformation of agricultural and rural practices through information and communication technologies (ICT), analysing the impact of digital technology on production systems, agricultural professions and territorial dynamics. Axis 2 focuses on innovation, adoption and diffusion of digital agriculture, studying innovation trajectories and the conditions for

1. <https://agriculture.gouv.fr/sites/default/files/rapport-agriculture-innovation2025.pdf>

dissemination among agricultural actors. Axis 3 concerns sensors and data acquisition, aiming to develop reliable, autonomous and interoperable sensors for real-time agronomic and environmental data collection. Axis 4 deals with information systems, platforms, and interoperability, with the design of open and interconnected digital infrastructures facilitating access, exchange and utilisation of data. Axis 5 addresses data mining, processing, visualisation and indicators, creating tools for big data analysis to extract knowledge useful for decision-making. Finally, Axis 6 concerns modelling, simulation, and decision support tools (DST), developing predictive models to simulate agricultural scenarios and provide operational recommendations.

These axes, which drive scientific communities, intersect with major identified and declared thematic issues (sustainable livestock farming, agroecology, value chains, etc.), addressed through interdisciplinary research.

► ...characterised by substantial funding and massive support for interdisciplinary research in digital agriculture

Since its inception, #DigitAg has structured a significant scientific community across 30 partner joint research units (UMRs), comprising approximately 600 affiliated researchers. The institute has contributed to the funding of 150 Master's grants, 56 doctoral grants (covering both salary and specific financial support for research activities), 50 labelled PhDs, 18 years of post-doctoral fellowships, 72 months of visiting scientist support, and 12 software developments for demonstrators derived from PhD results. All of this work has been drawn upon for this book, with a particular focus on PhD theses. Several doctoral students and post-doctoral researchers contributed to the writing of these parts.

This volume presents research conducted across the six axes while offering specific, transversal perspectives, including reflective ones and is organised in four parts.

Part 1 (Chapters 1–4) focuses on the development of tools for the digital transformation of agriculture: the sensors and their implementation necessary for acquiring high-quality field data; the processing of massive, multi-source data; the management and integration of data and knowledge to structure and interconnect heterogeneous information; and the modelling, simulation, and data integration required to develop decision support tools (DST).

Part 2 (Chapters 5 to 7) describes and examines in detail the digital transformation of agriculture from different perspectives (processes, systems, practices and actors). Agricultural digitalisation is first analysed in the context of transitions, exploring the accompanying processes, actors and systemic dynamics. Farmers' digital habits and practices are then examined to understand the links between digitalisation and the 'greening' (ecologisation) of agriculture. Finally, digital tools, when viewed as intermediation instruments, reveal the gaps between the many expectations and the realities observed in the field.

Part 3 (Chapters 8 to 10) presents three concrete applications of digital technologies in agriculture at three different scales. First, phenotyping tools for characterizing and analysing plant traits for varietal selection are presented, followed by solutions to assist livestock farmers in herd management, and finally, digital contributions to monitoring and analysing food security, particularly aimed at public policymakers.

Part 4 (Chapters 11 to 13) offers a reflective analysis on the operations and evolution of #DigitAg. First, the challenges of digital agricultural development in the Global South are presented. Next, the practice of interdisciplinarity is analysed in light of funded projects and modes of cross-disciplinary collaboration. Finally, the challenges and prospects of responsible research and innovation (RRI) approaches—resulting from the convergence between the social sciences and digital sciences—are analysed.

The book concludes with an appendix presenting other #DigitAg products aimed at fostering interdisciplinarity among students and promoting the dissemination of their research: namely, video recordings of student webinars and #DigitAg digital show-cases, which are web-based demonstrations illustrating PhD research results.

Part 1

Research for digital agriculture: development of digital tools

Chapter 1

Acquiring high-quality field data by improving sensors and their application

*Véronique Bellon-Maurel, Ryad Bendoula, Ludovic Brossard,
Jean-Michel Roger, Bruno Tisseyre*

Data collection is the first, crucial phase of ‘data-driven’ agriculture. The data concern the plants or animals that will provide agricultural products (monitoring their physiology, detecting dysfunctions such as diseases and deficiencies, predicted or actual yields, etc.), but also their biological environment (presence of pests, competitors) and abiotic environment (data on soils, meteorology, etc.).

In animal production, the functioning of a livestock system can be improved according to the principles of agroecology through animal monitoring: health, behaviour, welfare, performance (growth, ingestion, reproduction, milk production, etc.), and physiology. However, this monitoring is complex. Depending on the species considered, access to individual data is more or less difficult (for example, pigs or fish versus dairy cows), due to the number of animals and their ease of handling. This monitoring task is difficult in large-scale livestock operations. In extensive systems, this difficulty is also linked to whether or not the animals are accessible (as in pastoralism). Several studies by the #DigitAg community have enabled advances in this field: embedded sensors or remote measurement methods. They will be briefly described here and discussed again in Chapter 9.

In crop production, optical sensors offer the benefit of high acquisition speed, generally contactless detection, and, with some, high specificity. This is the favoured field of expertise for #DigitAg teams. This chapter will describe proximity sensors for measurement at a short distance from the object of interest, between a few tens of centimetres and a few tens of metres (drones). Remote sensing, which uses various types of electromagnetic sensors (optical, radar), has a fundamental place in digital agriculture. It is addressed in Chapter 2.

► Special optical devices

Certain phenomena are difficult to detect: changes of small magnitude (water stress), of small size (detection of droplets, spores, etc.), or of low intensity (early detection of a disease). In such cases, it is advantageous to design optical devices that improve signal sensitivity, as a prerequisite for any processing. #DigitAg has approached this subject from two directions: the coupling of hyperspectral imaging and polarisation, and evanescent wave optical interfaces.

Coupling hyperspectral imaging and polarisation

ITAP joint research unit developed polarised hyperspectral imaging (Xu *et al.*, 2019), a technique that is more selective than standard spectral imaging, as it differentiates information coming from the surface, the superficial cell layers, and the depth of the observed object (in Figure 1.1, a leaf). For each pixel, a spectrum is collected in several configurations of the polariser/analyser pair (Figure 1.1). Spectra of perpendicularly polarised reflectance ($R_{\perp}$), parallel polarised reflectance ($R_{//}$), and combinations of these spectra are obtained, providing access to specular reflection (RSS) or back-scattered reflection (RBS). RSS is similar to an image as viewed by a human. Here, different properties of sunflower leaves are detected: the variety, growth stage, and presence/absence of diseases (powdery mildew, Septoria leaf spot) (Xu *et al.*, 2019).

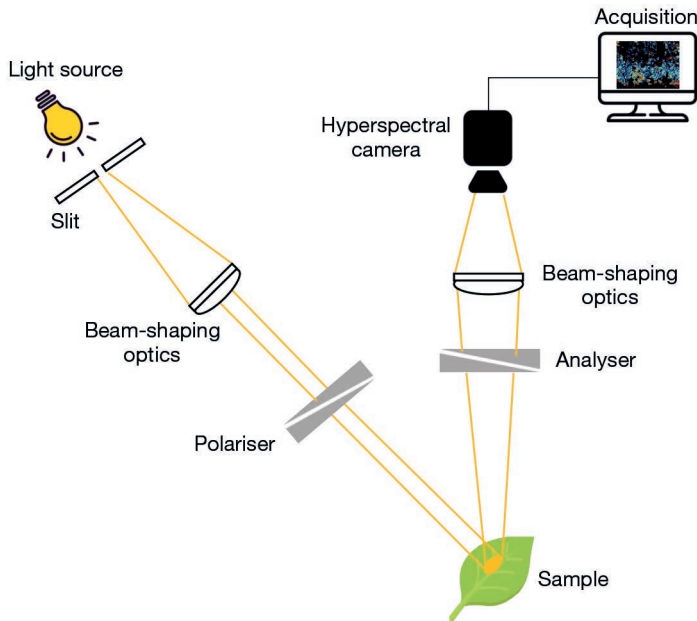


Figure 1.1. Set up for capturing polarised hyperspectral images at UMR ITAP. Source: R. Bendoula.

To detect diseases, the best model utilises the $R_{\perp}$ spectra, which means that the sub-surface or deep-tissue spectra are essential. Figure 1.2 shows the images of the upper surface of infected leaves in RSS and $R_{\perp}$. On one side in pseudo-colours, and on the other, the first and second principal components (PC 1 and 2) of their respective principal component analyses (PCA). These show that the infected areas, i.e. two spots on either side of the central vein, halfway up the leaf, which are very difficult to detect with the naked eye, appear clearly on the $R_{\perp}$ pseudo-image and on PC 1 and 2. This research paves the way for early disease detection via hyperspectral or multispectral imaging.

Another optical device using polarisation to monitor variations in the optical scattering properties of leaves employs the ‘biospeckle’ approach. This consists of creating patterns through the interference of a coherent laser beam with light backscattered by a scat-

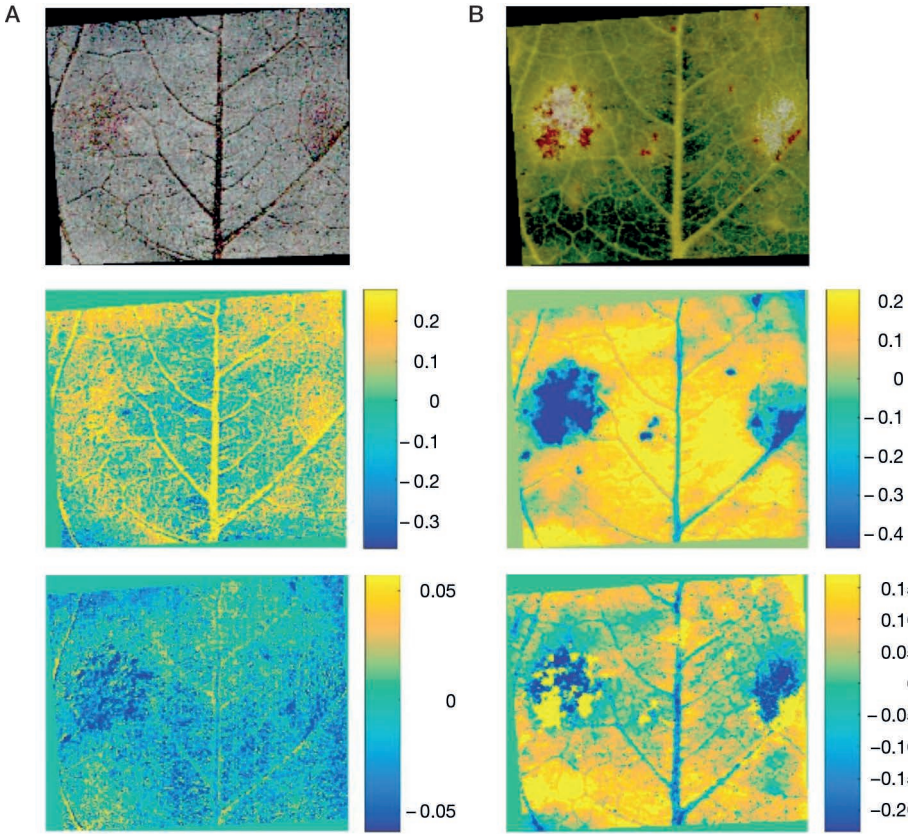


Figure 1.2. Disease detection using polarised hyperspectral imaging of the upper surface of sunflower leaves infected with *Septoria* leaf spot (SLS) and powdery mildew (PM), (A) in specular reflection (R_{ss}) and (B) in orthogonal polarisation (R_l) showing from top to bottom: pseudo-colour image, principal component 1, and principal component 2. Source: adapted from Xu *et al.* (2019).

tering medium—in our case, plant tissue—which depends on stationary particles and mobile elements within that tissue. The device, developed by Bouzaouia *et al.* (2024), comprises a 785 nm laser diode. This wavelength is located on a plant reflectance plateau that promotes interference patterns. Time-series of biospeckle images are analysed to derive a classic biospeckle indicator: the absolute value of difference (AVD) (Braga *et al.*, 2011). Throughout the experiment, AVD values decrease with the increase in water stress (Figure 1.3). The biospeckle approach is likely to become a tool for fine phenotyping of water stress, initially in the laboratory, and in the longer term, in the field.

Evanescent wave optical interfaces

The surface of a waveguide—an optical material that transmits light between a transmitter and a receiver—can become an optical transducer, i.e., a sensitive element, via the phenomenon of evanescent waves. The latter are electromagnetic waves formed at the interface between two media of different refractive indices. These waves are modified by liquids placed on the surface of the waveguide. Rib waveguides (Figure 1.4)

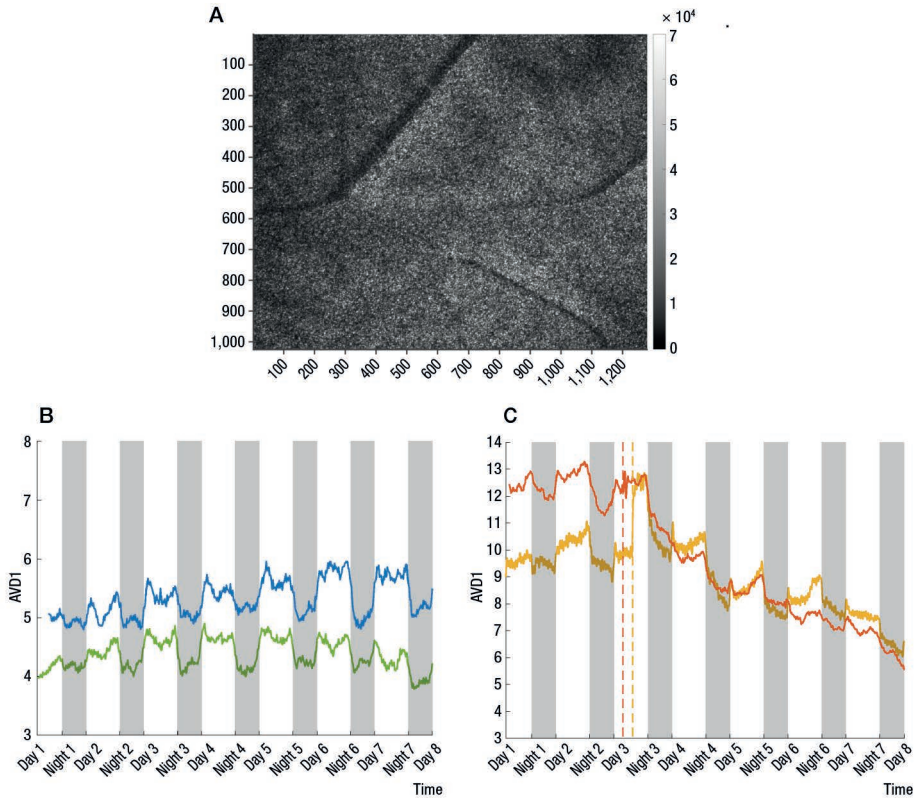


Figure 1.3. Biospeckles for assessing water stress in sunflower leaves: (A) biospeckle image and evolution of the absolute value of difference (AVD) derived from biospeckle analysis for (B) two control leaves and (C) two leaves stressed from day 3 onwards (dotted line). Source: Bouzaouia (2024).

coupled to a near-infrared spectrometer were developed by Taleb Bendiab *et al.* (2018) to measure droplet volumes, with the aim of characterising spray deposits of plant protection products (Taleb Bendiab *et al.*, 2019). A satisfactory correlation was observed between the predicted volumes and the measured volumes, from 0.1 to 2.5 μl , whereas classical detectors based on electrical resistivity do not detect volumes below 5 μl . Such optical sensors, placed within the vegetation sprayed with pesticides, could provide an indication of the treatment quality in farms (evaluating the setting of one's sprayer in the field). This same principle was adopted to detect fungal spores in the air in the doctoral research of Khouri *et al.* (2024). A simulation of the waveguide was produced, with the objective of optimising the geometry of the guiding structures in order to increase their sensitivity for spore detection.

► Visible light imaging

Visible light imaging is the oldest optical means for acquiring data in agriculture. Nevertheless, it remained confined to scientific publications for a long time, due to the difficulty of processing complex proximal images acquired outdoors due to light

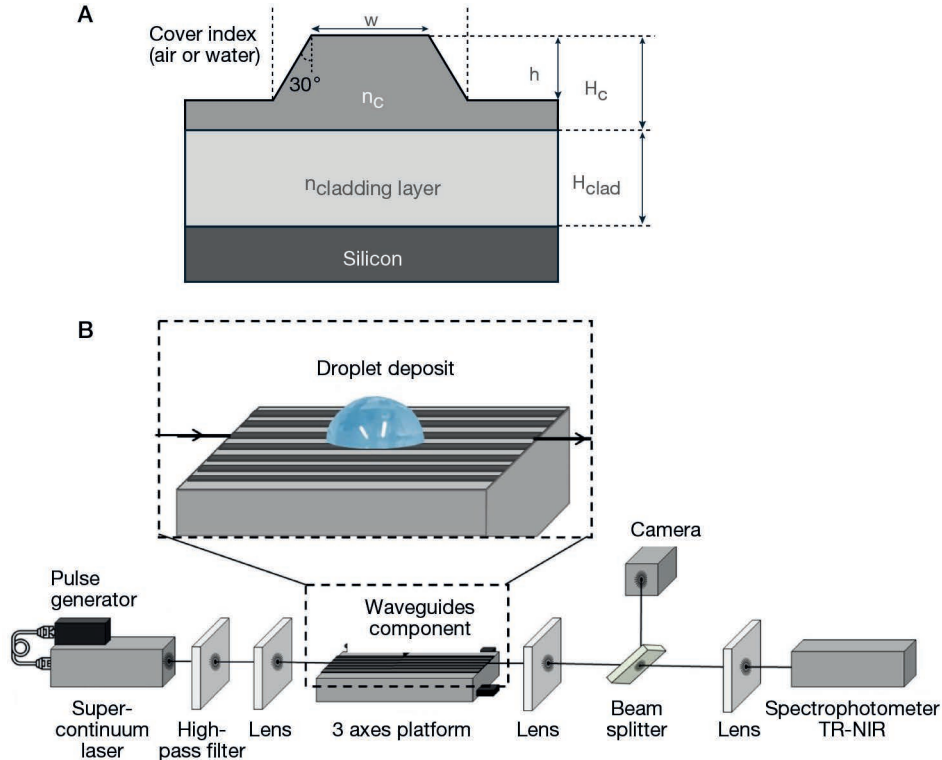


Figure 1.4. Rib waveguide (A) Cross-section of the waveguide and (B) utilisation of the waveguide coupled with an NIR (near infrared) spectrometer. Source: Taleb Bendiab *et al.* (2018).

variations, background, etc. Today, artificial intelligence (deep learning) leads to an explosion of use cases. The research conducted within #DigitAg has addressed several of these, all based on RGB (red-green-blue) cameras, in phenotyping equipment², on smartphones, or in low-cost devices (see Chapter 12). Several teams have worked on these deep learning methods applied to RGB image processing.

The longest-established and most advanced team is Pl@ntNet, from the AMAP joint research unit, which developed the application of the same name (Bonnet *et al.*, 2020a). As of 2025, this species identification application, based on smartphone images (Bonnet *et al.*, 2020b), has over 8 million subscribers and has received 1.2 billion queries³. Current research addresses other topics: modelisation of plant species distribution using satellite images processed by convolutional neural networks (CNNs) (Deneu *et al.*, 2022), and early detection of plant diseases (Lee *et al.*, 2020a, 2020b). In the latter application, using CNNs—i.e. networks traditionally adapted for image processing—pose problems, as CNN may inadvertently take into account the background or healthy areas of the plant. To avoid this, Lee *et al.* (2020a) use a dual network. First, a CNN produces a sequence of disease feature maps; then, this sequence

2. <https://www.hiphen-plant.com/literal-automated-plant-trait-assessment-hardware-software-package/>

3. <https://identify.plantnet.org/fr/stats>

is fed into a recurrent neural network (RNN), i.e. a network used to process sequential data, in order to create an attention mechanism that highlights salient disease features to strengthen their weight during learning. The performance achieved surpasses that of models based solely on CNNs.

The CAPTE joint technological unit focuses on the use of high-resolution RGB images to phenotype field crops: counting wheat heads (David, 2021), detecting wheat heading stage (Velumani *et al.*, 2020), maize density (Velumani *et al.*, 2021), and senescence status (Serouart *et al.*, 2022). In his doctoral research, Étienne David counted wheat heads in RGB images of wheat canopies, acquired with the 'Phénomobile' or the 'Literal' device (de Solan *et al.*, 2024). He applied pre-trained deep learning algorithms, which have the advantage of taking into account the spatial organisation of the signal. To make the prediction more robust, he proposed training the model on an exhaustive database. For this, a database of 4,800 RGB images (200,000 wheat heads) was created in collaboration with a dozen laboratories worldwide (David *et al.*, 2021). The models constructed with this ground-based database are then applied to images acquired by drones. This research raised questions of domain adaptation, a process made necessary when a model is used for predictions in another domain (here, drone images with lower resolutions). These questions were subsequently addressed by Kaaviya Velumani (2021) in her PhD work.

Finally, two other #DigitAg teams carried out more specific work on the subject.

In his doctoral thesis, Julien Sarron (2019) sought to estimate mango yields to meet the needs of several stakeholders: farmers, supply chains, and government institutions. RGB images acquired at three different scales (tree, orchard, and region) were processed using artificial intelligence (AI). The tree images were acquired by the farmer with their smartphone (Figure 1.5) to count the mangoes (Sarron *et al.*, 2023). The plot images were acquired by drones to identify mango trees and obtain plot-level yield (Sarron *et al.*, 2018). Remote sensing images allowed the identification of mango orchards and extrapolation of the production at a regional level, an essential indicator for food security (Sarron *et al.*, 2022).

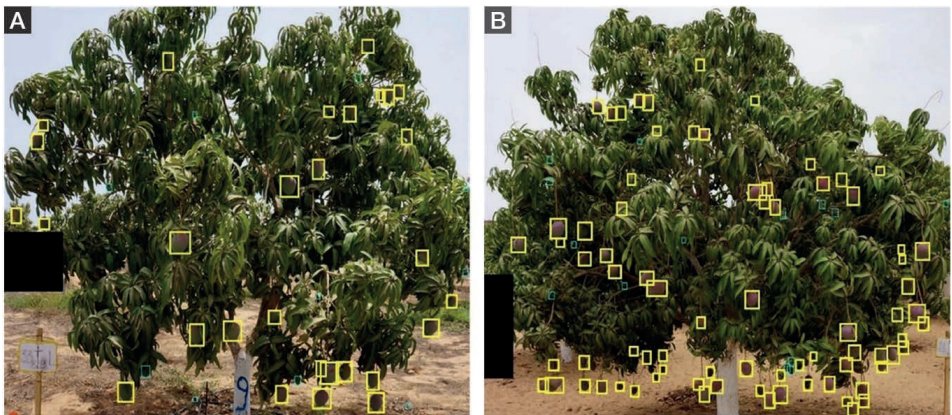


Figure 1.5. Detection of mangoes using RGB imaging for two trees in the same orchard (Senegal) with similar crown volumes and (A) low and (B) high fruit loads. Source: de Sarron *et al.* (2023).

Last, in his doctoral thesis, Paul Tresson (2021) sought to improve biological control against the banana weevil, by understanding the interactions between arthropod species, using cameras installed in banana plantations (Tresson *et al.*, 2022). Two image analysis approaches were evaluated to identify arthropod species: a classical CNN-based classification (Tresson *et al.*, 2019) and a classification combining hierarchical classification with a CNN to address the problem of ‘low-shot object detection’, i.e. the detection of numerous small objects with few reference samples (here, 22 classes of arthropods). This second approach led to the correct classification of 75% of the species, compared with 48% using the CNN alone (Tresson *et al.*, 2021).

» NIR

Near-infrared spectrometry has established itself as an essential method for rapid, non-destructive, and reagent-free analysis of agricultural samples, not only in the laboratory but also in the field using portable and embedded spectrometers. Near-infrared (NIR) spectrometry is based on the modification of near-infrared radiation (700 to 2,500 nm) by matter, due to its chemical characteristics (absorption by organic components) and physical characteristics (scattering), which produces a spectrum. The model linking a characteristic of interest (often a chemical content) to the measured light intensities, i.e. the spectrum, is built via chemometrics. The quality of the result depends heavily on the quality of the initial signal and the relevance of the applied chemometric processing. #DigitAg’s work in this field is organised around two complementary axes: on the one hand, the development of new chemometric tools capable of processing increasingly massive datasets, and on the other hand, multi- and hyperspectral imaging systems to acquire spatialised information and allow early detection of diseases or stress.

Chemometrics and Big Data

The rise of portable spectrometers and embedded sensors has multiplied spectral acquisitions, generating massive, heterogeneous, and potentially noisy datasets, for which new chemometric methods are required. All the studies carried out in #DigitAg demonstrate that the integration of machine learning methods and advanced chemometric techniques constitutes a promising avenue for processing massive data derived from NIR sensors.

Metz *et al.* (2020) proposed the Kernel Neural Network-Partial Least Squares (KNN-PLS) big data algorithm: massive spectral databases are structured into homogeneous clusters before calibrating local PLS models for each cluster. This strategy was notably put to use on massive spectral data to discriminate sunflower genotypes via the ParSketch-PLSDA method, which automatically selects relevant spectral subsets (Ryckewaert *et al.*, 2021). In the same vein, Metz *et al.* (2021) improved the robustness of PLS regressions against outliers by developing another new method, RoBoost-PLSR, which demonstrated its effectiveness in correctly predicting biochemical compound contents of fruits in viticulture and arboriculture (Courand *et al.*, 2022). An extension (RoBoost-PLS2-R) was developed for predicting multiple variables (such as predicting fat and protein content in milk samples) (Metz *et al.*, 2022). By constructing the PLS model from the most relevant spectra within a massive database, this approach improves the precision and stability of models on very large datasets.

Villesseche et al. (2022), who demonstrated the potential of unsupervised analysis (without reference measurements) of NIR data to describe complex traits such as leaf senescence. To do so, they considered jointly the spatial and temporal structures of spectral datasets. This technique allows the exploration of physiological phenomena for which the construction of a calibration database would be too complex or too costly.

MS/HS Imaging

Hyperspectral imaging (HSI) or multispectral imaging (MSI) offer the possibility to spatially map biochemical or physiological properties at high resolution. #DigitAg's studies use HSI/MSI in phenotyping, disease detection and water stress characterisation.

Gaci *et al.* (2023) developed an original method based on multi-block algorithms and machine learning, combining spatial and spectral information from hyperspectral images, for the early detection of apple tree diseases. Similarly, Mas Garcia *et al.* (2021) combined multivariate curve resolution and factorial discriminant analysis approaches to detect grapevine flavescente dorée on hyperspectral images.

Additionally, to monitor the temporal evolution of biomass or chlorophyll content, Eva Lopez Fornieles successfully analysed time-series of multispectral images using multi-way modelling methods, traditionally reserved for chemistry: unsupervised parallel factor analysis (PARAFAC) (Lopez-Fornieles *et al.*, 2022a) and multi-way PLS regression (N-PLS) (Lopez Fornieles *et al.*, 2022b). These authors also propose to use N-CovSel, a variable selection method adapted to multi-way data, to reduce data dimensionality and improve the robustness of predictive models (Lopez Fornieles *et al.*, 2022c).

Finally, the value of crossing chemometrics and artificial intelligence for the processing of spectral images is demonstrated by Mishra *et al.* (2021). They combine CNN and chemometric methods to detect water stress in *Arabidopsis thaliana* at an early stage, paving the way for the development of generic workflows.

» Capturing and representing the 3D structure of plants and animals

Knowledge of the 3D structure of plants is useful in varietal selection or production management to adapt interventions to the volume of the canopy. Two methods have been studied within #DigitAg: (1) LiDAR and (2) stereoscopic image reconstruction, a technique also used in animal production.

LiDAR

LiDAR is an optical device that generates a (x, y, z) point cloud by scanning the environment with a laser and measuring the time of flight of the radiation reflected by objects. Compared to stereoscopy or ultrasound, it offers the advantage of providing data not only on dimensions but also on canopy density. The primary bottleneck, which several #DigitAg doctoral students have tackled, is transforming this point cloud into relevant information.

Juan Pablos Rojas Bustos utilised a 3D LiDAR mounted on a drone for the high-throughput phenotyping of fruit trees (Figure 1.6), particularly to characterise their architectural traits. To process the point cloud, he constructed a semi-automatic processing workflow that operates in stages (identification and removal of unwanted elements, segmentation of individual trees, and characterisation of traits such as height, projected leaf area, volumes, and eccentricity) and utilises both statistical and deep learning approaches (Rojas Bustos *et al.*, 2023).

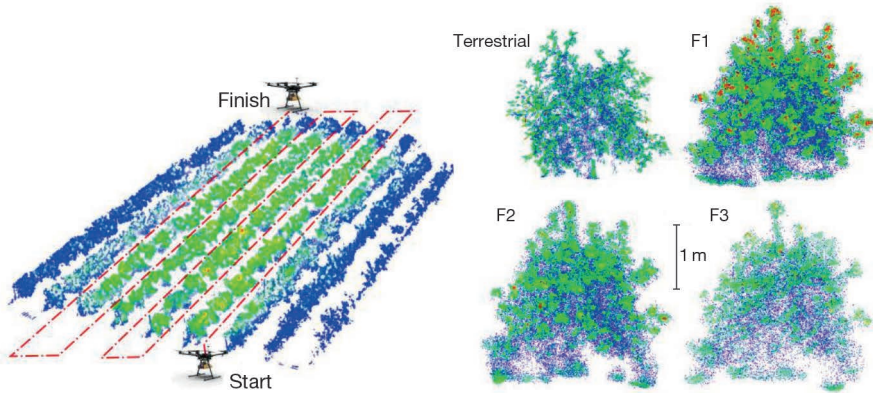


Figure 1.6. Acquisition of architectural traits in apple orchards using LiDAR: (left) drone-based and (right) ground-based; colours represent point density, from low (blue) to high (red). Source: Rojas Bustos (2024).

Anice Cheraïet used a 2D LiDAR mounted on a pesticide sprayer to collect information on vine architecture (height and width) (Cheraïet *et al.*, 2020). He applied an automatic Bayesian classification algorithm, combining filtering and clustering-based classification, to recognise the different zones of the vine (soil and grass, trunk, canopy, and wires). This method offered the same performance as manual and semi-automatic classification methods. It could even be improved by varying the classifier's cut-off threshold throughout the season to account for canopy evolution. Knowledge of the canopy architecture is used to simulate the spatial distribution of plant protection products sprayed on the vine according to the sprayer type. This will eventually lead to adapting the doses applied to the canopy architecture (Cheraïet *et al.*, 2021).

Stereoscopy via Structure from Motion (SfM)

A continuous sequence of 2D images can be used to reconstruct three-dimensional structures using the photogrammetric technique known as Structure from Motion (SfM). Various photogrammetry software packages are available that can perform this reconstruction.

Taugourdeau *et al.* (2022) used SfM to estimate above-ground herbaceous biomass in Sahelian pastures (savannahs) by recording videos at two scales: cameras mounted on drones and ground-based cameras over a 1 m × 1 m reference area. The images extracted from these videos were processed via photogrammetry using PIX4D software (Figure 1.7) to derive vegetation indices and height measurements. These indices allowed them to predict both dry and fresh above-ground herbaceous biomass with

very satisfactory correlation coefficients ($R^2 > 0.7$), even when using drones equipped with low-cost RGB sensors. This opened the door to quantifying and mapping herbaceous biomass across areas as large as 20 to 30 hectares in a single flight.

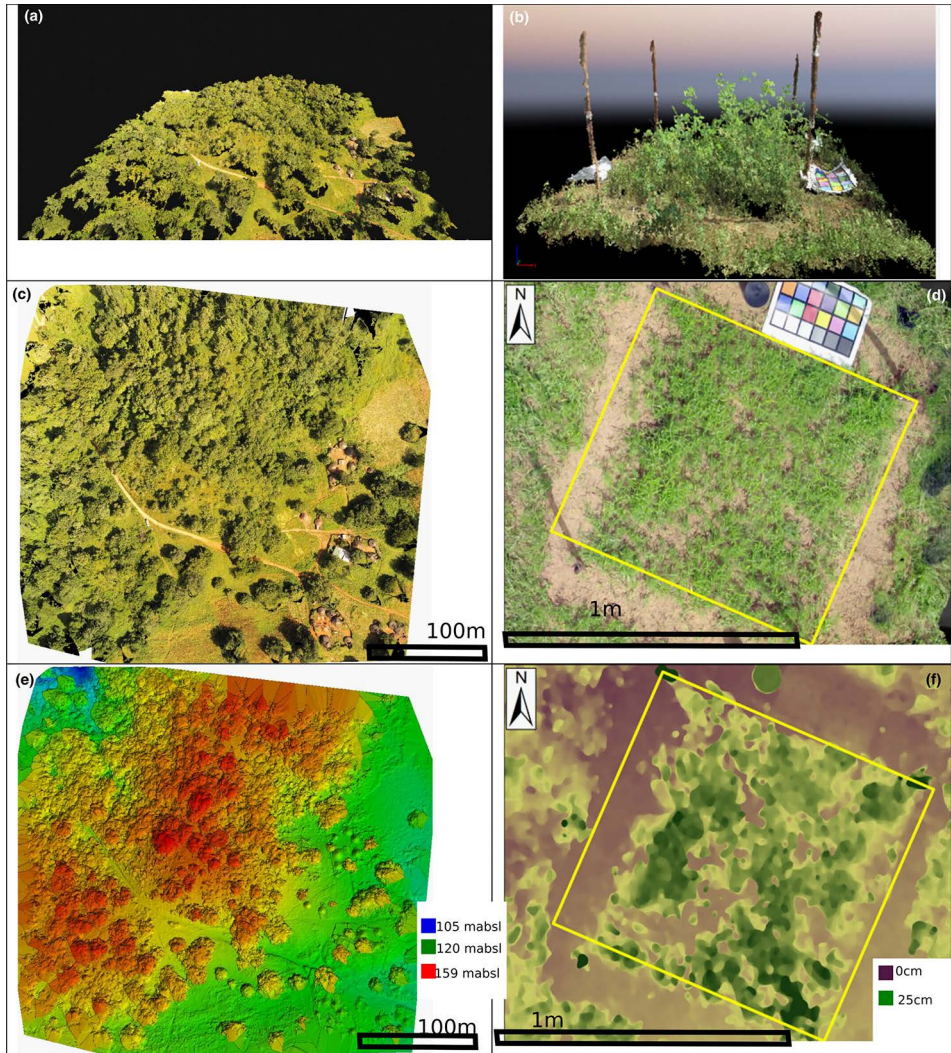


Figure 1.7. Image reconstruction by SfM. Point cloud obtained from (a) drone images and (b) camera images; orthomosaic obtained from (c) drone images and (d) camera images; digital terrain model obtained from (e) drone images (height given in metres above sea level) and (f) camera images (height given in centimetres above ground level) in Taugourdeau *et al.* (2022).

Stereoscopy in animal production

The Morpho3D system, a large-scale 3D imaging device equipped with five cameras—each coupled with a laser—was developed by the PEGASE joint research unit (Le Cozler *et al.*, 2019; Xavier *et al.*, 2022). Then, it was utilised in Caroline Xavier’s

doctoral research to estimate the body composition of cattle (Xavier *et al.*, 2024). This device, which originally required the animal to be immobilised for five seconds during image capture, was subsequently improved by Le Cozler *et al.* (2024) through the simultaneous triggering of the cameras ('one-shot' capture). The resulting 3D images allow the animal's live weight to be estimated with the same precision as before, but without the need for immobilisation.

►► How to improve manual data collection and sampling?

While sensors enable significantly greater amounts of data to be collected, human observation or human sample collection remains justified when automated sensors are impossible to use or inadequate to characterise agrosystems. This is particularly relevant for data with complex properties, such as yield or fruit maturity—which are essential for planning and scaling harvest operations—or for information requiring laboratory analysis (e.g., soil or water quality). Given that agrosystems are dynamic over time and can show significant spatial variability, and in light of the high cost of data collection, sampling strategies must be optimised in terms of the number, location, and frequency of the observations or samples collected. Two different, yet complementary, approaches to this aspect have been explored in three #DigitAg doctoral researches.

The first approach, based on crowdsourcing, argues that by mobilising the observational capacity of a vast community of contributors, it becomes possible to monitor dynamic and spatialised phenomena across multiple scales—sub-plot, plot, regional, or even global—providing unprecedented spatio-temporal coverage.

This was the assumption of Pl@ntnet's team, initially on flora (Bonnet *et al.*, 2020a and 2020b) and now on cultivated plant diseases (as cited above, Lee *et al.*, 2020b). This approach has been adopted in viticulture by the ITAP joint research unit. The latter demonstrates the potential of crowdsourcing to estimate and monitor the dynamics of grapevine water stress (Pichon *et al.*, 2021; Zhang *et al.*, 2024) by providing a free mobile application (ApeX-Vigne⁴) for facilitating the shoot tip (apex) observation method. Their experiment provided several thousand observations, allowing the delineation of relevant management zones in each vineyard and the understanding of intra- or inter-plot variations, revealing spatial structures of grapevine water status at both local and regional levels (Pichon *et al.*, 2022).

Furthermore, it led to two research findings. On the one hand, Pichon *et al.* showed that, to ensure the long-term engagement of contributors and guarantee the data flow necessary to achieve the 'mass' effect (network effect), the collection task must be simple, and the application must offer direct added value to the contributors for their own operational needs, such as a plot-level diagnosis (Pichon *et al.*, 2021). On the other hand, they realized that, as the quality of the collected data is inherently lower than that of experimental measurements, automated methods must be developed to detect errors and improve their overall reliability. This led to a new doctoral thesis initiated within #DigitAg in 2024, which aims to develop new methods that exploit spatial and temporal covariances to identify errors in a context of lack of reference data (thesis of Don Ced Ogoumond).

4. <https://apexvigne.agrotic.org/>

The second approach is based on the premise that the variable of interest must be estimated as reliably as possible, and as early as possible, to inform tactical decisions. This is the approach of Baptiste Oger's research, which seeks to estimate yield in vineyard plots, a major challenge for logistics and harvest management.

The challenge is to balance the precision of the estimate with the sampling effort (i.e. the time spent), which represents a significant cost in trellised vineyards, the dominant vine training management system, where the mobility of people (and machinery) is physically constrained by the rows and trellis wires.

Oger *et al.* (2021a) proposed a constrained sampling method, which combines stochastic methods with optimisation techniques derived from constraint programming and operational research (specifically optimising the length of the sampling path). This method leverages high-resolution auxiliary data (remote sensing images) to estimate the spatial structure of the vegetation within plots, which in turn dictates the selection of measurement sites (Oger *et al.*, 2022).

Applications to numerous real and simulated plots have shown that the optimal sampling strategy varies greatly depending on plot characteristics—such as row length, shape, and the structure of intra-plot variability. Notably, these optimal paths often deviate significantly from the traditional paths recommended and practiced by viticulture professionals (Oger *et al.*, 2021b). These findings pave the way for a mobile application designed to optimise sampling in viticulture and, potentially, for other crop types.

This focus on sampling trajectory optimisation was further developed in the doctoral research of Maxime Dumont (2025) for soil sampling in difficult-to-access areas, a key aspect of digital soil mapping. His Multi-Objective Operational Sampling (MOOS) method minimises sampling travel time while ensuring the representativeness of the sampled area. The method was applied to a region covering over 1,000 km² in Saudi Arabia and outperformed the Conditioned Latin Hypercube Sampling (cLHS) method—on which it is based—by saving up to one full day of work (20% of the time) in the case of large samples (200 collection sites) (Dumont *et al.*, 2024).

►► Conclusion

Data is the fuel of digital agriculture. This is why #DigitAg's research has focused extensively on this aspect through several key research angles: (1) development of new sensors: specifically optical and spectrometric sensors—incorporating novel devices or new chemometric processing methods (ITAP joint research unit)—and bioimpedance sensors (IES) (see Box 1.1); (2) use of more traditional sensors (RGB imagery, LiDAR) coupled with artificial intelligence to identify objects or construct 3D models (AGAP, PEGASE, ITAP, EMMAH, SELMET joint research units); (3) optimisation of data collection (ITAP)⁵. Current research efforts are directed toward systems that are non-invasive, robust and simple to use. A significant trend is the growing integration of RGB imagery with artificial intelligence, a trajectory that is expected to continue. Finally, the question of sampling remains crucial, as certain measurements are still difficult to capture through fully automated methods.

5. It should be noted that little research has been conducted on data acquisition by drone. Use of drones remains confined to research (to carry 'reference' sensors) and varietal selection, with the exception of Africa, where they are integrated into production management work.

Box 1.1. Bioimpedance in animal production

Evaluating oocyte (egg) development in fish is essential for ecological monitoring and, in aquaculture production, to determine the optimal fertilisation date. Conventional manual monitoring induces repeated sampling, which requires anaesthetising the female. To avoid this, a bioimpedance spectroscopy system was developed and tested *in vitro* on 69 sea bass (*Dicentrarchus labrax*). The results were stunning: three out of the four stages of oocyte development were determined with high precision—a world first (Détrez *et al.*, 2022)!

This chapter does not cover the entire spectrum of acquisition methods explored at #DigitAg. Remote sensing, which relies heavily on developments in artificial intelligence (AI), is the subject of the following chapter (Chapter 2). Applications of sensors in phenotyping and the management of animal production can be found in Chapters 8 and 9. Finally, a notable trend emerging to facilitate the adoption of digital technologies is the development of low-cost, self-built sensors to monitor critical crop production parameters (such as soil moisture sensors for irrigation or cameras for tracking crop growth). This aspect will be covered in Chapter 13.

» #DigitAg doctoral theses contributing to Chapter 1

Bouzaouia S., 2024.	Multimodal optical imaging for the detection of stress in plants, PhD thesis. https://theses.fr/2024AGROM045
Cheraïet A., 2020.	Experimental and statistical modeling of the relationships between vine morphological characteristics and spray deposits: application to precision agriculture, PhD thesis. https://theses.fr/2020AGRO0036
David E., 2021.	The challenge of robust trait estimates with Deep Learning on high resolution RGB images, PhD thesis. https://theses.fr/2021AVIG0733
Deneu B., 2022.	Interpretability of species distribution models based on deep convolutional learning, PhD thesis. https://theses.fr/s225911
Dumont M., 2025.	How to combine thematic expertise and machine learning to improve agro-environmental mapping methods using remote sensing?, PhD thesis. https://theses.fr/s321899
Gaci B., 2023.	Joint methods for spectral and spatial data analysis for characterizing fire blight on apple trees, PhD thesis. https://theses.fr/2023AGRO0046
Lopez-Fornieles E., 2022.	Potential of multispectral satellite image time series for the characterisation and dynamic monitoring of a crop: application to vines on a regional scale, PhD thesis. https://theses.fr/2022AGRO0019
Metz M., 2021.	Development of chemometric methods for the processing of massive data, PhD thesis. https://theses.fr/2021AGRO0034
Oger B., 2020.	Optimization of the intra-plot sampling route in crop production, PhD thesis. https://theses.fr/2020AGRO0018
Ogoumond, D. C., in progress	Identifying unexpected observations in territorial crowdsourcing projects for agriculture: the case of vine water status monitoring at regional scale. https://theses.fr/s400042
Pichon L., 2021.	Development of a crowdsourcing approach adapted to agriculture specificities: the case of monitoring vine water status with the shoot growth approach, PhD thesis. https://theses.fr/2021AGRO0025

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Velumani K., 2021.	Deep learning algorithms for high-throughput cereal plant and organ identification, PhD thesis. https://theses.fr/2021AVIG0737
Villesseche H., 2023.	Characterization of the spatio-temporal dynamics of complex processes in wheat using near infrared spectroscopy and hyperspectral imaging, PhD thesis. https://theses.fr/2023AGRO0002
Xavier C., 2022.	Fine estimation of cattle empty body and carcass compositions by three-dimensional (3D) imaging and dual-energy X-ray absorptiometry (DXA), PhD thesis. https://theses.fr/2022AGROB362
Zhang Y., 2024.	Inverse modeling of water balance model using Crowdsourcing data in viticulture, PhD thesis. https://theses.fr/s298065

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Chapter 2

Processing of massive and multi-source data

Dino Ienco, Roberto Interdonato, Alexandre Termier

In the digital age, we are witnessing a true revolution in data collection and exploitation. This transformation is particularly affecting the agricultural sector, where the proliferation of new sensors developed over recent decades now allows systematic daily collection of an ever-increasing amount of information, as mentioned in Chapter 1.

This information overload is profoundly transforming many areas of agriculture, and the digital revolution is catalysing major advancements that are redefining traditional practices in several key fields (plant phenotyping, crop protection, livestock farming, and land management).

At the heart of this digital transformation lies continuous access to huge quantities of heterogeneous data ('big data'), which serve as a strategic lever for optimizing production, reducing costs and improving environmental sustainability.

Agricultural data collection is carried out using various different technologies:

- Smart sensors: installed in the field, on agricultural machinery, on animals, or inside buildings, these sensors collect data on weather conditions, soil quality, crop growth progress, or livestock health, which they then transmit via the internet to analysis platforms.
- Observation satellites: provide data on changes in the Earth's surface over time.
- Aerial imagery and drones: enable precise monitoring of the evolution of a farm or agricultural holding.

In this context, two major categories of sensors are commonly used in agriculture, each addressing specific observation needs.

Proximal sensors provide detailed information at an individual level (plant, animal, field), monitoring their development precisely and at close range. This approach allows fine and continuous surveillance, offering high temporal and spatial resolution, which is particularly suited to the detailed monitoring of biological processes.

Conversely, remote sensing sensors (drones, satellites) provide information on a much larger geographical scale, covering a spectrum that extends from a group of agricultural plots to a regional or even national scale. This macroscopic view enables one to gain an understanding of agricultural phenomena in their entirety and identify large-scale spatial trends.

These two complementary approaches create a technological ecosystem where the precision of proximal sensing integrates with the large-scale vision of remote sensing, allowing an understanding of contemporary agricultural processes at different levels.

This enormous quantity of heterogeneous, multi-temporal and multi-source data requires new, innovative approaches and techniques to take advantage of the wealth contained within the complex mass of information.

While statistical and probabilistic approaches previously made up the core of agricultural data analysis, today, faced with the growing quantity and increasing structural complexity of collected data, approaches based on machine learning are being used ever more frequently.

These methods make it possible to derive models that are both:

- Descriptive: capable of identifying hidden patterns in the data (clustering, correspondence analysis).
- Discriminative: enabling the prediction and categorisation of objects into predefined categories (supervised learning).

With the proliferation of high-dimensional data (images, multivariate time series, acoustic data), which are becoming increasingly massive, approaches based on 'deep neural networks' have demonstrated, over the last decade, a remarkable capacity to exploit the large volumes of data available.

A key point of these methods lies in their ability to work as close as possible to the raw signal collected by sensors, taking into account the intrinsic specificities of the signal to be analysed. They naturally exploit the spatial correlations present in images, the temporal dependencies of time series, or the complex multidimensional structures of spectral data.

These neural network-based methods are becoming essential in the digital agriculture sector, where they now constitute a fundamental pillar for the advanced analysis of agricultural data, and reveal insights previously inaccessible with traditional approaches. The purpose of this chapter is to present these processing methods.

►► Temporal analysis methods

The ability to collect repeated information on the same object of study, with a variable frequency of acquisition, provides access to temporal series of observations to monitor the temporal dynamics of certain events and understand their evolution over time. This longitudinal approach offers a unique perspective on ongoing processes, revealing trends, cycles, and changes that would not be detectable through point observations.

Taking the temporal dimension into account is, however, not straightforward and requires suitable techniques capable of processing the fact that the information to be analysed is correlated sequentially. These temporal correlations introduce complex dependencies between successive observations, creating specific methodological challenges that require sophisticated statistical and algorithmic approaches.

Time series in remote sensing

In the field of remote sensing, access to time series of satellite imagery allows us to monitor and characterise the evolution of certain natural and semi-natural phenomena, as well as to characterise cultivated surfaces to improve crop monitoring systems. This capacity for repeated observation at different spatio-temporal scales constitutes a major asset for understanding environmental and agricultural dynamics, particularly in a context of climate change and increasing pressure on natural resources.

Incorporating the temporal dimension into the analysis of satellite imagery

In this scientific and technological context, the work conducted as part of the doctoral work by Jean Eudes Gbodio (2021) has contributed to the improvement of crop monitoring systems through a better use of satellite image time series, relying on deep learning and artificial intelligence techniques.

In particular, this PhD demonstrated that deep learning techniques allow for the explicit consideration of the temporal dimension in the analysis process, unlike traditional approaches that often treat each observation independently. This ability to model temporal dependencies constitutes a decisive advantage for the extraction of relevant information from satellite image series.

To address these methodological challenges, Gbodio's work explored various neural network models such as recurrent neural networks (RNN), gated recurrent units (GRU) and convolutional neural networks (CNN), and proposed extensions of these models to determine which were best suited for the analysis of multi-temporal remote sensing data.

This comparative approach enabled the evaluation of the relative performance of different neural architectures in varied application contexts. Examples of land-cover maps produced by one of the representative approaches, HOb2sRNN Jean Eudes Gbodio (2021), are shown in Figure 2.1. On one hand, the classification of land cover and land use with an agriculture-oriented nomenclature was done for varied agricultural situations and contrasting environments: conventional temperate agriculture areas, characterised by large plots and intensive practices, and family and mixed farming in tropical zones, marked by a greater diversity of cropping systems and specific environmental constraints. On the other hand, the research addressed end-of-season agricultural yield forecasting for a specific crop, millet in sub-Saharan Africa (Senegal). This application holds considerable strategic importance for regional food security, as millet constitutes an essential food crop in Sahelian agricultural systems, particularly adapted to the semi-arid climatic conditions of that region.

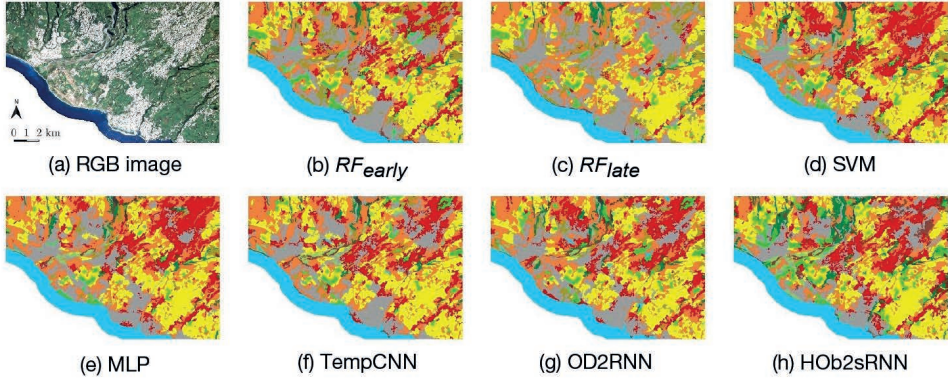
Incorporating spatial context into satellite image analysis

Temporal information, while essential for characterising crop phenology and distinguishing between different types of land use, reveals its limitations in particularly complex contexts. In tropical zones, where mixed cropping predominates, or in agroforestry environments, the temporal dimension alone may prove insufficient for precise and reliable crop mapping. This limitation is explained by the complexity of tropical agricultural landscapes, which are characterised by strong spatial heterogeneity and a diversity of cropping systems that generate ambiguous spectral and temporal signatures. Crops with similar phenological cycles but different spatial layouts can present comparable temporal profiles, making their differentiation difficult.

To overcome these challenges, the integration of spatial contextual information becomes necessary. Spatial patterns can help resolve ambiguities and better distinguish between different types of crops.

The PhD work of Azza Abidi (2024) developed novel approaches combining multi-scale information derived by satellite image time series data. More precisely, pixel-level information is combined with spatial context elements obtained by a preliminary

Extract 1 in mixed coastal urban and agricultural zone



Extract 2 in mixed agriculture and surrounding natural vegetation zone

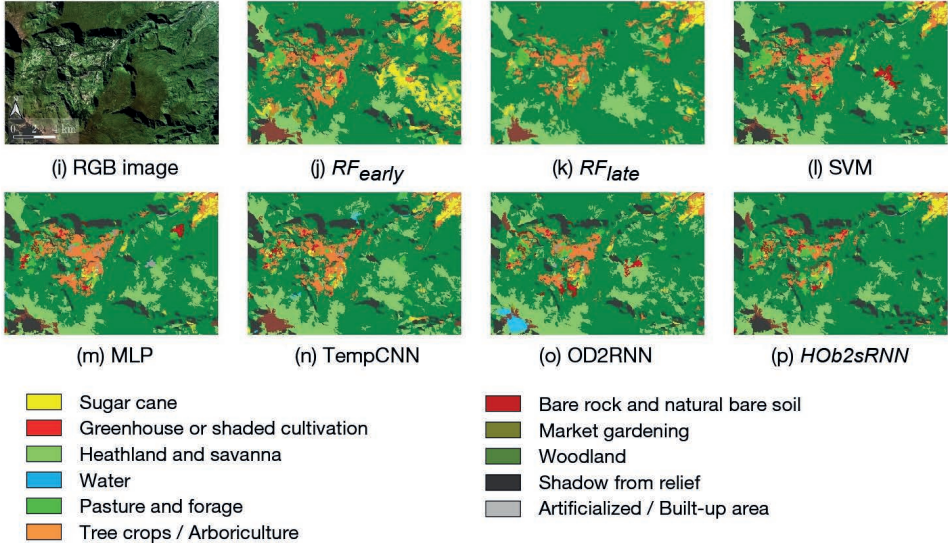


Figure 2.1. Qualitative analysis of land cover map details produced at the study site on Reunion Island using the following methods: random forest (RF), support vector machine (SVM), multi-layer perceptron (MLP) and the method proposed in the work of Jean Eudes Gbodjo (2021) (HOB2sRNN) on study areas with mixed urban/agricultural landscapes (top) and landscapes consisting mainly of agricultural areas/natural vegetation (bottom).

object-based image analysis stage. For the different scales aggregated statistics (mean, median, and standard deviation) of the radiometric content are used as multi-scale features for the underlying classification process. This hybrid method exploits deep learning techniques to process spatio-temporal information jointly, integrating time series of spatial descriptors for the further improvement of crop monitoring systems. Evaluations conducted in contrasting study zones (temperate and tropical environments) have demonstrated the effectiveness of this approach. The performance improvement is particularly marked in tropical contexts, where the heterogeneity of agricultural landscapes requires adapted techniques. These results confirm that contextual information becomes increasingly crucial as landscape complexity increases.

The reuse of historical data to train models

Deep learning and artificial intelligence methods require up-to-date training and calibration data to produce accurate land-cover mappings, which are essential for monitoring agricultural crops. However, data acquisition often faces significant economic constraints and exogenous factors that can limit, or even prevent, regular collection (adverse weather conditions, access restrictions, logistical constraints). A promising solution is to intelligently reusing available old or historical data to compensate for the lack of recent training data.

The PhD work of Emmanuel Capliez (2023) focused precisely on this issue: exploring the possibility of reusing historical data to implement deep learning methods in land-cover mapping in tropical environments. This research studied the temporal transferability of mapping methods, i.e., their ability to maintain performance from one cropping season to another using multi-temporal satellite data. The results obtained clearly demonstrated the value of reusing historical ground truth data to update land-cover maps effectively. This is a significant methodological advance for ensuring the continuity of agricultural monitoring systems despite the constraints of collecting up-to-date data.

Nevertheless, the reuse of historical data necessitates the development of techniques suitable for the requirements of temporal transfer. Indeed, conventional mapping techniques exhibit a high sensitivity to variations in the distribution of spectral characteristics of satellite data that can occur between two cropping seasons, due to variable acquisition conditions and changing meteorological contexts from one year to the next, creating specific methodological challenges to guarantee the robustness of temporal transfer approaches.

These innovative studies have made it possible to explore the potential of multi-temporal remote sensing data in depth, particularly the multispectral Sentinel-2 data from the European Space Agency's Copernicus programme. These data, available since 2017, are characterised by their high spatial resolution (10 to 60 metres depending on the spectral bands), their high revisit frequency (5 days), and their free access, constituting a precious resource for the development of operational agricultural monitoring applications.

Combining spatio-temporal information to improve the analysis of satellite imagery

In the context of spatio-temporal data analysis, 'spatial temporal graph convolutional neural networks' (STGCNN) (Wu *et al.*, 2020) are attracting growing interest due to their capacity to model both dimensions simultaneously, and are widely adopted for tasks such as traffic forecasting, flood prediction and human activity recognition in video data. However, no study had yet adapted these models to the context of satellite image time series analysis, likely due to the fact that satellite image scenes cover vast areas, resulting in graphs with potentially hundreds of thousands of nodes, limiting the adoption of standard STGCNN models.

As part of Alessandro Michele Censi's internship, an attentive spatial-temporal graph convolutional neural network was proposed to improve land-cover classification from Sentinel-2 satellite image time series (SITS) (Censi *et al.*, 2021). Unlike existing

approaches that focus mainly on the temporal dimension while neglecting spatial context, this model explicitly exploits both dimensions simultaneously by using two-level attention mechanisms: first, to automatically aggregate the spatial neighbourhood of a SITS segment by weighting the contribution of each neighbour according to its importance, and then to combine information from the target segment and its neighbourhood. The model uses spatial graph convolutions, making it possible to process raw data directly without global graph analysis, which, unlike previous methods, enables it to scale to large, real-world study areas. Experiments conducted on two study zones with contrasting landscapes (Reunion Island and the French department of Dordogne) and under real operational conditions (limited labelled data) show that this approach systematically outperforms all competing methods with a performance gain of at least five points in terms of F-measure, constituting the first application of spatial-temporal graph convolutional neural networks for the analysis of satellite image time series.

Temporal data series

Based on purely temporal data (without a spatial dimension), the doctoral work of Olivier Gauriau (2024) focused on better understanding the evolutionary dynamics of pathogens such as vine downy mildew or sugar beet cercospora. This work analyses weather data (predictive of the evolution of these pests) and epidemiological surveillance data from *bulletins de santé du végétal* (BSV, plant health bulletins), to produce rules that are understandable by specialists, helping to predict dynamics based on climatic conditions by relying on the development and application of advanced data processing techniques such as deep learning.

The analysis of temporal data can also be applied to precision livestock farming. In the PhD research of Kévin Fauvel (2020), the objective was to improve the detection of ovulation in dairy cows, based on time series from two types of sensors: a bolus capturing ruminal temperature and an accelerometer collar for the animal's activity. This is an important issue, because ovulation detection, usually performed visually by the farmer, is time-consuming (up to one hour per day) and faces the phenomenon of 'silent ovulation' in 30% of cows, where classical visual signs are not displayed.

The work of Kévin Fauvel (Fauvel *et al.*, 2019) proposed new ensemble learning algorithms that significantly improve ovulation detection compared with existing commercial solutions. They also demonstrated the value of combining activity and temperature information: with two types of low-cost sensors, one can obtain good prediction quality, approaching the ground truth of progesterone assaying, which is expensive. Combining explainability approaches such as the SHAP algorithm allows each ovulation detection to be enriched with the main factors that led to this detection (such as overactivity three days prior and a temperature reading taken the previous day). Kévin Fauvel also proposed a deep learning-based approach, combining precise classification (based on CNN) and an explanation via a gradient-weighted class activation mapping (Grad-CAM) approach. To date, this method is the most accurate for ovulation detection.

►► Multisource methods

Modern Earth observation systems provide multisource remote sensing data at different temporal and spatial resolutions, creating a major challenge for their joint exploitation in land-cover mapping. On one hand, Sentinel-2 images offer high

temporal (every 5 days) and spatial (10 m) resolution, allowing the monitoring of the temporal dynamics of land cover, while on the other hand, very high spatial resolution (VHSR) images remain indispensable for capturing fine spatial patterns (such as SPOT 6/7 images).

Satellite data integration

This methodological challenge is at the heart of the internship work of Paola Benedetti (Benedetti *et al.*, 2018), who focused on the understanding of how to effectively fuse these heterogeneous and complementary information sources to optimise land-cover mapping. To exploit this multisource complementarity, this study proposes M3Fusion (multi-scale/modal/temporal fusion), a deep learning framework specifically designed for the fusion of high spatial resolution and very high spatial resolution multi-temporal satellite data.

The multi-branch architecture integrates, simultaneously, temporal information from Sentinel-2 time series and fine spatial information from VHSR data (SPOT 6/7) through dedicated modules: one branch uses a gated recurrent unit (GRU) to process multi-spectral time series, while a parallel branch employs a CNN to extract high-resolution spatial context. This multisource approach follows a philosophy of complementary feature learning by integrating two auxiliary classifiers working independently on each data source, complemented by a final classifier operating on the fusion by concatenation of the descriptors extracted from each modality. The originality of this approach lies in its capacity to process heterogeneous data sources simultaneously in an end-to-end learning process, guaranteeing the extraction of optimal complementary features for each source while maximising their synergy. Experiments on Reunion Island demonstrate that this multisource strategy significantly outperforms conventional monosource methods.

The problems inherent to the spatio-temporal nature of multisource satellite data were also addressed during Olivier Monter's internship, more precisely in a research paper in collaboration with PhD student Jean Eudes Gbodjo (Gbodjo *et al.*, 2021). This study presents a multimodal deep learning framework for land-cover mapping, which simultaneously integrates multi-sensor remote sensing data with their native temporal and spatial resolutions: Sentinel-1 and Sentinel-2 SAR/optical time series, as well as very high spatial resolution SPOT optical imagery.

The framework relies on a multi-branch CNN based on spatial patches, using different specific encoders to process the specificity of each input source. A new 'self-distillation' strategy is introduced to improve per-source analyses and exploit the interaction between different input sources. This strategy allows the network to learn by itself using the framework's final multisource prediction to guide the learning of the per-source CNN encoders. Experiments conducted on two real-world benchmarks—Reunion Island and the Dordogne department—with reference data annotated under operational constraints (sparse ground truth) demonstrated the framework's effectiveness, with a global classification accuracy of approximately 94% for Reunion and 88% for Dordogne. These results highlight the effectiveness of the CNN-based and self-distillation approach for combining heterogeneous multi-sensor remote sensing data and confirm the benefits of multimodal analysis for land-cover mapping tasks.

Linking satellite data with heterogeneous open data

Beyond purely satellite-based multisource aspects (such as different typologies of satellite sensors), one of the main methodological challenges can be the use of these data in a heterogeneous context, i.e. by coupling them with data of a different nature (not originating from satellites). This is particularly of interest when addressing complex and multifactorial spatio-temporal phenomena, which cannot be entirely explained by considering only the aspect related to Earth observation, but need to be contextualised within a broader framework.

An illustrative example is food security monitoring, a major issue for anticipating and reducing crises (see Chapter 10). The use of heterogeneous data from different sources is indispensable for addressing this issue. This challenge has led #DigitAg researchers to work on new methodological proposals for exploiting heterogeneous open data, allowing improvement of solutions for tasks classically addressed by existing food security systems. These existing systems are typically based on a very limited set of data (remote sensing, survey data) and on work based on human expertise. Today, we see large quantities of heterogeneous open data available, which are linked to food security at different levels (with more or less direct impacts on this phenomenon). It should be noted that, beyond the processing of the data itself, the need to collect, integrate and evaluate the quality of these heterogeneous and multisource data adds several more challenges (Deléglise *et al.*, 2022).

In Hugo Deléglise's PhD work (2021), the Food Security Prediction based on Heterogeneous Data (FSPHD) framework was proposed to predict two major food security indicators: the Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS). This framework is capable of exploiting multisource data such as raster data (population densities, land-cover maps, and soil quality based on remote sensing data), GPS points (hospitals, schools, violent events), linear vectors (watercourses), quantitative variables (World Bank variables, meteorological data), and time series (smoothed temperature, precipitation estimates, maize prices).

The proposed framework relies on a set of data science techniques, such as random forest (RF), convolutional neural networks (CNN), and long short-term memory (LSTM) recurrent network. The results of the in-depth experimental evaluation of FSPHD, focusing on the Burkina Faso study area, are reported in Chapter 10. An improved version of this framework was developed during the postdoctoral research of Mehtab Alam Syed (Interdonato *et al.* 2025).

Starting from the observation that the regression task was too difficult for this type of model given the available ground truth data, a version of the FSPHD framework was designed to generate a classification to directly predict different levels of food security (Poor, Borderline, Acceptable), offering interpretable results for regional situations (see Chapter 10), i.e., maps with the spatial distribution of the predicted and actual FCS and HDDS classes for three African countries.

The framework was tested in different geographical contexts, thanks to the collection and processing of two new datasets in Rwanda and Tanzania, in addition to the one from Burkina Faso. The study presents three experiments using three data-splitting strategies: random splitting (85% training, 15% testing), spatial splitting (selection of districts/municipalities for training and testing on disjointed geographical areas), and

temporal splitting (recent data for testing, previous data for training). This study is one of the first to use deep learning for the direct classification of food security indicators in several countries using only publicly available heterogeneous data.

►► Conclusion

The body of work presented illustrates the emergence of a new paradigm in agricultural data processing, marked by the transition from traditional statistical approaches to deep learning methods capable of exploiting the richness of massive and heterogeneous data. These findings resonate with the work presented in Chapter 1 regarding image and spectral analysis in proximal sensing via deep learning methods. This research has demonstrated that the explicit integration of temporal and spatial dimensions, through recurrent neural networks (RNN) and convolutional neural networks (CNN), allows a more nuanced understanding of complex agricultural processes.

Beyond technical advancements, this research has revealed the crucial importance of the multisource approach in addressing the contemporary challenges of digital agriculture. Whether in crop monitoring via remote sensing, ovulation detection in precision livestock farming, or food security prediction based on heterogeneous open data, research has consistently shown that the intelligent combination of complementary information sources significantly outperforms monosource approaches.

This convergence towards integrative solutions, exploiting multi-temporal satellite data, proximal sensing, and meteorological and socio-economic variables, paves the way for more robust and adaptive decision support systems (DSS). Such systems are essential for meeting the challenges of agricultural sustainability and global food security in the context of climate change.

►► #DigitAg doctoral theses contributing to Chapter 2

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Chapter 3

Information systems, semantic modelling and knowledge management for agriculture

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Modern agriculture is facing a profound transformation driven by the digital revolution, the environmental emergency, and the necessary transition towards more sustainable systems. In this context, production, management, and sharing of data and knowledge, which in turn enable scientific discoveries and decision-making, are becoming essential leveraging factors for designing and managing complex agroecosystems. In particular, agroecology promotes a systemic, integrative and contextualised approach to agricultural production by leveraging the intrinsic functionalities of ecosystems. This approach requires the use of diverse data—environmental, agronomic, and socio-economic—as well as expert knowledge that is often heterogeneous, dispersed, and non-standardised. However, the complexity of the interactions between biophysical, technical and human factors makes information systems, databases or knowledge-based systems indispensable, as they are capable of structuring, integrating and enhancing these data in an efficient, interoperable and reproducible manner. In this regard, the FAIR Principles (Findable, Accessible, Interoperable, and Reusable) (Wilkinson *et al.*, 2016) represent an essential reference framework for organising, documenting and sharing agricultural data and knowledge in a sustainable and open manner.

The fourth axis of the #DigitAg Convergences Institute had the mission of advancing the design of these information systems in agriculture by tackling the challenges posed by the large scale arrival of heterogeneous data, the interoperability of data and knowledge, and their connections (as graphs). The axis adopted a strongly interdisciplinary approach, at the interface of agronomic sciences and agriculture, computer science, data science and knowledge engineering. The objective is to develop methods, tools, and models capable of structuring agricultural data at different scales, facilitating data analysis, and supporting decision-making and sustainability.

This chapter illustrates these contributions through two complementary approaches:

- The representation and management of knowledge to support the agro-ecological transition (knowledge-based systems, ontologies, logical rules).
- The integration and analysis of heterogeneous data, mobilising techniques from areas such as the Semantic Web, the Web of data, text mining, and Artificial Intelligence.

Through illustrative concrete case studies derived from doctoral and postdoctoral research, student internships, or other actions supported by #DigitAg, this chapter demonstrates the importance of semantic modelling and knowledge management for digital agriculture in the service of sustainability.

► Knowledge representation and management in agroecology

There is a crucial need for tools to assist researchers, technicians, and farmers in designing new, sustainable agro-ecosystems based on agroecology. These systems are intrinsically complex, and their design requires the integration of diverse data and scientific knowledge that are not stabilised.

The contributions gathered in this section illustrate the diversity of approaches employed to structure, formalise and exploit knowledge in agroecology. The first subsection presents a knowledge-based system dedicated to the identification of local biopesticides, integrating experimental data and respecting the One Health principles (Brown *et al.*, 2024). The second subsection describes a process combining formal modelling and the integration of heterogeneous data to support the selection of 'service species' that provide ecological functions in crops. Finally, the third subsection explores the use of Semantic Web techniques and ontologies in promoting interoperability and enhancing data value, notably through AgroPortal and the formalisation of a semantic resource for the official French registry of plant protection products. Together, these studies illustrate how knowledge representation and management contribute to strengthening the capacity for innovation and action in agroecology.

Concept lattice representation: application to the Knomana knowledge-based system for biopesticide identification

The Knomana knowledge-based system (Silvie *et al.*, 2021) aims to propose plant protection solutions derived from locally grown or wild plant extracts, used in aqueous or essential oil forms to support practitioners. To avoid unintended effects, animal, plant, environmental, human and public health are considered together, in accordance with One Health and Eco Health approaches. We created a database that aggregates descriptive elements of trials and uses published in the scientific literature. These data, manually curated, currently number 60,300, covering 3,700 plant species and 1,400 species of other organisms, including vectors.

Given the specific nature of this corpus—such as missing data regarding the chemical composition of tested extracts or species names obscured by abbreviations—the mining of these data requires the development of adapted tools. Formal Concept Analysis (FCA) (Ganter and Wille, 1999) and its extensions were used for data exploration and knowledge extraction. These allow the classification of data represented in the form of multirelational binary tables (Relational Concept Analysis) and multidimensional tables.

First, the formalisation of knowledge for FCA was addressed through the design of an analysis method for data with indeterminate values (Keip *et al.*, 2020) and a general method for converting relational data models (Keip, 2021). The capacity of FCA to process substantial volumes of data, such as those in the Knomana knowledge-based system, was evaluated by Braud *et al.* (2022).

For the first form of classification produced by FCA—namely, concept lattices—the impact of binary versus ternary data representation on the resulting outputs was evaluated by Keip *et al.* (2019). Subsequently, the RCAviz software program (Figure 3.1) was developed to facilitate navigation through relational lattices (Muller *et al.*, 2022; Huchard *et al.*, 2024).

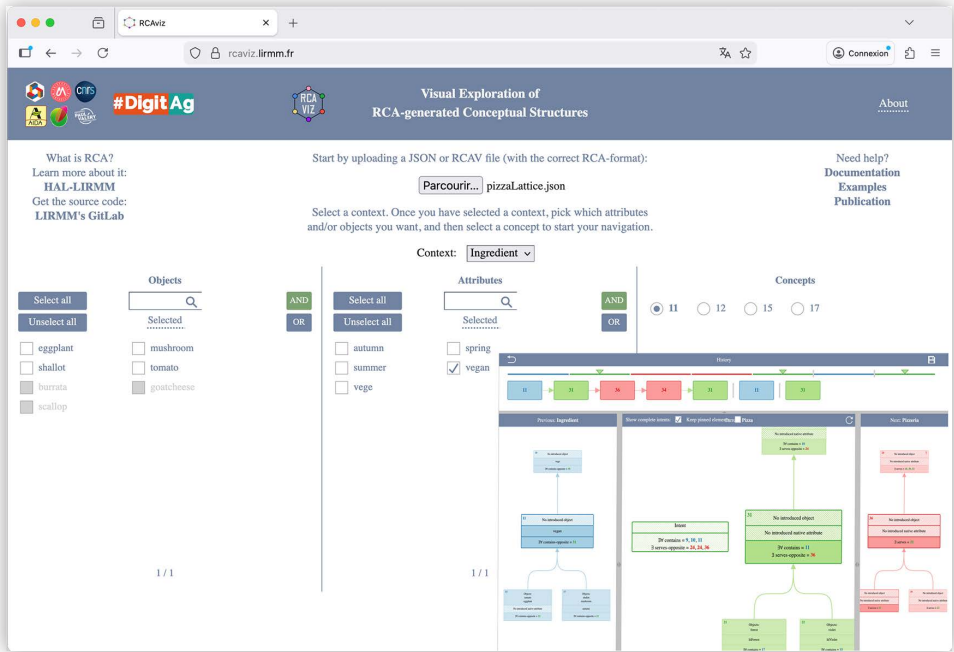


Figure 3.1. Visualisation of relational lattices with RCAviz (<https://rcaviz.lirmm.fr/>).

For the second form of classification, namely the rules of implication, the impact of the data model on the resulting rule set was investigated (Mahrach *et al.*, 2021). The FCAvizIR software program (Figure 3.2), dedicated to navigating rule sets that may contain relational data, was thus developed (Musslin *et al.*, 2024).

Finally, the navigation exercises conducted with these tools revealed anomalies within this type of corpus, which aggregates scientific literature from diverse disciplinary origins (agriculture, livestock farming, medicine). These anomalies concern: data (incorrect values relative to the data type); knowledge: (absence of critical data, such as the chemical composition of the tested extract); and the corpus (conflicting values for the same data across different articles, such as variations in species names reported by different authors).

In conclusion, #DigitAg has facilitated crucial developments for the success of this work by supporting six students: the PhD thesis of Priscilla Keip in 2021, and five Master's internships (Lina Mahrach, in 2020; Emile Müller, in 2021; Guilhèm Blanchard, in 2022; Lola Musslin, in 2023; and Romain Campillo, in 2025). The development of these software programs makes these different achievements both operational and shareable.

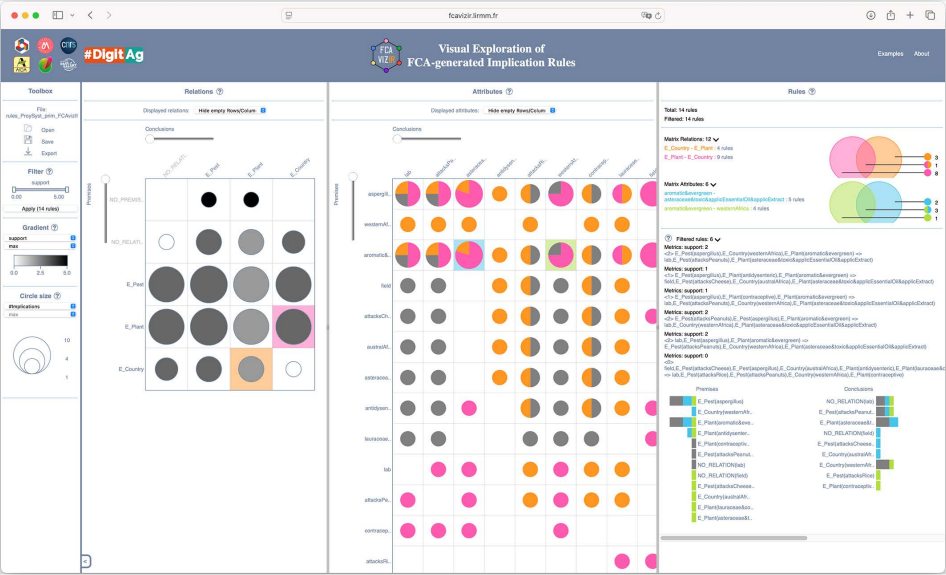


Figure 3.2. Visualisation of a system of implication rules with FCAvizIR (<https://fcavizir.lirmm.fr/>).

Logical formalisation and knowledge representation for the selection of service species in agroecology

Within #DigitAg, computer scientists and agronomists have collaborated to focus on the selection of service species based on their capacity to provide ecosystem services. The approach adopted combines a formalised representation of emerging knowledge in agronomy with the exploitation of independently collected data. This method was applied to vineyard ground cover choice to select herbaceous species capable of providing various services to the vines.

Research conducted during the PhD of Elie Najm (Najm *et al.*, 2024; Najm *et al.*, 2022) and the postdoctoral research of Guillaume Pérution-Kihli relies, on the one hand, on recent scientific results in agronomy that link functional traits (measurable characteristics of plant species) to ecosystem services. On the other hand, it utilises data on functional traits collected by the ecological research community.

This research proposes a methodology for acquiring scientific knowledge in the form of diagrams linked to data sources, as well as a formalisation in a rule-based logic language. A preliminary evaluation by agronomists deemed the results highly satisfactory, while also highlighting the significant issue of missing data.

Semantic modelling, ontologies, and data interoperability

AgroPortal: a pillar of semantic interoperability in agronomy and agriculture.

The Semantic Web and ontologies are fundamental concepts for structuring and interconnecting data in an organised and meaningful way. The Semantic Web aims to give data meaning by associating it with precise concepts and relationships, thereby enabling machines to process information more intelligently.

AgroPortal⁶ (Jonquet *et al.*, 2018) is an online repository dedicated to the management, sharing, and interoperability of ontologies and other semantic resources in the fields of agriculture, food and the environment (Figure 3.3). Based on the open-source OntoPortal⁷ technology (Jonquet *et al.*, 2023), it allows users to search, visualise, compare, and utilise semantic resources to annotate their datasets. This process facilitates the reuse of agricultural data and enhances its interoperability. Such interoperability is essential for data integration and knowledge extraction, and semantic resources are key components required to achieve these goals.

The work carried out as part of #DigitAg has made major contributions to the development and improvement of AgroPortal, particularly through the projects described below.

Production of the E-Phy ontology

Official reference databases, listings or catalogues are often not 'FAIR' and do not exist in RDF format, the pivotal language of the Semantic Web. This was the case for the E-Phy catalogue, produced by ANSES, which covers all phytopharmaceutical products and their uses, as well as the fertilisers and growing media authorised in France. This work set up a methodology for formalising the E-Phy catalogue into an Ontology Web Language (OWL) knowledge base, consisting of an ontological model, its instances and alignments with other ontologies (Bouazzouni and Jonquet, 2021). The difficulties encountered during this process and the limitations of the current modelling—which was kept retro-compatible with the original database—were inventoried. The added value of the E-Phy ontology was demonstrated: SPARQL queries that exploit the semantics and alignments allow for interrogations that were impossible with the original data.

Curation and improvement of metadata in AgroPortal

In agriculture, ontologies are often developed with metadata derived from diverse vocabularies and domains. The metadata used requires some curation effort to be made organised, harmonised, and more reliable. The objective is to make these semantic resources compliant with FAIR principles and to improve their metadata. Through #DigitAg, a metadata curation approach for semantic resources was initiated in AgroPortal, increasing the quality of resources hosted by the platform, and thereby strengthening user confidence and the impact of its use.

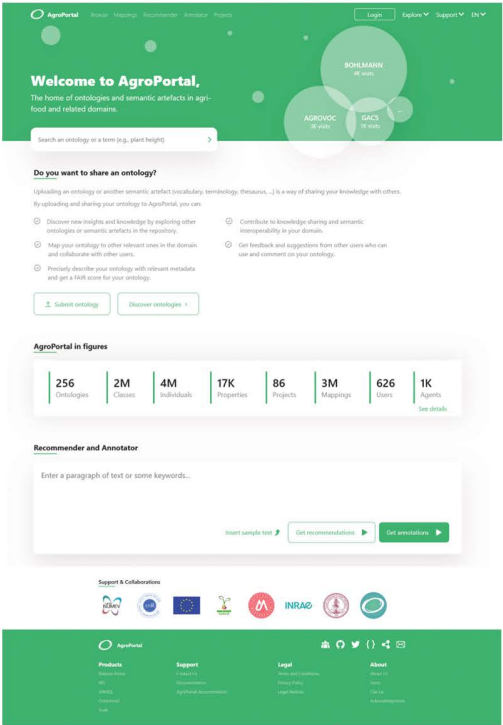
Design and implementation of the O'FAIRe method to evaluate the level of FAIRness

FAIRness assessment measures the degree of compliance of a digital resource with the FAIR Principles. We focused on semantic resources, as there was no clear, implemented and tool-supported methodology to automatically evaluate their level of FAIRness. The main objective of this work (Amdouni *et al.*, 2022) was to provide such a methodology and the necessary tools to guide semantic stakeholders: (i) to make their semantic resources FAIR through better use of standardised metadata; (ii) to select FAIR

6. <https://agroportal.eu/>

7. <https://ontoportal.org>

AgroPortal an ontology repository and semantic artefact catalog for agri-food



- Publish, search, download
- Browse, visualize
- Peer review
- Versioning
- Annotation
- Recommendation
- Mapping
- Notes
- Projects
- FAIRness assessment
- Federated with other OntoPortal(s)

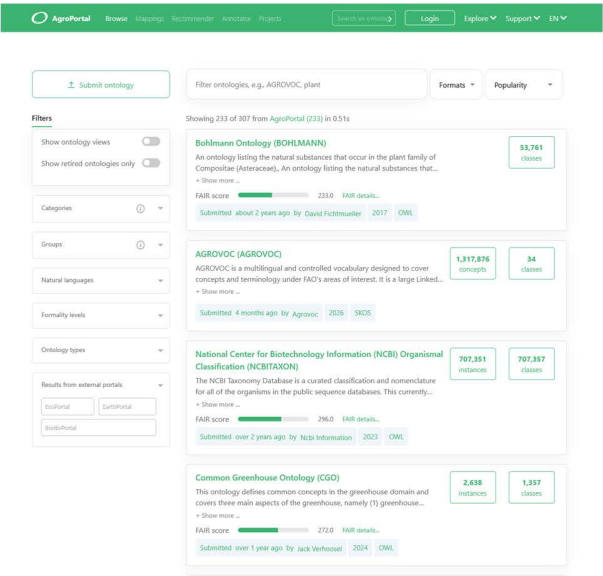


Figure 3.3. Interfaces of AgroPortal, which in 2025 hosts more than 230 ontologies and other semantic resources.

semantic resources relevant to their use needs. A method was created for the automatic FAIRness assessment based on metadata. Named 'Ontology FAIRness Evaluator' (O'FAIRe), this method integrates 61 questions, 80% of which are based on resource metadata descriptions. This demonstrated the importance of using ontology portals such as AgroPortal to harmonise and exploit unified metadata in order to evaluate FAIRness. O'FAIRe was implemented in AgroPortal, and a preliminary FAIRness analysis was carried out on 149 semantic resources in the agri-food and environmental fields.

In conclusion, the work carried out by the #DigitAg community has considerably increased the visibility of AgroPortal, notably through its contribution to the semantic building blocks for the construction of the European Open Science Cloud (EOSC) in the European Horizon Europe FAIR-IMPACT⁸ project. The O'FAIRe tool was transferred to seven other ontology repositories in other disciplines (Figure 3.4), positioning AgroPortal as a pioneer in providing FAIR semantic resources.

Ontology FAIRness Evaluator (O'FAIRe)

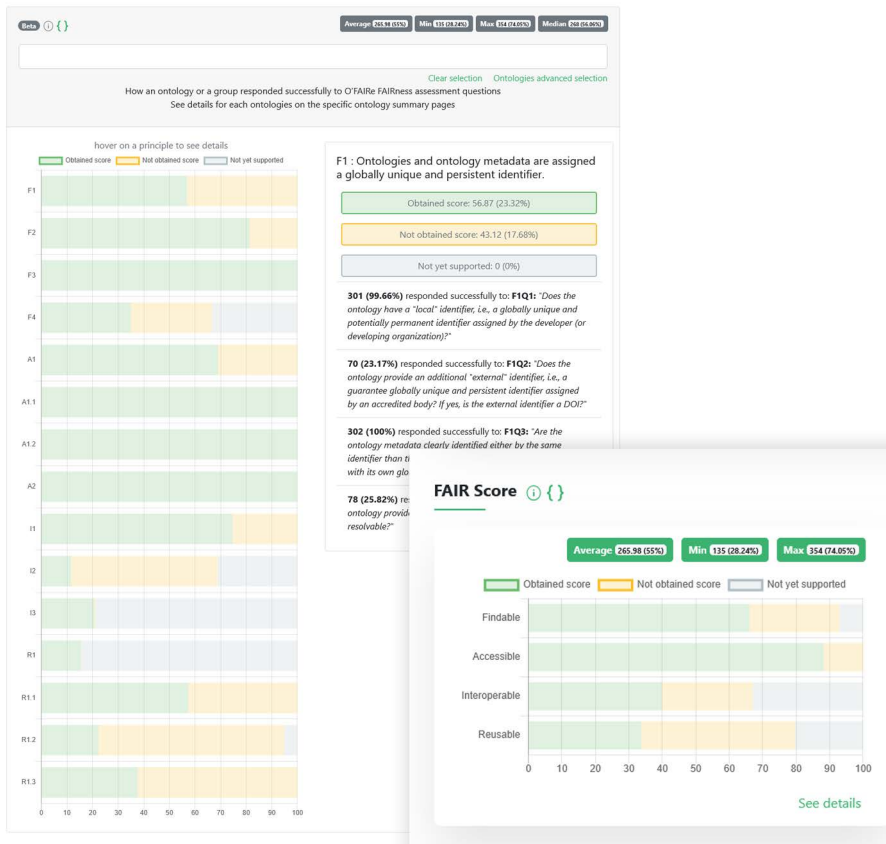


Figure 3.4. O'FAIRe tool interface, implementing the method of the same name within AgroPortal.

8. <https://fair-impact.eu, 2022-2025>

» Integration, analysis and exploitation of heterogeneous data

In recent years, experimental data have proliferated, ranging from those based on traditional experimental designs to the advent of high-throughput phenotyping, which enables the collection of vast datasets on genotypes exposed to diverse environmental conditions. Consequently, several challenges associated with using these data. We need, on the one hand, to limit errors by helping experimenters improve the structure of their data and, on the other hand, to align experimental data with modelling data. The examples presented here illustrate this diversity of challenges and solutions. They cover: the development of semantic resources and generic conceptual models to structure experiments and prepare for the generation of actionable ontologies; the integration and standardisation of heterogeneous databases through methods combining controlled vocabularies and artificial intelligence; the combination of Semantic Web and modelling methods to organise and analyse complex phenotypic data; and the exploitation of massive and varied datasets via 'data lakes', here applied to decision support in pastoral systems. Collectively, these studies demonstrate how data engineering and knowledge structuring contribute to making agronomic data more FAIR, interoperable and directly applicable to modelling and the support of agricultural practices.

Development of semantic resources for phenotyping and crop modelling

Agronomic experiments generate datasets, often in tabular format (CSV), which contain measured scientific variables without precise identification of the entities being observed. A scientific variable is defined as a quadruplet composed of a living organism entity (the species or variety), a measurable characteristic of this entity, a measurement method, and a unit or scale of measurement. The entity and its characteristic together constitute a 'trait'. Such databases are very often imperfect, heterogeneous in structure and content, and may contain redundancy, incomplete data or errors.

The objective of Lucry Choumélé's #DigitAg internship was to assist experimenters in structuring their data to identify the entities observed through variables and the entities necessary for measurement analysis. To this end, a relational Conceptual Data Model (CDM) was constructed that is sufficiently comprehensive and generic for application to various different types of agronomic experiments: phenotyping, biocontrol, etc. This model is formalised using the UML language and its Chowlk extension, which enables a transition to a graph-based form (graph CDM). Translation rules from 'relational CDM' to 'graph CDM' are proposed to automatically produce an initial version of the graph CDM. This preliminary graph CDM must be validated and enriched manually to become an ontology usable by an information system. This approach will be tested on the ICASA standard data exchange format (White *et al.*, 2013) used in agronomic experimentation.

Integration and standardisation of experimental databases in agroecology

Agronomic models (such as STICS)⁹ rely on databases derived from expert experiments; however, the reuse, integration and interpretation of these heterogeneous data remain a significant challenge. To mobilise this information for automated statistical

9. <https://stics.inrae.fr/>

or modelling approaches—and to FAIRify the data—these databases require curation. This process involves selecting the most relevant data and enriching them with the metadata necessary for their interpretation.

The objective is to map source variables from experiments to the variables required by models—known as 'candidate variables'—thereby facilitating the integration and automated processing of data collected at different scales and in varying contexts. A generic approach for automatically establishing links between source and candidate variables was proposed as part of Oussama Mechhour's PhD. This approach leverages semantic information derived from ontologies, along with text mining and artificial intelligence techniques, such as generic language models (e.g., BERT (Devlin *et al.*, 2019)), agriculture-specialised models (e.g., AgriBERT (Rezayi *et al.*, 2022)), or Large Language Models (LLMs).

To address the challenge of heterogeneous source variables, which are often multi-lingual and non-standardised, researchers from the AIDA research unit have developed a list of candidate variables derived from the dictionary of the AgroEcological Global Information System (AEGIS) platform. This controlled and better-structured vocabulary serves as an intermediary between field observations and the requirements of simulation models.

This mapping between source variables and candidate variables (Figure 3.5) is one of the most complex aspects of the process, primarily due to significant discrepancies in naming conventions, descriptions and the units of measurement associated with these variables.

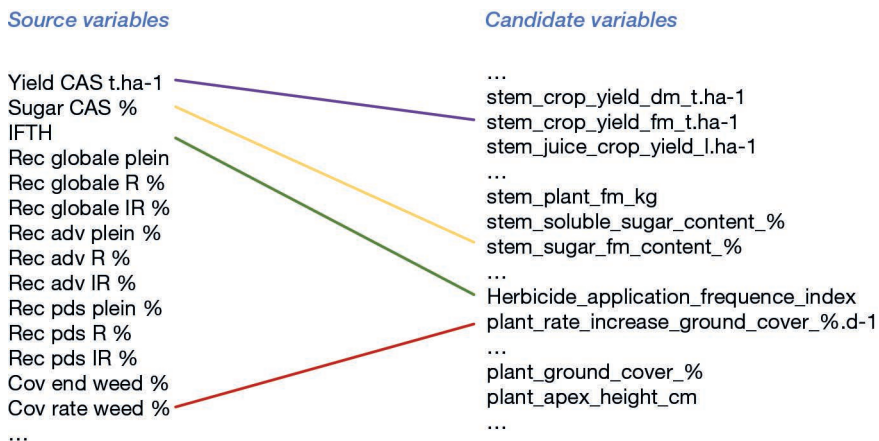


Figure 3.5. Examples of variable mapping.

Two approaches were taken as part of this doctoral research (Mechhour *et al.*, 2025a). First, a hybrid approach called 'Matching Agroecological Experiment Variables' (MAEVa) aims to pair source and candidate variables using four methods based on (1) names, (2) descriptions, (3) a linear combination of the two, and (4) a selection method for the final evaluation. Regarding names, the BERT-base model was enhanced by adding an external multi-head attention layer (BERTmha). Regarding descriptions, existing texts were enriched using LLM-based methods (GPT-3.5). This approach achieved a correct mapping rate of 86%. The second approach (Mechhour *et al.*,

2025b) consists of adapting language models (BERT and AgriBERT) to specialised corpora composed of scientific articles from the studied domain.

To carry out this work, original data were produced within a multidisciplinary framework: these are experimental data from service plant trials in the Réunion island (Auzoux *et al.*, 2023). These data were made available to the scientific community to analyse the quality of the results from this research, which combines text mining with semantic information.

For future work, two avenues for improvement are envisaged. First, extending the second approach by transforming it into a hybrid one, by adapting general language models to specific data, notably measurement units and variable descriptions. Second, exploring Retrieval-Augmented Generation (RAG) methods, which currently represent one of the most promising AI strategies and can be adapted to specialised domains for linking variables.

Combining the semantic web and modelling to organise phenotypic data

A major current obstacle to the reuse of phenotypic databases is the lack of analytical methods capable of effectively processing massive and heterogeneous data to extract biologically relevant traits (Tardieu *et al.*, 2017; Roitsch *et al.*, 2019). Based on Semantic Web technologies, several tools, such as the PHIS information system, have been developed to exploit complex and heterogeneous data from plant phenomics (Neveu *et al.*, 2018). However, data analysis still largely relies on ad hoc code, which is poorly suited to exploiting knowledge graphs (KG). This complicates harmonisation, hinders traceability, and limits the reuse of results (Arend *et al.*, 2022). Furthermore, current pipelines often integrate mathematical formulas that depend on contextual metadata such as units, location and time.

In this context, the interdisciplinary doctoral research of Luis-Felipe Vargas-Rojas (2023), co-supervised by the LEPSE and MISTEA joint research units at the interface of biology and computer science, focused on using Semantic Web technologies to represent and exploit data from phenotyping platforms.¹⁰ The limitations of current approaches—particularly regarding representation, calculation methods and expressivity—were identified. To overcome these, a Semantic Web framework was proposed, aiming to: (1) represent mathematical formulas while respecting Linked Open Data principles and FAIR to improve adoption and reproducibility; (2) enable on-demand execution of numerical relationships, acknowledging that the materialisation of results is unfeasible for voluminous and heterogeneous KGs; (3) express mathematical formulas using KG data in the form of values of quantity (value and unit of measurement), by exploiting semantic resources and metadata such as unit ontologies; (4) facilitate aggregations within mathematical formulas, recognising that most of these numerical data operate on multiple scales.

Semantic resources were utilised, notably recognised ontologies such as QUDT, SOSA and OM, as well as W3C standards such as SHACL. Furthermore, all code and data produced are publicly accessible. The results of this doctoral work (Vargas-Rojas *et al.*, 2024; Vargas-Rojas *et al.*, 2023) open new avenues for research into improving the performance of numerical data exploration on the semantic web.

10. <https://tinyurl.com/d7fw9yhk>

►► Exploitation of heterogeneous data with a data lake: application to decision support in pastoralism

Farming of both plants and animals presents significant challenges in terms of data structuring and analysis, particularly due to the complexity of interactions between living organisms (plants, animals) and variable natural environments. While data from varietal experiments involve management challenges, the livestock sector adds further complexity through an additional interaction (the animals) and an additional dimension (mobility). Scientific study of these systems is often hampered by limited reproducibility, linked to the diversity of geographical and ecological contexts (terrain, climate, soil, flora).

The doctoral research of Urcel Kalenga Tshingomba (2023) focused on pastoral livestock farming—based on the grazing of natural vegetation by ruminants (primarily sheep, goats and cattle)—and specifically on the analysis of the spatial behaviour of small ruminants in the French Mediterranean zone (Kalenga Tshingomba *et al.*, 2022). A conceptual model of pastoral livestock farming was developed with farmers to identify the key determinants to be integrated. The system is based on the exploitation of heterogeneous data: satellite imagery, digital elevation models, environmental vector data and GPS herd tracking.

These data, which vary in format, resolution, and spatio-temporal granularity, were integrated into a platform using a data lake architecture (Madera, 2018). This architecture preserves the original formats while standardising the metadata. The prototype is based on Hadoop HDFS (storage), GeoNetwork (metadata) and Kibana (visualisation), drawing notably on the work of Rodrique Kafando (Kafando *et al.*, 2020). It has demonstrated a strong capacity for integrating heterogeneous data and serving as a support for advanced analyses.

This work confirms the value of data lake architectures in describing agroecological systems, while highlighting two key points: the necessity of rigorous data selection in collaboration with experts, and the importance of planning for processing or support tools to make the most of the stored data.

►► Outlook and conclusions

The work presented in this chapter illustrates the diversity of approaches developed within #DigitAg to structure, interconnect and exploit data and knowledge in agriculture. These contributions cover varied fields, ranging from the design of knowledge-based systems for identifying plant protection solutions derived from local plants to the reasoned selection of service plants in agroecology. They also encompass the modelling of scientific variables, the structuring of heterogeneous experimental data, and the exploitation of the Semantic Web for phenotyping data analysis. This chapter thus demonstrates the methodological and instrumental advances enabled by interdisciplinary research, serving a knowledge-based, sustainable agriculture.

These contributions have highlighted major technical and scientific challenges, particularly in the face of the rapid growth in data volume, complexity and heterogeneity. Interoperability, supported by ontologies and semantic resources, has emerged as a key issue. AgroPortal, now hosting over 230 semantic resources—compared with around 100 at the launch of #DigitAg—illustrates this dynamic very well with

regard to agricultural data interoperability. This tool serves as a reference foundation for the standardisation and reuse of agricultural knowledge. New perspectives are emerging, particularly concerning neurosymbolic Artificial Intelligence, which aims to combine machine learning capabilities with explicit knowledge graphs, providing both analytical power and the ability to provide explanations.

More broadly, this work is part of the global digital agriculture movement, in which data becomes a central lever for addressing sustainability, resilience and innovation challenges. Better exploitation of data—collected, organised, shared and analysed according to FAIR Principles—is now essential for designing more sustainable, smarter and more adaptive agricultural systems.

In just a few years, several major European initiatives have underlined the growing importance of data-related challenges in agriculture, as #DigitAg predicted in 2017. The Digital Agri Hub programme has networked hundreds of digital agricultural solutions globally to promote their adoption and evaluation.¹¹ The European 'Agriculture of Data' partnership aims to improve the availability, quality and interoperability of agricultural data for public policy, research and innovation purposes.¹² Finally, the creation of the Common European Agricultural Data Space (CEADS) marks a structural step towards shared governance of agricultural data in Europe, within a framework of trust, standardisation and openness (see Chapter 13). These three initiatives, in which several #DigitAg scientists participate, have emerged over the last decade. They reflect the political and institutional recognition of data as a strategic common good for the future of agriculture.

►► #DigitAg doctoral theses contributing to Chapter 3

Kafando R., 2021.	Integration and analysis of massive and heterogeneous data for an intelligent observation/monitoring of the territory, PhD thesis. https://theses.fr/2021MONT062
Kalenga Tshingomba U., 2023.	Definition, design and assessment of a spatial information system for pastoralism in French mediterranean areas, PhD thesis. https://theses.fr/2023AGPT0004
Keip P., 2021.	Automatic model and dataset transformation for conceptual exploration: application to a knowledge base in life science, PhD thesis. https://theses.fr/2021MONT069
Mechhour O., <i>in progress</i>	Integration and standardization of experimental databases in the field of agroecology: text mining approaches driven by semantic information. https://theses.fr/s386591
Midingoyi C.A., 2020*.	Semantic and modular representation of crop models using a declarative metalanguage, PhD thesis. https://theses.fr/2020AGRO0037
Najm E., 2022.	Data-driven reasoning in agroecology: application to the selection of service plant species, PhD thesis. https://theses.fr/2022UMONS049
Vargas-Rojas F., 2023.	Semantic Representation and Computation of Mathematical Formulas for Plant Phenomics Data Exploitation, PhD thesis. https://theses.fr/2023AGRO0053

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11. <https://digitalagrihub.org>

12. <https://www.horizon-europe.gouv.fr/european-partnership-agriculture-data-37047>

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Chapter 4

Supporting decision-making through digital modelling, simulation and data integration

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As demonstrated in the first three chapters of this section, data—which are becoming increasingly diverse and numerous—represent a new input capable of transforming agriculture. For these data to provide genuine agronomic value and support the ecological transition, they must be structured and transformed into actionable information. The previous chapter focused primarily on information systems for data, knowledge, and decision support. This chapter focuses strongly on modelling, which, while referred to in the singular as an activity, encompasses a highly varied set of methods and objectives. These forms of modelling are therefore developed to address the diverse cognitive, decisional and operational functions involved in decision support.

This chapter addresses the various stages and stakeholders involved in the decision-making process, from diagnosis and agricultural advice to implementation in the field. We have chosen to group the scientific questions addressed in #DigitAg regarding the use of modelling, simulation and optimisation for decision support into four sections concerning: (1) monitoring the status of crops and agroecosystems in general; (2) risk prediction and management; (3) system optimisation, both at the design stage and during production management; and finally, (4) the evaluation of these systems' performance.

►► Monitoring crop status

Monitoring the dynamics of crop status is one of the essential elements of agricultural decision-making. This theme is addressed through several data acquisition principles, ranging from human collaborative observation supported by models to automated analysis of images taken from the ground or by drones.

Crowdsourcing for monitoring grapevine water status

A promising approach for monitoring water stress is the collaborative collection of observations by stakeholders in the viticulture sector, known as crowdsourcing.

During the #DigitAg research, it was shown that this method allows a significant volume of data to be collected (Pichon *et al.*, 2021), particularly through the ApeX-Vigne mobile application (see Chapter 1). This application uses a simple, accessible method for visual assessment of shoot growth (Pichon *et al.*, 2023), with the resulting data used to predict the grapevine's water status based on predictive modelling and Bayesian resampling (Zhang *et al.*, 2024). This new data source offers opportunities to estimate variables that are difficult to access at a regional scale, such as soil available water capacity (Zhang *et al.*, 2025).

One of the major challenges for the democratisation of this crowdsourcing approach is the development of methods for estimating—and improving—the quality of the collected data. Automatic approaches based on seasonality and the known spatial dynamics of the phenomena under study were explored during the doctoral research of Léo Pichon to identify observations with surprising behaviour. These can either be eliminated as outliers or, conversely, studied in greater detail (e.g., resistant grape varieties, resilient cultivation systems).

Multi-scale spatialised estimation of mango yields by image analysis

In countries of the Global South, estimating fruit crop yields is a major challenge, complicated by the socio-economic and agronomic context of production in small, diversified, and heterogeneous plots—a context to which standard digital tools are often ill-suited. Taking the mango industry in West Africa as a case study, various digital agriculture approaches have been implemented to estimate and spatialise mango yields at both the tree and orchard scales, through two PhD projects supported by #DigitAg (see Chapter 1).

At the tree scale, the objective is to count fruits using image analysis. It has been demonstrated that individual mango tree production can be estimated by taking two photographs of each tree with a smartphone (Sarron *et al.*, 2023). These photos are processed by deep learning algorithms trained on the main West African mango varieties (Borianne *et al.*, 2023).

At the orchard scale, drone imagery allows the extraction of 3D tree variables and their correlation with individual production (Sarron *et al.*, 2018), enabling the generation of spatialised yield maps. In parallel, extrapolation models have been developed. Integrated into the PixFruit® tool, these models allow the estimation of orchard yield based solely on images acquired from a sample of trees (see Box 11.3, Chapter 11).

► Predicting and managing risks

Agriculture is a human production activity inherently defined by the high uncertainty of several foundational factors, particularly weather conditions. Improving our control of this uncertainty requires the development of high-quality predictive models.

Improving weather forecasting with ensemble forecasts

Many decision support systems (DSS) in agriculture rely on weather forecasts that can be highly uncertain. To quantify these forecast uncertainties, meteorological centres, including Météo-France, have developed probabilistic forecasting systems based on 'ensemble forecasts', which represent the possible variability of the atmosphere.

Several initiatives have been conducted within #DigitAg through collaborations between ACTA, Météo-France, and INRAE, aiming to explore the operational use of these ensemble forecasts in agricultural DSS.

The doctoral research of Ivana Aleksovska (2020) demonstrated the value of ensemble forecasting in helping farmers anticipate the application of plant protection products. This work focused on two operational DSSs: EVA for grapevine moth management in viticulture and Septo-LIS for wheat septoria leaf blotch.

The potential benefit of ensemble forecasts for these models was established by comparing them with a common agricultural approach based on historical series of weather observations (Aleksovska *et al.*, 2018). DSSs require high-spatial-resolution short-term forecasts as well as longer-term forecasts (up to two weeks), which are typically available at a lower resolution.

A method was proposed to take advantage of these complementarities between forecasting models with different characteristics, such as spatial and temporal resolutions and lead times (Aleksovska *et al.*, 2021).

Following the work of Léo Pichon on monitoring vineyard water status at a regional scale, Yulin Zhang's internship and the subsequent post-doctoral research of Bachar Tarraf (Tarraf *et al.*, 2024) focused on a DSS for forecasting grapevine water stress, associated with the WaLIS crop model and ensemble weather forecasts. Improvements in water stress forecasts were evaluated using performance scores appropriate for probabilistic forecasts. The results show a significant improvement when using ensemble forecasts compared with sets of historical observations. The forecasts can be further improved by adjusting them with local data from weather stations installed by farmers. A sensitivity analysis, aimed at comparing the impact of different sources of uncertainty, was also conducted. The results indicate that all sources of uncertainty are important, and that the significance of each source varies according to the lead time (Figure 4.1).

Finally, this work led to the proposal of the AléaPluie tool, a completely free service providing probabilistic forecasts for cumulative precipitation in agriculture. It provides probabilities in the form of maps of reaching a specific precipitation threshold over a two-week period. Farmers and advisors use it for various different purposes in their regions, notably for rapeseed sowing (Brun *et al.*, 2023).

Predicting disease risk with machine learning

The informed choice of plant protection products, or alternatives such as biological control (biocontrol) solutions, and their timing of application require precise information on pest epidemic risk over the growing season. In her doctoral research focusing on grapevine downy mildew—a disease that necessitates numerous fungicide applications—Mathilde Chen (2019) statistically evaluated the value of initiating control measures based on the date the disease symptoms first appear. Epidemiological observations collected throughout the Bordeaux region were analysed using survival models (Chen *et al.*, 2019a), and local expertise was also studied (Chen *et al.*, 2019b). It appears that, on average, the first treatments in the Bordeaux region are carried out three weeks before the initial symptoms appear. Under the hypothesis of starting the first treatments only upon the appearance of these first symptoms, it would theoretically be possible, with a bi-weekly application rhythm, to reduce treatments by an

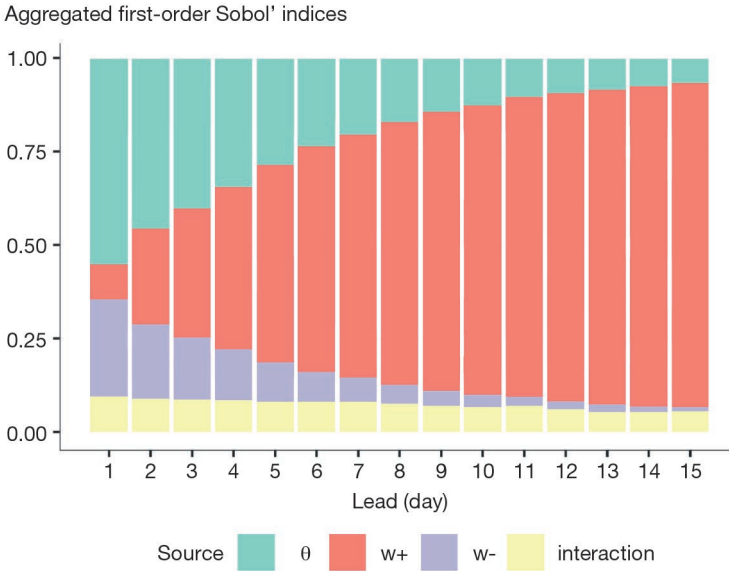


Figure 4.1. Sources of uncertainty in the outputs of the WaLIS vineyard water stress model: in green, the model parameters; in purple, past meteorological observations; in red, meteorological forecasts. The x-axis of the graph represents the number of lead time. Source: Taraf *et al.* (2025).

average of 56% compared with current practices in this region (Chen *et al.*, 2020a). Using machine learning methods, Chen *et al.* (2020b) showed that the earliness and severity of downy mildew epidemics were strongly linked.

The doctoral research of Olivier Gauriau (2024), presented in Chapter 2, applies these machine learning approaches to two diseases (grapevine downy mildew and sugar beet cercospora), while opening up the question of model interpretability. The prediction focuses on the date of the first symptom appearance and the end-of-season disease intensity, based on meteorological and agronomic indicators. To find a compromise between the performance of machine learning approaches and the complexity of the learned models (estimated by their size), pattern-based approaches were applied and compared with commonly used methods (Gauriau *et al.*, 2024). These models were then used in the development of a prototype for the exploration and visualisation of predictive models intended for crop protection experts (Anemone¹³: mapping for pathogen prediction, featured in the #DigitAg digital showcase).

► Supporting design and decision-making for optimised management

Models, in various formalisms, accompany every stage of managing a cropping system, from its design to its operational management. We will first look at modelling for analysis and simulation, before turning to optimisation through combinatorial analysis and control theory.

13. <https://anemone.hdigitag.fr>

Modelling, simulating and visualising to support action

This section addresses the use of modelling to explore possibilities, aiming to make informed design or management choices through augmented reality, mapping, zoning and crop management.

Augmented reality to facilitate the design of agroforestry systems

Agroforestry is a promising path towards a sustainable, resilient agriculture adapted to climate change. However, the great diversity of planting configurations and management methods, combined with the long-time scales inherent to tree growth, make the transition to these systems difficult. Assisting farmers is therefore particularly useful, for example through design workshops bringing together farmers, experts and specialists from several fields.

In the doctoral research of Laetitia Lemièr (2023), augmented reality techniques were developed to facilitate these workshops. This allowed the user-friendliness of a physical model (using coloured tokens whose colour and position are identified by image analysis) to be combined with the power of computer modelling. This modelling visualises and projects the three-dimensional evolution of objects, plants and trees depicted on the model (point, linear and area-based, plus their interactions over time).

This modelling, based on the formalism of combinatorial maps (a type of multi-dimensional graph; Lemièr *et al.*, 2023), is compatible with representations used in existing agroforestry tools, thereby facilitating their coupling with economic and environmental performance models. Users can visualise data in augmented reality, either on the model or directly on a plot, to project themselves into their future system. The various modules of this processing chain were tested with agricultural advisors. A public demonstrator, AgroforestAR¹⁴, designed to visualise agroforestry systems in the field, was developed as a free app for iOS and Android as part of the #DigitAg digital showcases.

Designing soil quality maps to facilitate the integration of uncertainty into decision-making

Maps of environmental indicators—such as ecosystem services, soil quality, and biodiversity indicators—are essential for supporting land-use planning decisions. However, decision-makers often tend to ignore the significant uncertainties typically associated with these maps, despite their importance for understanding data limitations and identifying zones where decisions must be made with caution. Although cartographers, particularly in soil science, have made various efforts to better communicate these uncertainties, public decision-makers still struggle to fully comprehend this information and its implications.

The doctoral research of Léa Courteille (2025) addresses this challenge of visualising uncertainty in soil quality maps. By studying their entire life cycle—from the initial spatialisation of the quality index to the use of the map for territorial decision-making—she developed methods to facilitate the integration of uncertainty into the decision-making process (Courteille *et al.*, 2024) and involved users to evaluate the operability of the maps that were produced (Courteille *et al.*, 2025).

14. APK App available to download from the Play Store and App Store

Her research demonstrates that the conventional representation of environmental maps is not optimal for supporting decisions. Consequently, she formulated recommendations for cartographers to ensure they provide more effective support for land-use planning decisions.

Zoning of agricultural plots and yield maps

In the context of precision agriculture, which is based on site-specific management, the differentiated management of areas within a single plot, intra-plot zoning consists of dividing agricultural plots into coherent management zones. These zones must be interpretable from the farmer's perspective and compatible with agricultural machinery (e.g., tool working width, response time for changing specifications such as input quantities).

#DigitAg research has defined a numerical criterion to evaluate the quality of such zoning (Loisel *et al.*, 2019). This criterion takes into account both the internal homogeneity of the zones and the difference between neighbouring zones, and can integrate a technical management performance model. An optimisation procedure uses this criterion to refine zone boundaries based on the statistical distribution of data, represented by quantile partitioning.

The method was successfully tested on both simulated and real-world data, demonstrating its capacity to produce a set of zonings relevant for practitioners. The final choice of the most appropriate map depends on the user or the expert, taking into account the specific context and the desired granularity. The method has been implemented in an R package called *geozoning*. This package has since been translated into Python, and the performance of technical routes (in terms of yield under irrigation constraints) has been integrated into it.

Precision viticultural spraying: rationalising applications based on plant architecture and needs

The doctoral research of Anice Cheraïet (2020) proposes a novel approach to precision viticultural spraying. This is based on a functional goal of dose application relative to the plant, expressed as a statistical distribution of the product deposits obtained (Cheraïet *et al.*, 2021). This distribution depends on the morphological characteristics of the plant, its growth stage and the sprayer efficiency.

The decision support framework combines sensors, statistical modelling, and multi-criteria evaluation. An automated data processing chain derived from a mobile terrestrial LiDAR makes it possible to construct three complementary structural indicators: canopy height, thickness and optical porosity (Cheraïet *et al.*, 2020). Over several campaigns, these indicators were cross-referenced with the distributions of deposits measured within the canopy with the use of different sprayers. Predictive models of deposit distributions were developed based on these data. These predictions were integrated into a simulation and evaluation framework for technological scenarios to assess the impact of the spatial scale of decision-making and hypotheses of risk management. What is termed 'precision' here is not based solely on the embedded technology, but also on revealing the potential trade-offs for the farmers between input reduction, quality of protection and operational constraints.

Optimisation for decision-making and control

Modelling provides the opportunity to optimise the management of technical operations based on the differentiated situations faced by the farmer. Two examples illustrate approaches adapted to innovative agricultural operations: combinatorial optimisation for selective harvesting and optimal control for irrigation.

Operational research for optimising selective harvesting in agriculture

By identifying appropriate differentiated actions, precision agriculture creates a need to optimise the coordination of these operations—a need for which operational research offers suitable scientific methods. The doctoral research of Gabriel Volte (2021) focused on optimising the path of a grape harvester for selective grape harvesting, using a machine equipped with two hoppers capable of harvesting two different grape qualities.

Not all paths between rows are equivalent because, firstly, each time a hopper is full, it must be emptied into a trailer, and secondly, different rows contain varying amounts of each grape quality. This problem, identified in Briot *et al.* (2015), was previously studied using constraint propagation methods and modelled using the discrete event system paradigm for resolution via optimal-cost reachability analysis (Saddem-Yagoubi *et al.*, 2020). In those studies, due to the very high number of possibilities (the combinatorial explosion phenomenon), exact resolution was only effective for a limited number of rows (fourteen rows in Saddem-Yagoubi *et al.*, 2020).

Within #DigitAg, this issue was addressed using an operational research approach. Grape quality is pre-classified and mapped using satellite observation and heuristic prediction. The problem was treated using the VRPSolver tool, which is particularly efficient in terms of computation time for solving vehicle routing problems. The very specific constraints—notably the driving ergonomic constraint that requires alternating the direction of travel at each new row—render this problem significantly more complex than standard vehicle routing problems with limited load capacity.

Several algorithm combinations were proposed, allowing for the resolution of realistic row numbers (24 in the case study) and realistic parameters for the minimum quantity of high-quality grapes to be sorted. Resolution times for these cases are under one minute, a performance vastly superior to previous work (Volte *et al.*, 2023).

Two other PhD projects (UMR MISTEA) focused on assisting farmers in crop planning. These concern agroecological market gardening systems, characterised by short crop rotations and high diversity.

Baptiste Darnala proposes two approaches—a semantic approach based on the construction and publication of a domain ontology (C3PO) (Darnala *et al.*, 2023) and a machine learning approach to predict the next crop based on a sequence of historical data—and demonstrates the value of their complementarity.

With the same objective of planning rotations in market gardening, Margot Challand combines constraint programming with participatory approaches involving market gardeners in a highly interdisciplinary process to plan these rotations (Challand *et al.*, 2025).

Optimal control of irrigation: dual agronomic and mathematical modelling applied to the Optirrig model

In the context of climate change and the imperative to conserve water resources, the design of irrigation strategies that allow farmers to minimise water application represents a significant challenge. Following the #DigitAg post-doctoral research of Nesrine Kalboussi (Kalboussi *et al.*, 2022), irrigation strategies were analysed as optimal control laws associated with simplified crop models in the doctoral work of Ruben Chenevat (Chenevat *et al.*, 2024).

This approach led to the emergence of threshold-based optimal policy structures, which are highly consistent with those currently used by farmers (Figure 4.2). These tactical feedback strategies are adapted to variables accessible in the field, and their properties can be studied through numerical explorations that would be too computationally intensive to conduct on more detailed models.

These strategies can subsequently be refined using more complex models, such as the Optirrig model, in a dual modelling approach that bridges mathematical analysis and numerical simulation. This work has contributed significantly to both the mathematical theory of optimal control and to water management.

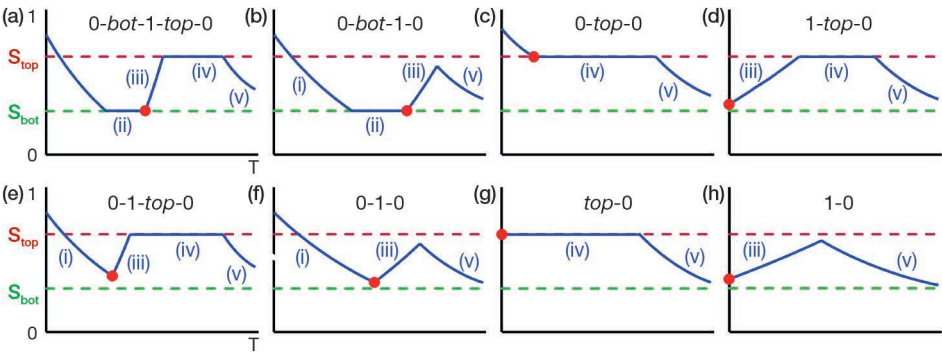


Figure 4.2. Eight scenarios for changes in soil moisture from (a) to (h) based on 8 optimal control sequences consisting of sequences of decreasing (no irrigation), increasing (maximum irrigation) or constant (irrigation adjusted to maintain a constant moisture level) arcs. These sequences are calculated using optimal control theory based on the characteristics of the soil-crop system, the initial conditions and the available water budget. S_{top} and S_{bot} are thresholds. On the y-axis, soil moisture evolution; on the x-axis, time. Source: Chenevat *et al.* (2025).

► Informing collective decision-making via modelling and simulation

The transformation of agriculture also takes place via collective decision-making and public policy. Modelling at scales that transcend the individual farm helps us to understand mechanisms and guide these policies. Although this objective is not the primary focus of #DigitAg—which is oriented toward supporting farmers and advisors—it has given rise to several research projects described below and in other chapters (see Chapter 10).

Regional assessment of the role of crop-livestock integration in carbon sequestration in cultivated soils in West Africa

In the semi-arid Sahel region, mobile pastoral livestock farming allows herds to efficiently exploit natural resources, thereby contributing to fertility transfers to cultivated areas. To monitor these fertility transfers, a multi-agent system (MAS) was developed (Scriban, 2024). This spatially explicit model formalises agricultural practices and provides a dynamic representation of their biophysical functioning. Its development required the use of experimental setups and methodologies from various disciplines, particularly GPS tracking of livestock and training of machine learning models on the resulting data to characterise herd interactions with their environment (Scriban *et al.*, 2024). Furthermore, a comparative life cycle assessment of Senegalese livestock systems helped identify critical emission factors.

The simulation model demonstrated that agrarian systems integrating crop and livestock production are more efficient and also enable the sequestration of organic carbon in cultivated soils. This sequestration reduces the quantity of greenhouse gases in the atmosphere while contributing to improved soil fertility. The model, the machine learning script, and their documentation are available as open source¹⁵.

Integration of heterogeneous data for simulating contacts between livestock and wildlife

Direct or indirect contact between wild and domestic herbivores can lead to the transmission of pathogens, with negative impacts on food security and human income, wildlife conservation, and human health in the context of zoonotic diseases. Modelling these inter-species contacts is a powerful tool for identifying the areas and seasons where such contacts are most likely, for understanding different scenarios of climate change or agricultural and livestock practices, and for informing land-use planning decisions where necessary.

A spatially explicit dynamic model was developed to simulate the movements of wild buffalo and domestic cattle in interface zones between protected and communal area near Hwange National Park, Zimbabwe (Rumiano *et al.*, 2024). The model (Figure 4.3) incorporates heterogeneous data describing the resources available to the animals (pastures and water points) as well as their changes over time, and the use of protected and communal areas for agricultural activities and livestock management (Lee-Cruz *et al.*, 2025).

The use of this model, validated by telemetry data on buffalo and cattle movements, would allow various stakeholders (farmers, protected area managers, tourism operators, wildlife conservation organisations) to engage in concerted decision-making for the sustainable management of shared resources such as water and grazing areas.

Other modelling systems in livestock farming, particularly event-based systems and individual-centred models, are described in Chapter 9.

15. <https://gitlab.cirad.fr/selmet/hamac>

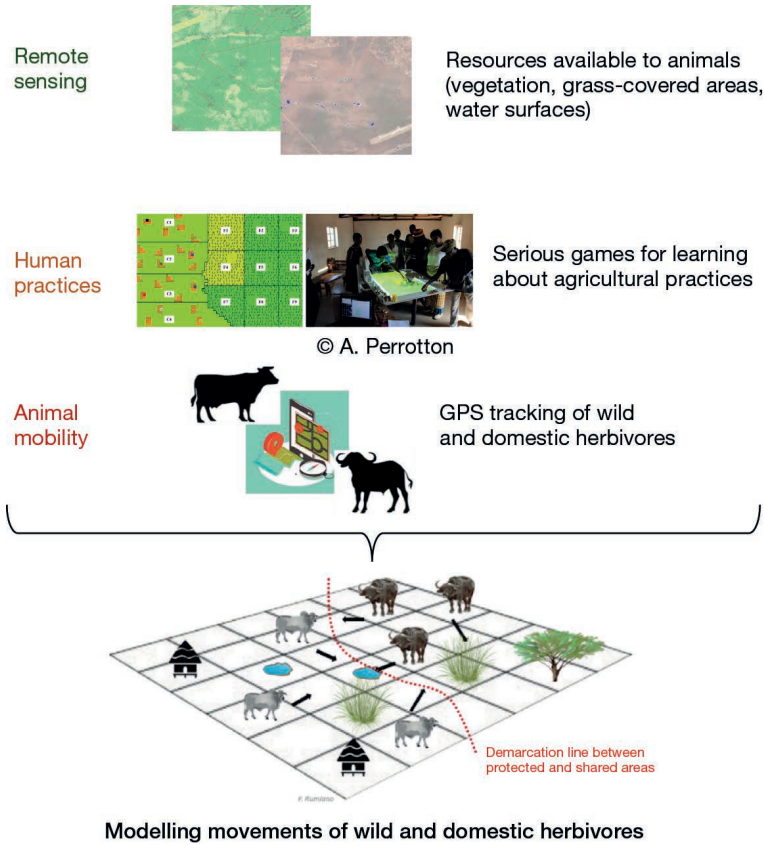


Figure 4.3. Integration of heterogeneous data for modelling contacts between wild and domestic herbivores.

Simulation and evaluation of alternative practice scenarios for hormone-free reproduction in dairy sheep farms

Faced with controversies surrounding the production conditions of equine chorionic gonadotropin (eCG)—a hormone used to induce and synchronise oestrus in dairy sheep farming—the sector is exploring alternative reproduction management methods. The goal is to maintain animal insemination and genetic selection schemes while ensuring production consistency.

The REPRIN'OV simulator, based on multi-agent modelling, was developed to simulate the functioning of dairy sheep farms incorporating hormone-free reproduction practices. It models individual reproduction and lactation processes, the interactions between animals, the farmer and the environment, as well as the consequences for the technical, economic, environmental and organisational performance of the farms (Laclef, 2022).

Calibrated on four typical farms within the Roquefort and Ossau-Iraty AOP production basins, the tool allowed for an *ex ante* evaluation of the impacts of alternative practices, particularly the use of the 'male effect' (introducing a ram into the flock to induce

and synchronise oestrus). The results, which vary depending on the context—such as decreased fertility, spread-out lambing periods, and reduced milk production—served as a basis for the co-construction of adaptation scenarios with stakeholders (Lurette *et al.*, 2024). This illustrates the utility of a simulator in supporting the transition toward sustainable livestock farming systems.

Modelling the diffusion and adoption of smart water metering technology in agriculture

Modelling and simulation approaches also offer a valuable perspective for analysing the barriers to the adoption of digital agricultural tools. This is the objective of the interdisciplinary work led by Loïc Sadou, a #DigitAg PhD candidate, which led to the development of an original simulation tool: the Midao model (model of innovation diffusion with argumentative opinion).

This model, based on an agent-based modelling approach, draws on the theory of planned behaviour and formal argumentation to provide a detailed representation of the actors' decision-making processes and how they evolve through the exchange of arguments (Figure 4.4). The model is informed by empirical data collected from stakeholders (interviews, questionnaires and statistical data).

Midao has been applied to the case of smart water meters, a technology introduced to irrigators in a context of high pressure on water resources. It allows the simulation of different scenarios regarding the diffusion of these meters and enables the exploration of the impact of public policy measures or the spread of misinformation on adoption dynamics. Through its empirical grounding, its ability to capture the complexity of individual decisions, and its openness to interdisciplinarity, Midao fully illustrates how digital technology can contribute to understanding agricultural transitions and supporting innovation policies.

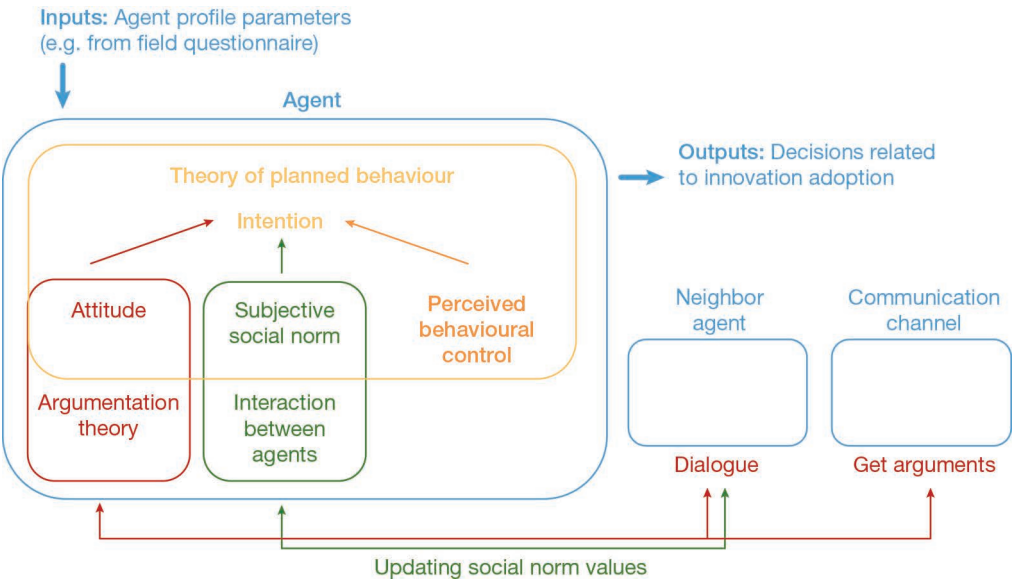


Figure 4.4. General architecture of Midao agents.

» Outlook and conclusions

Process simulation, individual-centred simulation, data-driven predictive modelling—whether resulting from statistical approaches or deep learning—spatial process modelling, stochastic modelling, crowdsourced data modelling, image analysis, cartographic visualisations, augmented reality, optimisation or optimal control synthesis, and heterogeneous data integration: here we have presented an idea of the diversity of what is termed ‘modelling in support of digital agriculture’. These methods are employed at every stage of agronomic design—for example, in the case of a farm's transition to agroecology (strategic decision support)—or during operational production decisions. They concern analysis scales that vary widely depending on the context and the entities or individuals responsible for those decisions, ranging from the individual plant to the region.

A major challenge is to work simultaneously toward the operationalisation and validation of these methods within production contexts, while providing stakeholders with maximum autonomy in their development and the validation of the models. Sustainable agriculture is likely not an agriculture whose processes are optimal and designed by a few actors in a position to impose them. It will more likely result from balances struck between actors and their environments, which requires the adoption of models by a diverse range of stakeholders, as well as a continuous movement of improvement and adaptation to specific contexts. The openness and availability of data, reference frameworks, and models will play an essential role.

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Part 2

Processes, practices, and instruments:
understanding the multiple dimensions
of agricultural digitalisation

Chapter 5

Agricultural digitalisation in the face of transitions: processes, stakeholders and systemic dynamics

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Agricultural digitalisation is receiving increasing attention, both as a lever for eco-efficiency and as a vehicle for transforming farming practices. However, rather than being a uniform or neutral process, it is part of an agricultural landscape marked by tensions between diverse development models, economic competitiveness requirements, and growing societal expectations for sustainable agricultural systems. Recent research (Alexandre, 2022; Bechtet, 2024; Biao, 2022; Florez, 2023; Schnebelin, 2022), funded by #DigitAg, demonstrates that digitalisation contributes to greening trajectories in various ways. Nonetheless, such research also raises concerns about the risks of lock-in within an agro-industrial model that remains largely incompatible with agroecological transition objectives.

An innovation systems approach, supplemented by multi-scale interpretation, allows digitalisation to be situated within these social, economic, and political contexts. This approach offers a dynamic reading of innovation, highlighting the interdependencies between the micro (usage), meso (organisations and systems), and macro (institutional and policy frameworks) scales.

Given the environmental and social challenges facing agriculture, the question is no longer whether digitalisation will transform agricultural systems, but rather how it will do so and under what conditions this transformation can be compatible with sustainability imperatives. Indeed, agriculture stands at a historical crossroads: it must mitigate its environmental impact while maintaining productivity; reinvent its economic models while preserving the food sovereignty of territories; and rethink the farming profession in the light of quality-of-life and knowledge-transfer challenges. In this complex equation, digital technologies represent both an opportunity and a challenge.

This chapter aims to describe agricultural digitalisation as a complex socio-technical process by examining its dynamics, actors and effects. We shall first examine how it fits into a multifaceted innovation ecosystem before analysing the role of key actors in its construction and dissemination. Finally, we will discuss the sustainability issues it raises, and the conditions required for a responsible digital transition.

► Digitalisation: a process and an ecosystem

The digital agricultural innovation ecosystem

Agricultural digitalisation is not merely the introduction of isolated technological tools. It is embedded within an innovation ecosystem where a multitude of stakeholders interact. These increasingly include specialised start-ups seeking to address the specific needs of the sector (Birner *et al.*, 2021), and digital companies extending their activities into the agricultural digital sphere, such as software producers (Schnebelin, 2022). Furthermore, large agricultural input or machinery companies, such as John Deere, or even aerospace companies like Airbus, are involved (Bechtet, 2024). This landscape also encompasses traditional agricultural innovation stakeholders, such as specialised research centres (Klerkx *et al.*, 2019), farmers themselves, professional agricultural organisations, agricultural cooperatives and traders (Santos *et al.*, 2024), technical institutes, agricultural advisory services, as well as chambers of agriculture, consultants, public institutions and local authorities (Lajoie-O'Malley *et al.*, 2020). This configuration corresponds to what innovation economics terms a 'sectoral innovation system' (Malerba, 2002). Moreover, in the Global South, this system includes international donors and NGOs (Alexandre, 2022).

Mauro Florez (2023) describes this ecosystem as a tangle of networks for the production, dissemination, and validation of digital technologies, driven by a high heterogeneity of stakeholders with differentiated yet interconnected roles. Start-ups and technology companies design tools according to business models and visions that are not always aligned with the needs, economic constraints, or practices of end-users. Public institutions intervene to support the development or acquisition of these technologies via financing mechanisms, aiming to broaden their accessibility.

Noémie Bechtet (2024) explains these public policies in France, ranging from supply-side support through the 2020 France Relance plan and PIA4 (Investments for the Future Programme), to demand-side support via subsidies to farmers. In doing this, public institutions guide innovation trajectories by directly influencing research activities. Intermediate structures—cooperatives, agricultural merchants, chambers of agriculture and advisory bodies—play a crucial role in the diffusion of tools on the ground by reducing technical or economic barriers, both upstream of adoption (pre-adoption) and after their integration into actual use (post-adoption). To achieve this, they leverage the long-standing relationships of trust developed with farmers (Bechtet, 2024). Other stakeholders, such as researchers or cooperatives, participate in the design, development, experimentation, adjustment, and evaluation of technologies through information, training, and testing activities, thereby contributing to their legitimisation and adaptation to field realities. This network, far from being uniform, varies significantly according to regional dynamics, value chains, governance modes, and tool types, directly influencing the conditions of access, adoption, and use of digital tools.

This interconnection can result in the emergence of regional clusters where resources and expertise are concentrated. In these local ecosystems, universities and technical institutes often act as catalysts, producing both fundamental knowledge and concrete applications. However, this spatial concentration may also exacerbate territorial inequalities in access to innovation, creating some highly digitalised zones while others remain outside these dynamics.

Éléonore Schnebelin (2022) emphasises that digitalisation is embedded into the reorganisation of the entire agricultural innovation system, modifying interactions between stakeholders, knowledge and institutions, and potentially strengthening the role of intermediaries. Bechtet (2024) shows that digitalisation transforms the ways in which knowledge is produced in the agricultural sector, particularly within intermediate organisations, thus altering the nature of intermediation itself.

Regarding digital agricultural advisory services in West Africa, Chloé Alexandre (2022) refers to ‘innovation networks’ involving a diversity of organisations including technology companies, NGOs, agricultural producer organisations (APOs), state services, international donors, and national and international research institutions.

A dynamic vision: digitalisation as a process

Rather than being a ‘technological shock’, digitalisation manifests as a series of processes involving technology production, adoption, adaptation, contestation and reinterpretation. Biao *et al.* (2025) demonstrate that the production of these technologies by ‘AgTech’ companies is an open innovation process, integrating multiple stakeholders from the innovation ecosystem at various stages. They distinguish three non-linear stages: ideation and development (Phase 1); prototype testing and validation (Phase 2); and marketing and dissemination (Phase 3). This process involves numerous stakeholders, including farmers and, crucially, agricultural organisations and agri-supply businesses, particularly during the identification of needs and the validation of prototypes and tests. However, it appears that stakeholder involvement is more significant in the later phases of the process than at the outset. The number and nature of stakeholders involved, thus depend on the stage of the innovation process. Furthermore, the diversity of stakeholders varies according to the type of innovation. Consequently, partnerships evolve throughout the innovation process and are neither constant nor continuous (Biao, 2022).

Chloé Alexandre (2022) also considers that innovation within the digital agricultural services sector in West Africa is an open innovation process. She notes that the innovation network configuration most conducive to innovation is a hub-and-spoke (star) formation centred around a pivot organisation. She further highlights the negative impact of geographical and organisational distance between actors within such a network. Thus, in the context of the Global South, the imperatives regarding geographical and organisational distance in international development project management constitute significant constraints for these innovation networks, which require proximity. Finally, she underlines the difficulty of aligning the interests of stakeholders from different sectors within these open innovation processes.

Through field analysis of arable farms, Éléonore Schnebelin (2022) shows that the use of digital technologies varies enormously depending on socio-economic contexts, professional trajectories, and the networks of which farmers are part.

Ethnographic surveys reveal that the adoption of digital technologies is part of long-term trajectories, often marked by phases of enthusiasm, disillusionment and subsequent critical appropriation. Farmers are not merely passive recipients; they evaluate, test, adapt and sometimes repurpose the tools provided. This active dimension of appropriation is particularly visible in peer-to-peer exchange groups, where feedback circulates and influences collective technological choices.

The rapid pace of development of digital technology contrasts with the long timescales of transformation for agricultural production systems. This temporal tension creates frictions: the rapid obsolescence of equipment versus multi-year agricultural investment cycles, and a proliferation of technological offerings versus the limited capacity for integration into daily practices. The training of farmers and advisors often constitutes the weak link in this temporal chain, creating a ‘knowledge debt’ effect that limits the leverage of the tools’ true potential.

Challenges and tensions of digitalisation

Beyond the technical efficiency with which it is credited, and the potential social, economic and environmental benefits it may provide, digitalisation raises ethical, economic and political issues due to the transformations it can generate within agriculture and society at large. Moving past the digitalisation of farming practices and systems, “the development of the use of digital technologies is accompanied by significant social implications” (Biao, 2022; p. 6). Consequently, we need to question not only the actual impact of digital technologies on agricultural sustainability—the argument generally used to justify their development—but also, as with all emerging technologies, their social acceptability. Thus, conflicts of values may exist between dominant productivist paradigms and agroecological or localised approaches. Tensions crystallise around fundamental questions: does digital technology strengthen the autonomy of farmers or increase their dependence on external suppliers? Does it promote ecological intensification or capitalistic intensification? These questions translate into tangible choices regarding investment, training, and work organisation on farms.

The emergence of digital technology also redraws the boundaries between private and collective spheres, notably through the issue of ownership and governance of agricultural data. Who controls the data? Who profits from it? These questions, also discussed in Chapter 13, reveal the power asymmetry between data producers (farmers), the platforms that capture it (tech companies), and public actors who sometimes struggle to regulate these flows.

The massive collection of plot-level, crop, or husbandry data creates a new form of agricultural wealth. However, the value derived from this wealth is subject to divergent strategies: extractive economic models on one hand, where data is captured by platforms that monetise it without significant returns to farmers; and on the other, approaches based on digital commons, where data is pooled and managed collectively to produce shared knowledge.

Several theses have explored different aspects of this issue. Éléonore Schnebelin (2022) studied the extent to which the digitalisation and greening of practices were necessarily compatible trajectories—in other words, the link between digital use and greening. She observed that digitalisation trajectories are multiple and non-linear and shows that oppositions exist between digitalisation and strong greening. However, she notes that hybridisations are possible between digitalisation and forms of industrial greening, subject to certain adaptations. According to her, ‘industrial’ agricultural trajectories are characterised by “specialisation, concentration, the increasing use of wage labour and subcontracting, and integration into agri-food value chains” (Schnebelin, 2022; p. 412).

Boris Biao (2022) conducted a detailed study of innovation governance by companies that design and market these technologies—the so-called ‘AgTech companies’—to determine whether the innovation process is ‘responsible’. This implies compliance with a set of procedural values that give the innovations produced greater acceptability and even social desirability. He shows that digital technologies are often designed within a mindset focused on removing technical bottlenecks and capturing competitive advantages for the innovator, to the detriment of social and ethical considerations.

Noémie Bechtet (2024) examined the role of intermediaries in the evaluation of digital technologies. She concludes that new modalities for evaluating digital technologies—in this instance, decision support tools (DSTs) for nitrogen management—do not reduce the risk of technological lock-in to the conventional, productivist model of agricultural practices. The environmental dimension of evaluation, when performed, is often reduced. Finally, Chloé Alexandre (2022) observed that digital agricultural advisory services in West Africa favour top-down, standardised information rather than the learning of the farmers who received the advice.

► Process stakeholders

Start-ups and technological solutions: between promise and specialisation

The development of digital agriculture relies heavily on start-ups, which position themselves as drivers of innovation. These young companies design precision agriculture tools, connected sensors, drones, data management platforms and DSTs. According to Mauro Florez (2023), AgTech start-ups often operate at the crossroads of agriculture, data science and the platform economy. For instance, in France, companies such as AgreenCulture—which develops agricultural robots that reduce the use of chemicals—or ConnectingFood—which utilises blockchain technology to ensure food product traceability—illustrate how these start-ups make concrete contributions to the sustainability of food value chains on environmental, social and economic levels (Florez *et al.*, 2022).

The AgTech start-up ecosystem—including those companies focused on the development of digital technologies for agriculture—has expanded considerably over the past decade, both in terms of the number of actors and technological diversity. This growth has been sustained by a substantial influx of capital, with investments increasing twenty-fold between 2012 and 2021¹⁶. Despite the slowdown observed since 2022, investor interest remains high, reflecting its strategic importance for agricultural innovation and the sector's sustainable transition. These companies specialise by sub-sector or function, leading to market fragmentation where each start-up addresses a specific segment without necessarily offering integration with other components of the farm system.

Florez *et al.* (2022) demonstrate how business models play a central role in the diffusion of innovative technologies by structuring the mechanisms of value creation, capture and distribution. They determine the economic viability of start-ups as much as their ability to embed their solutions within the practices of field actors. This strategic role

16. How agtech start-ups can survive a capital drought. <https://www.mckinsey.com/industries/agriculture/our-insights/how-agtech-startups-can-survive-a-capital-drought>

is garnering increasing interest in both professional and research circles, where business model innovation is studied as a key driver for generating new value strategies. Yet, despite this increased attention, digital agriculture is rarely addressed from this perspective, particularly at the intersection of digital AgTech start-ups, which are nevertheless essential vectors of the sector's digital transformation (Birner *et al.*, 2021).

In one of the few empirical studies dedicated to this issue, Schirmer *et al.* (2021) analyse the business models of 116 AgTech start-ups in digital agricultural and identify 18 business model innovation strategies. The study highlights the diversity of value capture mechanisms implemented: the sale or leasing of technologies (for example, agricultural robots), subscriptions to digital services (such as climate data or satellite imagery), data monetisation and transaction commissions, facilitating intermediation between producers and consumers. To these classic forms are added more recent models such as 'smart business in a box', which offers an integrated turnkey solution to democratise automated agriculture; 'predictive risk management', which leverages data analytics to anticipate agricultural risks; or 'smart charged products', where connected objects embed intelligent functionalities such as automated livestock guidance. These models reflect a growing trend towards hybridisation between technological artefacts, digital services and 'data-oriented' value-added services.

Furthermore, a major gap remains between designers originating from engineering schools or urban start-up studios and the daily realities of farms. Innovators often consider their innovations to be universal and do not perceive the divergent expectations among their different categories of clients. This mismatch is also found in the design of tools for digital advisory services in West Africa. To overcome this discrepancy, certain initiatives promote bridges between these two worlds: agricultural hackathons, specialised incubators within agronomy schools, and cross-mentoring programmes between experienced farmers and young tech entrepreneurs.

Intermediaries: cooperatives and agricultural advisory services

Intermediary actors play a pivotal role in structuring innovation dynamics. Schnebelin (2022), drawing on studies of viticultural cooperatives, highlights their dual function: as a support for innovation and a channel for dissemination. Cooperatives act as relays linking research, technology companies and farmers. They can also offer pooling models that facilitate access to technologies for small and medium-sized farms.

The capacity of cooperatives to perform various innovation intermediation functions varies considerably depending on their size, organisation, production orientation, resources and governance. It is also influenced by whether or not they are engaged in environmental or sustainability certification and labelling schemes (Kouassi *et al.*, 2025). Large cooperatives often possess their own research and development departments or even establish structured partnerships with start-ups or research laboratories. Smaller cooperatives have more limited resources but sometimes compensate through greater agility and a more nuanced understanding of their members' specific needs.

Noémie Bechtet (2024) focuses on the role of agricultural advisory services. She demonstrates that advisors have become an essential channel of knowledge transfer, but on condition that their role is reassessed. The transition from technical advice to digital support involves new skills, thereby altering their professional identity. The 'digitally enhanced' adviser becomes a mediator between complex information

systems and farmers. Digitalisation involves new intermediary actors, occasionally lacking agronomic expertise, and modifies the modalities and criteria for tool evaluation. This evolution meets with resistance within advisory bodies, with generational or cultural divides emerging between digital proponents and sceptics.

Farmer-users: heterogeneity of usage

The end-users—the farmers themselves—constitute one of the most decisive links in the success or failure of digital technologies. Mauro Florez (2023) identifies several user profiles, ranging from enthusiastic pioneers to cautious sceptics. Adoption factors are multifaceted, including the size of the farm, access to finance, level of education, network membership, and trust in suppliers. Contrary to common misconceptions, age is not the most determining factor in the adoption of digital technologies. More significant are the level of education, integration into professional networks, and the pre-existing innovation trajectory of the farm.

The adoption of technologies is thus embedded within varied professional strategies: the optimisation of existing processes for some, and a lever for transitioning towards new productive models for others. This diversity of motivations partly explains the heterogeneity of the observed usage. Technologies are sometimes used in a repurposed or symbolic manner. However, genuine peer-to-peer learning practices are emerging via agricultural social networks or farmer collectives, creating margins of autonomy in technological appropriation.

Beyond technical aspects, digitalisation is transforming the farming profession more profoundly. It alters the required skills, work timescales and professional relationships. Data management and analysis are becoming activities in their own right, sometimes at the expense of time spent in the field. This evolution raises identity-related questions that permeate debates within the profession.

► Digitalisation and sustainability challenges

Digitalisation and SDGs: conditional convergences

Digitalisation is sometimes presented as compatible with the Sustainable Development Goals (SDGs), particularly regarding improved input efficiency, emissions reduction, traceability, or natural resource management. Mauro Florez (2023) qualifies this convergence by insisting on the conditional nature of these effects. The same tool can yield very different results depending on the contexts of its use.

Several studies on digital technologies in agriculture highlight their potential contribution to various aspects of sustainable development—be these social, environmental or economic—such as those based on artificial intelligence, the Internet of Things (IoT), or blockchain (Benyam *et al.*, 2021; Del Río Castro *et al.*, 2021). Socially, mobile applications enable faster and more informed decision-making, facilitate data recording, and offer access to platforms based on big data providing up-to-date information. They thus play a significant role in agricultural extension services, linked to SDG 4 regarding education and access to information. Environmentally, the use of agricultural robots to manage weeds allows a reduction in the use of plant protection products while decreasing soil compaction due to their light weight (Rübcke von Veltheim *et al.*, 2022).

Additionally, precision agriculture technologies contribute to improving soil, water and air quality, thereby supporting SDG 6 (clean water) and SDG 12 (responsible consumption and production). Finally, economically, mobile phones strengthen the connection between farmers and suppliers, customers and financial or extension services. They are also used as a medium for video-based learning (Michels *et al.*, 2020), thus facilitating inclusion in agricultural value chains, in alignment with SDG 2 (zero hunger) and SDG 8 (economic growth).

Precision agriculture technologies can significantly reduce the use of plant protection products and fertilisers when integrated into a global agroecological transition approach. However, these same technologies, used with a purely productivist approach, may simply rationalise conventional practices without challenging the intensive agriculture model.

Other studies draw attention to the social risks that unguided digitalisation may bring. As Ragnedda and Gladkova (2020) point out, the digital divide is a phenomenon manifesting at three levels: inequalities in access to technology, differences in the skills required to adopt them, and gaps in the capacity to derive tangible benefits. This can result in a digital divide between countries or regions, between genders, or to the detriment of small farms due to differences in access to resources, skills, or infrastructure. These effects may be reinforced when the digital transition is motivated primarily by productivity imperatives, without sufficient consideration for social or ecological dimensions (Lajoie-O'Malley *et al.*, 2020).

The contribution of digital agricultural technologies to the SDGs can only be analysed in light of the specific contexts in which they are implemented. Technological choices, conditions of use, governance models, and regional dynamics strongly influence the effects—positive or negative—that they may have.

Furthermore, digitalisation produces unequal redistributive effects: large farms capture the benefits more easily, while small farms may be excluded from the process without active solidarity or cooperation mechanisms. In the face of these disparities, various initiatives seek to democratise access to digital technologies: low-tech solutions adapted to the constraints of small farms, targeted training programmes, and models for the pooling of expensive equipment.

Moving towards responsible innovation

The concept of responsible innovation presupposes that technologies are developed with a wide diversity of stakeholders, including civil society actors such as NGOs, by integrating their needs, values and capacities for action at all stages of the innovation process.

However, Biao *et al.* (2025) note that many societal issues and risks, such as the need to control energy consumption caused by data storage, are not taken into account by users alone. Societal actors (particularly NGOs) are very rarely consulted. Perceptions of both the challenges and risks of digital agriculture differ between AgTech companies and other categories of stakeholders: “Innovators perceive the risks very little, with the exception of those relating to the environmental dimension. Conversely, stakeholders such as research organisations, network structures and agricultural sector organisations have a more pronounced perception of risks” (Biao *et al.*, 2025; p. 31).

Boris Biao (2022) thus advocates for an open governance of these processes, including different categories of stakeholders, allowing for the anticipation of both the negative and positive implications of innovation and reflexivity, leading to a continual adaptation of the process. Thus, the early inclusion of a wide diversity of stakeholders, the exercise of foresight aimed at identifying farmers' needs, and regular feedback at different stages make it possible to guide, or even reorient, tools towards the actual needs of participants, but also to broaden the co-design of tools with farmers and the recognition of empirical knowledge.

This approach can translate into concrete participatory methods where end-users, as well as civil society actors, are involved from the initial design phases and throughout the process. Agricultural 'living labs' (see the OccitANum living lab, described in Chapter 13) constitute a promising example: these systems bring together farmers, researchers, developers and advisors in co-innovation approaches anchored in regional realities.

Responsible innovation also implies a reflection on the ethical implications of technologies, extending to the societal level: informed consent regarding data use, transparency in agricultural data management, reversibility of technological choices to preserve farm autonomy and the environmental consequences of data storage management.

The responsibility of public authorities is also engaged. Innovation policies can guide digitalisation towards greater sustainability and fairness through a diversity of levers: conditionality of digital investment aid, targeted support for collaborative approaches, regulation of agricultural data, and the integration of ethical criteria in public procurement for technology.

► Conclusion: moving towards a systemic, multi-level and responsible approach to agricultural digitalisation

Agricultural digitalisation appears to be a complex and multi-dimensional process. Far from being the mere application of technologies to an economic sector, it constitutes a cultural, socio-technical and institutional transformation that mobilises and reconfigures the entire agriculture and food system. Its analysis requires a systemic approach capable of articulating different scales and integrating the multiple dimensions (technical, social, economic, environmental and ethical) of this evolution, as well as the heterogeneity of actors and the complexity of their interactions.

AgTech start-ups develop specialised solutions based on business models focused on technology-led value capture, yet they frequently encounter obstacles due to their distance from the true situation in the field and its imperatives. More traditional intermediaries—cooperatives, advisory bodies, and chambers of agriculture—retain a significant role in appropriation processes, leveraging their established relationships with farmers. Finally, the farmers themselves cannot be regarded as mere passive adopters, but rather as intermediaries capable of selecting, or even criticising, the proposed solutions.

The question of compatibility between digitalisation and sustainable development goals reveals potential convergences, depending on the objectives pursued by the technologies. Precision agriculture can contribute to reducing inputs and improving environmental efficiency when it is part of a broader agroecological transition approach.

However, these same technologies, when deployed within a purely productivist strategy, may simply rationalise conventional practices without challenging the intensive agriculture model.

The analysis of innovation processes reveals limitations in how societal and environmental challenges are addressed. AgTech companies have little perception of the risks associated with their innovations, in contrast to other stakeholders. Innovation governance remains largely closed, with late and limited involvement of end users and a near-total absence of civil society. This situation calls for an evolution towards responsible innovation approaches, integrating a diversity of stakeholders from the initial design phases. These approaches also imply a reflection on ethical issues: informed consent regarding data use, transparency in its management, and the reversibility of technological choices to preserve farmers' autonomy (Chapter 13).

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Chapter 6

Digital practices and usages among farmers: insights into the relationship between digitalisation and the greening of agriculture

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Théo Martin, Jeanne Oui, Louis Rénier, Nadège Ressia, Cadeau Rushigira,
Éléonore Schnebelin, Jean-Marc Touzard*

The objective of this chapter is to demonstrate the contribution of doctoral research in the humanities and social sciences—funded, labelled or supported by #DigitAg—to the analysis of the usages and effects of digital technologies among farmers. In particular, these studies offer an understanding of the links between the development of digital technologies and the greening of the agricultural sector.

When the Convergences Institute was established in 2017, few studies focused on the digital practices and usages of farmers (Klerkx *et al.*, 2019). On the one hand, qualitative studies, often rooted in sociology, were generally critical regarding the compatibility between digital development and the greening of agriculture (Lamine, 2011). These viewed digitalisation as a risk to farmer autonomy and as a source of increased dependence on the actors of agricultural industrialisation (Bronson and Knezevic, 2016). On the other hand, quantitative studies, frequently in economics or digital sciences, analysed the conditions for the adoption of digital technologies, focusing primarily on precision agriculture (Barnes *et al.*, 2019).

These earlier studies had three limitations. Firstly, by focusing on precision agriculture for arable crops, this research failed to account for the diversity of the digital sphere, overlooking elements such as social networks, frugal innovation (low-tech) tools or robotics within the livestock sector. Moreover, by prioritising the analysis of technical or economic conditions for ‘digital technology adoption’ without studying actual usage, these studies provided little insight into actual effects on farmers’ practices or their learning processes. Finally, the inquiry into the links between greening and digitalisation required more systemic and historical visions to analyse the embedding of digital usage within networks of actors or institutions at a sectoral scale.

The PhD research covered in this chapter has contributed to addressing these limitations by proposing empirical analyses based on surveys and interviews, generally combining quantitative and qualitative methods. They provide insight on the concrete and contextualised perceptions and practices of farmers regarding digital technology.

This return to the field aligns with a social science movement that prioritises understanding farmers' everyday practices (Forney *et al.*, 2023) and challenges linear, diffusionist conceptions of agricultural innovation (Faure *et al.*, 2018).

►► Understanding the diverse uses of digital technology

A primary contribution of the doctoral research presented in this chapter is an empirical addition to the understanding of agricultural usages of a broad range of digital technologies. This provides original insight into existing categorisations, which are generally based on the nature of the technologies themselves (Birner *et al.*, 2021). The PhD work Éléonore Schnebelin thus proposes a general distinction between digital production technologies (DPTs) and digital communication technologies (DCTs)—a distinction we adopt here to present the technologies addressed in the nine doctorates.

Digital production technologies

Precision agriculture

Digital production technologies encompass technologies used directly within the production process. These notably include precision agriculture technologies, which formed the field of study for several PhD projects, particularly those of Éléonore Schnebelin (2022), Noémie Bechtet (2024) and Jeanne Oui (2021). This form of agriculture relies on the use of satellite guidance technologies, plot mapping and sensors. It can impact input management (plant protection products, fertilisers, seeds, etc.), farm results (yield and production quality, production costs, etc.), the implementation of practices such as soil tillage or crop rotation, and the nature, organisation and arduousness of labour. An original feature of the #DigitAg research here is the inclusion of both the hardware components of DPTs (robots, machinery, equipment) and their software components (software, decision support tools, applications).

Decision support tools and agricultural advice

Without necessarily focusing on precision agriculture, several PhD theses have focused on digital decision support tools (DSTs), which assist farmers in their decision-making and can facilitate relationships between farmers and advisors.

This is the case for the PhDs of Jeanne Oui and Noémie Bechtet, which deal with digital DSTs helping farmers manage nitrogen fertilisation in arable crops (Bechtet and Labarthe, 2024). These digital DSTs generate personalised recommendations on the nitrogen doses to be spread at different locations within wheat, barley or oilseed plots, for example. The progressive integration of digital technologies into their operation has increased the precision with which the recommended nitrogen dose is calculated and subsequently applied to the fields. Today, the market is sufficiently mature for one to observe the farmers' usages and the activities of intermediaries linked to their design, distribution and associated advice, as well as the discrepancies between technical and commercial promises and the way these tools are actually used (Oui, 2023).

The PhD research of Chloé Alexandre (2022) also focuses on these tools, but within the African setting. She studied a diversity of digital services aimed at family farms in Burkina Faso. The technologies are relatively simple: information services via telephone or smartphone, video sites, social networks for peer-to-peer advice (WhatsApp,

Facebook) and digital applications (for example RiceAdvice) for personalised advice on input application (Alexandre, 2023). These situations also offer an interesting North-South comparison framework, facilitating an exploration of frugal innovation (low-tech) challenges in the agricultural sector.

Agricultural robotics

The PhD work of Théo Martin (2023) concerns robotics, focusing on dairy farming with cattle, a sector where these tools are most widely utilised. In agriculture, robots are part of a promise to resolve the sector's labour shortages, reduce the physical strain of agricultural labour and even serve as a substitute for farmers. However, despite these techno-scientific promises, automated milking constitutes the only case study offering both massive deployment and sufficient historical perspective to inform us about the actual transformations of the work. The first milking robots arrived on French farms during the 1990s and, by 2023, represented 68% of new milking installations.

Digital communication and marketing technologies

A new field of research on digital usages

One of the paradoxes of social science research on digital technology in agriculture is that it has long concentrated on DPTs, whereas recent studies (Calvignac *et al.*, 2025) demonstrate the intensity of farmers' social network usage. DCTs encompass technologies used to access information and communicate with peers, advisors or customers in order to exchange or co-create knowledge (Schnebelin, 2022). They include the use of specialised agricultural websites, social media such as YouTube or Facebook and other digital platforms or media. These technologies can impact the process of knowledge acquisition and training (Burton and Riley, 2018), or the gathering of information on markets, social movements or policies which, in turn, impact the production process.

Examining the influence of agricultural social networks

The doctoral research of Louis Rénier (2025) thus examines the usages of YouTube within the farming profession, focusing on the 'agri-YouTuber' phenomenon: farmers who—for nearly a decade in the case of the pioneers—have YouTube channels and publish weekly videos filmed to camera on their own farms. These videos narrate their working days throughout the seasons and transform their daily lives into a shareable experience for an increasingly broad audience (Rénier *et al.*, 2022). The results of this thesis echo studies showing that farmers tend to view social networks as a space for showcasing their skills.

The doctoral research of Cadeau Rushigira (2023) also addresses the role of digital technologies in informing farmers, based on an analysis of the rice value chain in the Democratic Republic of the Congo, with a focus on the Ruzizi Plain (Rushigira *et al.*, 2023). In this region, mobile phones are used there by all traders and by half of the rice farmers; however, only 10% possess smartphones with internet access. Digital usages are a strategic issue for controlling information within the value chain, and the use of simple SMS-based information-sharing technologies is the low-cost option favoured by rice farmers. Applications are beginning to be used by smartphone owners, primarily young people engaged in new marketing circuits.

The rise of digital platforms

The doctoral research of Romane Guillot (2024) also addresses information on agricultural marketing, focusing on the development of platforms in France (Guillot *et al.*, 2022). To offer their products online, farmers can create their own e-commerce site or use a platform. Platforms are organisations that manage websites where products from various farmers can be purchased. These have been developing in France since the early 2010s, with a surge in interest during the COVID-19 health crisis. They compete with and reinvent distribution across a multitude of sectors. Far from being a digital tool with homogeneous characteristics, these platforms are marked by diverse modes of governance and intermediation (Guillot *et al.*, 2024).

The research conducted by Nadège Ressia¹⁷ examines crowdfunding platforms dedicated to agriculture and agricultural land. These platforms, which link a farmer with investors, were initially based on donation models, with or without reciprocal benefits. They now also offer formulas such as loans, shares, bonds or tax advantages, sometimes promising up to 14% interest for the investor. The crowdfunding market is highly heterogeneous, both in terms of the platforms and the profiles of the farmers (small farms in transition or specialised businesses) or the investors (ranging from individuals to investment funds).

►► Beyond adoption: understanding the integration of digital technologies on the farm

#DigitAg doctoral work contributes to a better understanding of how the various digital technologies are integrated into farm operations, through farmers' decision-making processes, their learning dynamics and the organisation of labour.

Digital technology and farmers' decision-making processes

Farmers' decisions have long been studied in connection with the analysis of their rationales or the functioning and changes of their production systems: tactical or operational decisions, strategic steering or investment, restructuring or agroecological transformation? Digital technology modifies the information mobilised for these decisions, but also the objectives, reasoning, comparisons and trade-offs that lead to them, as well as the interactions between 'humans' and 'non-humans' that underpin them. The doctoral research presented in this chapter does not focus solely on the 'decision to adopt digital technology' or on the 'contributions of digital technology to decisions', but rather, they highlight new questions induced by digital technology regarding the contexts and mechanisms of decisions, and their role in the greening of agriculture.

Deciding to use a digital tool: navigating uncertainty

The decision by a farmer to acquire and use a digital tool is addressed in several of the PhDs, considering it a process more complex than a choice determined only by farm characteristics, the farmer's skills or their attitudes to risk (Bougherara and Thoyer, 2024). Surveys also demonstrate the importance of the uncertainties surrounding the adoption of a DST, a robot or traceability management software.

17. <https://hal.inrae.fr/DIGITAG/hal-04938628v1>

These uncertainties prompt information-seeking from other farmers, cooperative advisors, agri-YouTubers or platform forums. However, these social interactions cannot resolve all uncertainties regarding the efficacy and impacts of digital usage. For instance, Noémie Bechtet shows that precision agriculture technologies are rarely evaluated on technical and environmental levels. Surveys of farmers who have adopted, not adopted or abandoned digital DSTs for nitrogen fertiliser use highlight that, in the absence of established benchmarks, adoption decisions rely primarily on trust between farmers and their advisors or neighbours (Bechtet, 2023).

The difficulties in evaluating digital tools also play a significant role in Sub-Saharan African settings, where decisions to adopt technical advisory or market information applications are limited by uncertainty regarding their reliability and are also grounded in relationships of trust.

Routinisation of technical decisions and risks of dependencies

Once acquired, used and tested on the farm, digital technologies allow a routinisation of technical decisions within a more complex informational context. Larger volumes of information, which are difficult for human reasoning to process, are integrated into tractor guidance, the decision of whether or not to apply a spray, the optimisation of rations based on the milk production of each cow, financial analysis, etc. This substitution of repetitive operational decisions by digital technology and machines remains generally associated with progress and a recognition of the farming profession in the different contexts studied.

However, they also raise questions regarding their mechanisms of control or the dependencies they may induce. These criticisms notably concern the nature, compatibility and range of information taken into account, the risks of ‘manipulation’ or lock-in within a discussion group, the consideration of specific situations for which the farmer’s vigilance is no longer solicited, the reciprocal use by companies of data produced by the farmer, etc. The challenge of data control is confirmed in the PhD research on digital DSTs (Schnebelin, 2022; Oui, 2024). In the case of the milking robot, there is a crucial dependence on the location and the system’s maintenance infrastructure (Martin, 2024). Chloé Alexandre also shows how, in Burkina Faso, a service intended to provide technical advice to producers was ultimately used primarily to monitor their practices and those of advisors (Alexandre, 2022).

Opportunities for strategic exploration and co-decision making

Digital technologies are also used to support strategic decisions, investments or even the farm restructuring. Software—including gamified business simulation tools or scenario exploration applications—is garnering increasing interest. However, the research in this chapter indicates that farmers tend to rely more on examples provided by agri-YouTubers, social media networks, and websites or platforms dedicated to promoting ‘new’ production methods or agricultural models (e.g., regenerative agriculture, agroecology).

In several studied cases, digital tools are also associated with collective decision-making. For example, among members of wine cooperatives surveyed by Eléonore Schnebelin, digital development is integrated into the management of plant protection products, the organisation of harvests, or traceability from grapes to wine, thereby

supporting collective decisions (Schnebelin *et al.*, 2022). It also facilitates consultations for making investments or monitoring experiments. The usage of ICTs allows for a combination of local interactions between farmers and remote interactions that can broaden strategic options—a relational combination already identified as conducive to agroecological transition decisions (Lamine, 2011).

Learning and knowledge management

Beyond providing context for farmers' decisions, the #DigitAg doctoral research presented here highlights the role of digital technologies in learning processes and knowledge sharing.

Virtual interactions for knowledge sharing

The analysis of farmers' use of social networks and platforms demonstrates that, in the longer term, digital technologies contribute to learning processes and the acquisition of new skills linked to the evolution of agricultural activity. These processes can take on a new collective dimension facilitated by digital tools. Surveys by Louis Rénier show that the emergence and dynamism of the 'agri-YouTuber' phenomenon must be understood through this collective lens. These individuals are acquainted with one another, meet regularly at agricultural shows, and interact continuously via online discussion groups. They draw inspiration from one another, offer mutual advice, collectively encourage their professional peers to emulate them, and organise events to meet their subscribers. Furthermore, their self-mediation practices are subject to collective definition, regarding both the meaning attributed to making agricultural work public and the ways in which it is portrayed. Learning therefore occurs both between agri-YouTubers and between them and their numerous followers, with whom epistemic communities are built.

In a different context, Chloé Alexandre's thesis shows that digital technology can foster learning through interaction with remote advisory services. These services are provided by partnerships between digital firms and agricultural development organisations, which have also learned to collaborate. However, a key condition for successful farmer learning lies in the 'relay' systems established between the digital advisory service—which provides standardised information in a language (French or English) that is not the producers' native tongue—and local intermediaries (advisers from producer organisations or NGOs, 'lead farmers,' etc.). These intermediaries play an essential role in translation and in hosting face-to-face spaces, where information discussed in the local language is adapted to the specific needs and environments of the farmers.

Towards new collective learning within local areas

In fact, maintaining a local dimension to learning is vital for linking digitalisation with the greening of agricultural practices. Admittedly, the knowledge dynamics driven by agri-YouTubers prioritise individualised interaction, highlighting resourceful actors who seek to re-evaluate the status of the farming profession in the face of environmental criticism. However, the technical practices they portray also inform shared references within local cooperatives or unions and contribute to a weak greening of agriculture, aimed at incrementally reducing its environmental impacts (Schnebelin, 2022).

In the networks and platforms dedicated to agroecological transition, such as those studied by Romane Guillot or Nadège Ressia, the geographical embedding of knowledge exchange is more fundamental—whether for developing new projects, supplying organic value chains, or establishing an online presence for the farm. The analysis of the links between digital usages and the greening of practices within agricultural cooperatives further underscores the importance of local learning dynamics. This challenge is even more pronounced in the case of wine cooperatives, which remain tied to a *terroir*, are concerned with water and landscape management, and build their communication around a product inextricably linked to a local area. Agricultural cooperatives thus emerge as potential spaces for experimentation and learning, both for digital technologies and for more ecological practices, although the integration of these two dynamics varies depending on the organisation's collective project (Schnebelin *et al.*, 2022).

Work management and organisation

The #DigitAg theses also demonstrate that digital integration affects the organisation of agricultural labour through two contrasting dimensions: firstly, by supporting trajectories of farm expansion and input intensification; and secondly, as an option that may facilitate the greening of practices, albeit with new uncertainties. These uncertainties relate notably to the potential to reduce the drudgery associated with agroecology without generating new constraints for farmers.

Flexible working and new management and monitoring tasks

Théo Martin's PhD work addresses this issue through the case of transitioning to robotic milking, which is based on a principle of 'industrial fluidity' (Rot and Vatin, 2017) aimed at the continuous movement of cows towards the robot. If viewed positively, this fluidity also translates into new surveillance, monitoring and intervention tasks necessary to ensure milking continuity. This new work requirement leads to a reorganisation of labour. The livestock farmer must monitor and control the cow flow; interventions are sometimes required at night to respond to robot alerts sent via telephone. It is necessary to push late cows, train the robot to recognise the teats of heifers, and manage imperfections that challenge this ideal of fluidity. At the same time, work organisation becomes more flexible: there is greater porosity between tasks, workspaces are less fixed, and the timing of work is more dispersed. New temporalities are associated with this flexibility. While farmers report working just as much, if not more, the daily working window widens for the same reasons that organisation becomes more flexible: the removal of the twice-daily milking work requirement eliminates a major temporal constraint. Freed from the labour burden and rigidity of manual milking, the farmer can offer employees a standard working day, closer to the employment conditions in other sectors and aligned with urban social rhythms.

Standardisation vs complication and new labour relations

Beyond this example, doctoral research often reveals paradoxical situations where digital technology facilitates both standardisation and tinkering, as well as the simultaneous simplification and complexification of tasks. For instance, the work of Noémie Bechtet, Éléonore Schnebelin and Jeanne Oui demonstrates that digital DSTs enable farmers to standardise tasks and formalise the recording of their practices, particularly

for traceability purposes. However, the deployment of digital tools for traceability does not necessarily lead to a simplification of administrative work for farmers (Oui, 2023). Their utilisation incurs costs and requires specific skills often provided by management consultants. Behind a promise of standardisation, farmers must perform new and complex actions, such as configuring and updating tools, engaging in technical tinkering to account for unique situations, exercising monitoring and vigilance, and managing relations and negotiations with maintenance services.

These tensions are also evident in the usage of platforms. On one hand, these offer farmers new degrees of freedom in their work organisation by freeing them from the relational labour required with certain actors, such as banks. On the other hand, they bring with them new tasks relating to digital skills, such as showcasing one's farm to promote offers and communicate.

These tensions appear not only at the level of the farm manager but also concern labour relations: within the farm itself, particularly in relations with employees (as shown by research on robotic milking); between farm managers (as illustrated by the links between digitalisation and the greening of practices in wine cooperatives); and between farmers and various intermediaries who develop and work within service-based relationships for and with farmers.

►► What the analysis of usage patterns reveals about the links between digitalisation and the greening of agriculture

The analyses of actual usages and systems collected in this chapter are not only useful for understanding the reciprocal effects between technology adoption dynamics and farmers' practices. They also provide information on the relationships—both positive and negative—between the greening and digitalisation of agriculture, at the farm scale as well as at the level of intermediaries and innovation systems.

A fresh look at the role of intermediaries in the transition

A key aspect concerns the role of innovation intermediaries in the transition towards greener agriculture. Digitalisation is one of the dynamics blurring the roles played by different actors (Howells, 2024), and researchers have called for a reality check regarding innovation intermediaries (Kivimaa *et al.*, 2019): who performs which role in supporting farmers during the adoption and evaluation of technologies? The doctoral research brought together in #DigitAg has contributed to this reality check by taking farmers' practices, their networks and the services they do (or do not) receive as a starting point.

These studies reveal the predominant role played by new intermediaries. This is particularly true for dealerships that sell digital technologies and equipment to farmers, whether this is precision agriculture equipment for arable farming (Bechtet, 2023) or milking robots (Martin, 2024). The geographical analysis proposed by Théo Martin shows that distance (between dealerships and farmers) is one of the main factors in the diffusion of these technologies, as it determines access to maintenance and advice on their usage conditions. The spatial distribution of these services is therefore fundamental (Martin, 2024), concerning the maintenance of both hardware and software. Noémie Bechtet's work has shown that the abandonment of certain high-tech equipment or machinery can be linked to the bankruptcy of start-ups that provided the applications required to

operate them (Bechtet, 2023). More broadly, the challenge of greening also lies upstream of usage, at the level of the technical design of the tools themselves and in the way they reconfigure the relationships between farmers and their regulatory environment. Jeanne Oui's research has shown that the configuration of algorithms at the heart of certain DSTs can allow farmers to circumvent regulations (Oui, 2024), for example, by enabling the 'unlocking' of legal limits on nitrogen doses applied to fields.

This issue is not merely a question of actors, but also of intermediation functions. Noémie Bechtet's thesis reveals a lack of investment in evaluating the effectiveness of digital technologies and a fundamental lack of environmental criteria within such evaluations. Other work suggests considering intermediation activities during earlier phases of the innovation process, starting from the design stage. Éléonore Schnebelin's thesis shows that certain AgTech actors ignore the diversity of farmers' situations and practices, overlooking conditions that would allow the development of digital tools serving the transition—for example, by better identifying the specific needs of producers engaged in organic farming (Schnebelin *et al.*, 2021). Chloé Alexandre's PhD research demonstrates that accounting for this diversity of needs and expectations requires the development of specific capacities among digital technology designers, or even an alignment of values between technology designers (private sector, private and public research, agricultural development organisations) and the users (Alexandre *et al.*, 2023).

Synergies and contradictions between digitalisation and greening trajectories

The work conducted under #DigitAg has also produced a body of nuanced knowledge regarding the links between greening and digitalisation trajectories, accounting for the diversity of digital technologies involved as well as the variety of farms and their business models.

A first set of results confirms that most digital production technologies remain rooted in the precision agriculture paradigm and reinforce a form of agricultural industrialisation characterised by expansion, simplification, standardisation and financialisation. This is demonstrated by surveys on certain digital DSTs (Schnebelin, 2022; Higgins *et al.*, 2023; Oui, 2024). These tools allow the standardisation of decision-making across large areas, thereby supporting new 'corporate farming' models. These are characterised by the outsourcing of productive activities to agricultural contractors who use DSTs to simplify decision-making and automate traceability. Théo Martin found a similar trend for robotic milking. This research tends to confirm theoretical frameworks suggesting that digitalisation reinforces the lock-in of agriculture to a model based on the intensive use of chemical inputs (Wolf and Buttel, 1996; Visser *et al.*, 2021). However, #DigitAg research also shows that digital tools can support greening at the margins of these models: by financing the decarbonisation of certain farms—for example, through investment in solar energy, as shown by Nadège Ressia—or by helping to substitute chemical inputs with robotics or mechanical solutions, as Éléonore Schnebelin showed for weed removal.

A second set of results focuses on digital communication and marketing technologies. These allow farmers to broaden the knowledge to which they have access, confirming other recent research on the importance of social networks in transforming the modes of continuous professional development for farmers (Calvignac *et al.*, 2025).

In a different vein, the PhD work of Romane Guillot and Nadège Ressia attest to the potential of platforms to support farms that struggle to access markets or financing because their models do not align with the sector's professional standards and norms. While some crowdfunding platforms only superficially integrate sustainability issues, they allow certain marginalised farmers to access credit vital to the survival of their farms—credit that is often refused by banks (due to high debt levels, the crisis in organic farming, or specific production choices, etc.).

» Conclusion

This chapter brings together doctoral research funded by or associated with #DigitAg, which conducted surveys and field studies involving farmers. This body of work frequently relies on mixed methods, combining quantitative and qualitative approaches, the relevance of which has been demonstrated by recent literature reviews for analysing contemporary agricultural transformations (Gonçalves and Ferru, 2025). These studies highlight the necessity and the analytical richness of returning to concrete production systems, to stakeholder networks, to practices and to learning processes. The granular knowledge thus produced regarding the diversity of usages allows researchers to move beyond debates that pit industrialised precision agriculture (without denying that this dynamic is still at work) against the ‘economy of promises’ surrounding digital technology. Other forms of digital technology can indeed support greening trajectories. Ultimately, this research calls for a closer link between studies on digitalisation and the research frontier analysing the coexistence of agricultural models and different forms of agroecology (Gasselin *et al.*, 2020).

» #DigitAg doctoral theses contributing to Chapter 6

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Chapter 7

Digital tools as instruments of intermediation: from multiple expectations to contrasted realities

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In an environment where markets are shaped by political dynamics and controversies described as ‘ordinary consequences’ (Geiger *et al.*, 2014), there is a growing propensity to resort to digital tools, which are frequently imbued with ‘technological solutionism’ (Vigouroux-Zugasti, 2018). The advent of digital technologies generates promises regarding their ability to contribute to the improvement of a variety of economic sectors, including agriculture and food. These tools are often presented as powerful vectors for empowerment, transparency, and disintermediation (Jouanjean, 2019). From simple matchmaking to the complex management of Big Data or secure transactions, the expectations placed upon these technologies are manifold and diverse. However, concrete experience reveals a reality that is often more nuanced, if not contrasted, where initial promises collide with technical, social, economic and governance challenges (Pandey *et al.*, 2022). This chapter proposes to explore this tension between the expectations raised by digital tools as intermediation instruments in the agricultural and food sectors and the realities observed through several studies funded or labelled by #DigitAg, alongside an analysis of recent literature.

► Digitalising intermediation in agriculture: which tools? which challenges?

The tools

The agricultural and food sectors have witnessed the emergence of a diversity of digital tools aimed at facilitating the ways in which actors exchange and coordinate. The #DigitAg social science PhD research projects mentioned in this chapter primarily focused on three tools: digital platforms, data platforms and blockchain technology.

Digital platforms create interfaces that facilitate interactions between different types of actors (Chen *et al.*, 2022). While food platforms organise transactions between farmers and their clients (Chiffolleau *et al.*, 2018), data platforms concentrate their solutions

on data collection, storage, cleaning, transformation, analysis and governance, etc. Blockchain is “a digital, decentralised, and distributed ledger in which transactions are recorded and added chronologically with the aim of creating permanent and time-stamped records” (Treiblmaier, 2018; p. 547).

Digital farm food platforms

Farm food platforms provide websites that aggregate the offerings of multiple farmers, allowing consumers to order and subsequently collect their purchases from collection points or have them delivered (Chiffolleau *et al.*, 2018). These platforms appear to meet a dual objective: adapting to the growing demand for e-commerce and bringing farmers closer to consumers (Guillot *et al.*, 2022).

Although grouped under a single name, farm food platforms cover a diversity of operational methods and services. They can be managed by private entities or associations of farmers and/or consumers, involving varied governance and funding models. Some are organised into national networks, such as *La Ruche qui dit Oui!* (The Food Assembly) or *Les drives fermiers, Bienvenue à la ferme* (farm drive-thrus). Others are independent entities operating at a local or national scale, such as the *pourdebon.com* website. These platforms also differ in terms of the services (e.g. logistics) offered to farmers. Furthermore, the degree of farmer involvement in governance and decision-making varies significantly from one platform to another.

Food data exchange platforms

Food data exchange platforms enable the collection, sharing and analysis of data along the complete agricultural and food value chains (OECD, 2017). These platforms aim to centralise and share information (climate, yield, input prices, seed varieties, etc.) across the entire supply chain, from production to distribution. The objective is to improve traceability, compliance with standards, and logistical efficiency (Jouanjean, 2019).

In particular, these agricultural data-collection and sharing platforms allow farmers to make more informed decisions, thereby improving their productivity and competitiveness.

The blockchain in the agri-food sector

Initially developed to enable cryptocurrency exchanges within a peer-to-peer network without the need for a central authority, the blockchain has been introduced into food supply chains to establish end-to-end traceability systems (Momot *et al.*, 2018; Taherdoost and Madanchian, 2023; Saucède, 2022). It should ensure the origin and traceability of products, provide transparency regarding stakeholder practices, and promote the sustainability of supply chains (Giganti *et al.*, 2024). A key promise, underpinned by the decentralised governance of blockchain technology, is the positive evolution of the principles for integrating the fragmented networks of actors that comprise agri-food supply chains (Srivastava and Dashora, 2022). This technology is perceived as a tool capable of establishing trust between actors and facilitating exchanges without the intervention of a central authority.

The hopes raised by these technologies: for whom? and why?

The adoption of these digital tools in agriculture has raised numerous hopes by providing transparency, sustainability and competitiveness.

Expectations regarding transparency

Food value chains have been at the forefront of exploring blockchain since it emerged as a promising technology for their management. Applied to the food supply chain, it could ensure the security of records and data, while eliminating the risks of hacking and data theft (Duan *et al.*, 2020). The integration of this technology is presented in the literature as having significant social impacts (Mangla *et al.*, 2022), such as local integration, rural development, the reduction of food fraud, animal welfare, food safety, education, the promotion of healthy eating, and social acceptability through greater transparency.

For instance, inspections, certifications and other intermediary validations of a product with a Geographical Indication (GI) could be recorded on a blockchain. This transparency for stakeholders would assist the GI rights holder in recording and clearly communicating product compliance (Aronzon, 2019). Within this type of value chain, blockchain would enable the provision of information derived from continuous verification rather than simple sampling. Naturally, it is recommended that this data be shared in a useful and actionable format that complies with the standards used by the relevant actors (Brett *et al.*, 2020).

Consumers, as well as supply chain actors, expect digital tools—particularly blockchain and data exchange platforms—to provide improved transparency concerning the origin, production conditions and prices of agricultural and food products (Cozzio *et al.*, 2023).

Hopes for disintermediation

Blockchain, through its capacity to facilitate peer-to-peer transactions, is frequently cited as a driver of such disintermediation. Described as a ‘trustless’ technology, it allows entities that do not know or trust one another to conduct exchanges by relying on the protocol and embedded rules (Goldsby, 2024; De La Rosa *et al.*, 2017).

Beyond blockchain, the use of data exchange platforms for managing landrace seeds (or ‘farmers’ seeds’) also illustrates the potential for disintermediation within the agricultural sector. Indeed, in the current dominant model, seeds are integrated into a complex intermediation system where seed companies, certifiers and regulatory bodies (at both national and supra-farm scales) play a central role as intermediaries between genetic resources and farmers. This intermediation relies on legal mechanisms for protecting intellectual property that favour technical progress in the sector (patents, Plant Breeders’ Rights), which limits producers’ autonomy. To address this, movements engaged with landrace seeds propose a radical disintermediation by treating seeds as commons (Aboueldahab, 2023). Within this framework, digital tools are envisioned as supports facilitating this disintermediation, notably through:

- The documentation and sharing of knowledge regarding landrace varieties directly between producers, bypassing centralised official catalogues.
- The collective management of seed resources at local area scales.
- The organisation of seed exchange and reproduction systems that operate outside traditional commercial circuits.

In certain economic sectors, online sales platforms have provided an opportunity to restructure value chains by offering direct access to the final customer (Gandia *et al.*, 2016). Traditional food value chains are characterised by a high number of

intermediaries between the farmer and the consumer (processors, central purchasing bodies, hauliers, distributors). Food platforms can thus limit, or even eliminate, these traditional intermediaries. In the case of a platform managed by a private entity, only one intermediary remains between the farmer and the consumer. This offers the possibility of bridging the gap between these actors, as the digital interface facilitates direct exchange. Platforms managed by farmer groups, for their part, eliminate intermediaries entirely. They represent a compelling opportunity for farmers to develop direct sales, as the costs and resources required are pooled among the users.

Prospects for empowerment and regaining control

Farm food platforms represent several opportunities for farmers to better control the marketing of their products. Firstly, they could offer access to new markets, both local and international (Giampietri and Trestini, 2020). Indeed, the digital interface could improve the visibility of producers' offerings to new audiences or those further afield compared to traditional value chains. These platforms would thus constitute new outlets, allowing better anticipation of commercial fluctuations and increasing bargaining power relative to traditional actors and intermediaries.

These tools could enhance the economic benefit of the efforts undertaken by farmers to offer higher quality products. Most platforms allow producers to describe their production practices, thereby providing more information to consumers. This enables farmers to communicate with clients while limiting the financial and time costs, which are pooled among platform users (Wang *et al.*, 2022). This approach is thought to bolster consumer trust and loyalty (Morris and Penri, 2017), thereby securing sales and granting the producer greater control over marketing.

This regain of control is also shown in the reduction of the number of intermediaries between the farmer and consumers.

Blockchain for food value chains has also been discussed as a technological expression of a 'modern inverted panopticon' or 'horizontal panopticon', in which the 'monitored' could become 'monitors', and *vice versa* (Robb *et al.*, 2020). The horizontal panopticon would thus be characterised by the surveillance and monitoring of everyone by everyone, with the objective of visibility and transparency.

» Intermediation revisited in the light of recent research and #DigitAg publications: findings and recommendations

A study of the uptake of digital tools in agriculture reveals tensions and paradoxes that significantly temper initial hopes.

Tensions and paradoxes associated with digital intermediation

Whilst these digital tools offer undeniable benefits, they are also the subject of criticism.

Factors of exclusion

Firstly, the access to and effective use of digital tools require specific skills, infrastructure and investment that may exclude small-scale farmers and create a new digital divide (Viano *et al.*, 2022). Furthermore, if data generation systems are too costly or complex, they may create a gap between developed and developing economies (Jouanjean, 2019).

Secondly, poor connectivity is not the sole reason for farmer exclusion or non-participation in certain digital projects (Zheng *et al.*, 2018). Other reasons, linked to strategic or organisational choices, come into play. These may involve the farmers' own choices—some preferring not to engage beyond the minimum requirements for traceability—or indeed the orientations of project leaders. The latter may voluntarily restrict farmer participation by confining them to a secondary role or by only partially informing them of the usage made of their data.

Another critique concerns the technological dependency induced by certain digital tools. When a tool is developed by an external actor—such as a start-up, tech company, or institution—and the farmer becomes dependent on its proper functioning, updates, or technical maintenance, it can lead to a loss of autonomy. In the event of a service disruption, the developer abandoning the project, or an evolution of the business model (e.g. transitioning to a paid service), the farmer faces difficulties if they do not master the tool or lack alternative options. This power asymmetry between designers and users highlights critical issues regarding technological sovereignty and farmer independence.

Finally, when it comes to sharing traditional farming knowledge through a digital tool, it is essential to ensure the protection of everything shared. Initiatives such as the CONECT-e platform illustrate this approach by transforming knowledge into digital commons (Calvet-Mir *et al.*, 2018): knowledge is freely accessible, protected by 'copyleft' licences, and documented through participatory methods. However, it is vital that this sharing is conducted with respect for the communities holding the knowledge, ensuring their consent, recognition, and an equitable return of any benefits. The challenge lies in finding a balance between openness and knowledge sovereignty to prevent any form of exploitation.

Data centralisation and power asymmetry

Research into digital platforms highlights the sector's domination by actors who concentrate access to infrastructure and data. While blockchain promotes decentralisation, digital platforms can, conversely, lead to a new form of centralisation of power and data in the hands of platform operators (Thompson and Rust, 2023). This can create new information asymmetries and dependencies for farmers.

The digital tool does not, therefore, significantly alter the power dynamics between actors within a value chain (Commandré *et al.*, 2023). It merely maps out an existing coordination pattern. Blockchain projects reveal that producers remain confined to their production roles. They are rarely actors in the communication conducted via the blockchain. They do not obtain additional information about the value chain despite their indirect participation in it. Certain aspects of these projects remain beyond their reach (how data is hosted, the types of information recorded in the blockchain, or what the technology itself concretely entails). It appears that only the actor steering the project (often the project owner) understands and controls the entire system.

Remediation rather than disintermediation

While platforms raise hopes of bridging the gap between farmers and consumers, they actually constitute a new intermediary. Their operation as a two-sided market and their role in orchestrating the co-creation of value can be difficult to grasp (Saucède and Vidal, 2024).

Platforms employ two distinct intermediation strategies (Guillot *et al.*, 2023). The first consists of fostering interactions between farmers and clients to create cooperation (*iungens*). The second, in contrast, aims to keep them relatively separate by communicating little information and limiting meetings or interactions (*gaudens*). A platform adopting the *gaudens* strategy uses its intermediary role to capture power and make itself indispensable to the exchange. Consequently, the use of a platform is not always synonymous with disintermediation for the farmer.

While blockchain offers potential for decentralisation and disintermediation, its adoption and impact on power dynamics are complex and depend heavily on the institutional and socio-cultural dynamics at play (Thompson and Rust, 2023).

In the Australian seafood supply chain sector, for example, key stakeholders such as wholesalers—who hold considerable power and established networks—might resist blockchain adoption if it threatened their competitive advantage by reversing information asymmetries regarding prices and origin (Thompson and Rust, 2023).

Although blockchain offers mechanisms for transparency, traceability and potentially decentralisation, its adoption by the central actors of a chain does not guarantee a modification of power dynamics. Dominant actors can influence the adoption of the technology or even configure it in such a way as to preserve or reinforce their position.

What recommendations? Should the adoption of digital tools be a strategic decision?

The adoption of digital tools as a strategic decision raises the fundamental question of how these instruments can genuinely satisfy the expectations they have generated.

Genuine transparency and fair information-sharing

According to Arduin and Ziam (2024), digital tools must be designed to guarantee effective transparency and a balanced sharing of information among all actors in the value chain. This implies establishing clear and participatory governance mechanisms to oversee the collection, use and sharing of data (Viano *et al.*, 2022).

The development of digital tools must also be conducted inclusively, integrating farmers from the earliest design stages (Hanappe, 2018). Their active participation ensures that solutions truly meet their needs. This co-construction promotes better appropriation and increased trust in the proposed technologies. Furthermore, it is essential to implement legal and technical protection mechanisms that guarantee data control for farmers (Chapter 13). This presupposes clear terms of consent, traceability of data usage, and the possibility for producers to retrieve or transfer their information. It is also advisable to design open and interoperable models that avoid technological lock-in and ensure data portability. Finally, beyond technical aspects, recognising the central role of the farmer as an actor in innovation is crucial. This implies an equitable sharing of the value derived from data and tools, as well as the strengthening of local capacities to maintain and adapt these technologies over the long term.

The imposed or chosen dimension (depending on the farmers) and co-design

The adoption of digital tools must not be imposed upon farmers, particularly small-holders. It is crucial to account for their specific needs, skills and constraints, and

to offer them alternatives alongside tailored support. Regarding blockchain, Viano *et al.* (2022) suggest that the design of blockchain platforms must be intuitive and accessible, even on low-cost devices.

The positive outcomes of using digital tools for marketing depend greatly on whether their adoption is imposed or chosen. Farmers are sometimes forced to use tools by downstream actors within the value chain, or they adopt them under competitive pressure. In these situations, digital technology induces more negative repercussions for the farmer, such as an increase in transaction costs (Guillot *et al.*, 2023). Conversely, when the digital tool is chosen by the farmer and adapted to their overall commercial strategy, numerous advantages are associated with its use.

Thus, a better understanding of how farm food platforms function is necessary for the farmer to choose the one best suited to their needs. Different types of platforms can, in fact, serve distinct commercial strategies. If a farmer wishes to create a new outlet to market a large portion of their production, an *iungens* platform is more appropriate. It will involve them in decision-making and offer them direct contact with consumers. In contrast, a farmer seeking an outlet to periodically dispose of surpluses will find it advantageous to use a *gaudens* platform, which requires less commitment.

The key question of governance

Research from #DigitAg referred to in this chapter (Aboueldahab, 2023; Commandré *et al.*, 2023; Coulibaly *et al.*, 2023 and 2024; Guillot *et al.*, 2022 and 2023) has shown that food supply chain actors are involved to varying degrees in the governance of the digital tools they employ. Governance refers to the rules, procedures, and processes used to control and coordinate the actions of an organisation's members (Lumineau *et al.*, 2021; Coulibaly *et al.*, 2024).

This question of governance, rarely considered at the time of platform selection, would benefit from being considered as a genuine strategic choice. Likewise, regarding blockchain, it is imperative to address the issue of governance from the design phase, carefully considering the various actors involved and their specific expectations. The choice of governance mechanisms (consensus, smart contracts, on-chain and off-chain mechanisms, access rules, etc.) must be strategically aligned with these considerations to ensure the success and sustainability of the blockchain platform (Goldsby, 2024).

It is therefore indispensable to implement transparent, inclusive, and accountable governance models to prevent abuses of power and ensure an equitable distribution of the benefits of these technologies. Furthermore, Chen *et al.* (2022) explain that particular attention must be paid to the legal and regulatory dimensions surrounding the implementation and operation of these technologies, as legal uncertainty and the absence of specific regulations hinder the large-scale adoption of blockchain technology. The issue of the legal aspects of agricultural data governance, which was the focus of Laura Tomasso's #DigitAg law thesis (Tomasso, 2023), will be examined in Chapter 13.

► Conclusion

Digital tools represent a powerful lever for transforming intermediation within the agricultural sector by fostering the empowerment of actors, strengthening transaction transparency, and improving the efficiency of value chains. However, behind

these promises, major critical challenges emerge. The use of digital tools in the agricultural sector can at times reinforce farmer autonomy, yet at others increase their dependency on the actors behind these systems. These tools also reconfigure relations between different stakeholders by establishing new intermediation dynamics. Thus, they may play an emancipatory role but also engender new forms of dependency or power asymmetries.

These tensions are part of socio-technical lock-in dynamics, understood as forces and power relations that tend to produce stabilised forms, which sometimes ‘become irreversible’ for at least a certain period (Callon and Ferrary, 2006; p. 38), thereby limiting transformation capacities. In the agricultural context, these lock-ins can hinder a much-desired agroecological transition (Guichard *et al.*, 2017) and fuel local controversies that can take many forms and yield results of varying degrees of satisfaction, with a transition that is “in practice, marginal” (Pahun, 2020; p. 4).

For digital tools to fulfil their promises and contribute to a more equitable and beneficial intermediation for all value chain actors, it is imperative to adopt a strategic approach. This must be focused on transparency, inclusion, informed governance, and the consideration of farmers' specific needs. Only such an approach will enable us to move from (multiple) expectations to realities more closely aligned with the hopes raised.

» #DigitAg doctoral theses contributing to Chapter 7

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Tomasso L., 2022.	The legal framework for data in the digital agricultural environment, PhD thesis. https://theses.fr/2022UMOND031

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Part 3

How digital technology contributes
to key agricultural challenges

Chapter 8

Contributions of digital technology to plant phenotyping

Benoît de Solan, Marie Weiss

Phenotyping in agriculture aims to characterise the state and functioning of crops to establish the link between genetic information, plant functioning, and varietal traits within an agricultural context or to compare cultivation practices. The same applies to livestock farming where there is a long tradition of linking animal genetics to performance, particularly in dairy production. Traditionally, for plants, measurements were carried out through visual scoring, which lacked precision, or through destructive methods that did not allow for the temporal monitoring of the same plants. As with animal phenotyping, data acquisition is often costly and tedious; they are therefore frequently collected in small quantities, which represents a bottleneck for varietal or animal selection in the exhaustive study of genotype $\times$ environment interactions. For approximately fifteen years, high-throughput phenotyping has received much attention. Indeed, technological progress and the development of various sensors (RGB, hyperspectral, thermal imaging, LiDAR, multi-vision)—either fixed or embedded on robots or drones for plant phenotyping (see Chapter 1)—and rapid non-intrusive analytical methods (tomography, NMR, ultrasound) have profoundly changed this situation. Measurements are becoming non-destructive, non-invasive in most cases, low-cost, repeatable, and suitable for regular monitoring throughout the entire vegetation cycle.

Phenotyping data processing methods have also been developed. These aim to interpret an electromagnetic signal reflected or emitted by the phenotyped object (crop canopy or animal). Depending on the acquisition system, this signal is characterised by a specific spatial footprint (for example, a projected surface in RGB or spectral imaging, or a 3D point cloud in stereovision or with LiDAR) and a given spectral domain. It is the exploitation of these various characteristics that gives access to a particular trait. The development of artificial intelligence, specifically deep learning techniques, has revolutionised image processing practices through high performance and relative ease of implementation. Indeed, numerous neural network architecture models, often pre-trained, are available as open source and are therefore reusable and adaptable for a given application. Deep learning establishes a direct relationship between images and expert-annotated representations, such as an object located within the image (a wheat ear) or a spatialised measurement (canopy temperature on a micro-plot). To achieve this, the algorithm calculates a large number of simple descriptors within the image (edges, gradients, textures, colours, etc.) and assigns them a non-zero value if the form

is present in the object of interest. This combination of a large number of multi-scale simple descriptors allows the definition of complex objects in a manner similar to human vision.

This chapter primarily presents plant phenotyping research in arable crops and arboriculture that has received support from #DigitAg. These studies address issues at various scales—the organ, pure stands and species mixtures—and different dimensions—reflectance spectra, images and 3D information—providing a panorama of the current possibilities enabled by these technologies. Phenotyping is also used on animals as described in details in Chapter 9 of this volume.

► Global Wheat Challenge: An international initiative to automate wheat ear counting via image analysis

Estimating wheat ear density is emblematic of traditional phenotyping and its limitations. It involves visual counting in the field, typically performed over an area of approximately one square metre. It is a time-consuming, tedious and relatively imprecise measurement due to restricted sampling. Nevertheless, this density is a critical component of final yield. Consequently, automating counting through image analysis has been the subject of extensive research for some fifteen years. However, the diversity of the ‘ear’ object—varying with genotype or growth stage—combined with complex spatial arrangements involving visual obstruction and overlap, hampered good detection performance (Cointault and Gouton, 2007). The doctoral research of Etienne David (2021) led to a robust solution that is now used operationally in high-throughput phenotyping processing chains.

Initial applications of deep learning to ear counting in small trials demonstrated that detection in field-acquired images was satisfactory, provided there was training on a dataset representative of the domain of application (Madec *et al.*, 2019). The primary constraint of these techniques is the requirement for a sufficient dataset to allow the algorithm to generalise the ‘ear’ concept effectively, enabling its application to varied lighting, colour and morphological conditions.

The subsequent step involved building a diversified dataset. On the initiative of Arvalis, INRAE, and the Universities of Saskatchewan and Tokyo, the Global Wheat¹⁸ consortium was established with partners from Europe, Asia, America and Australia, who pooled images acquired from wheat fields worldwide. This shared dataset contains 6,000 images in which over 300,000 individual ears have been expert-annotated (David *et al.*, 2020; 2021).

This dataset was then proposed within the framework of data challenges organised in 2020 and 2021. The first, the Global Wheat Challenge, was hosted by the Kaggle¹⁹ platform. The 2,235 participants were evaluated on the performance of their detection models using a dual dataset: data from Europe and America were provided to competitors to train their models, which were then evaluated against ‘hidden’ data from Asia and Oceania. Interestingly, the performances of the teams achieving the highest detection rates on this data were similar, despite using different algorithms. All participants emphasised the importance of data augmentation, which involves

18. <http://www.global-wheat.com/>

19. <https://www.kaggle.com/c/global-wheat-detection>

artificially increasing the size and diversity of a dataset without collecting additional data (for example, by modifying brightness or contrast, or adding noise). The fusion of results from different models also appears beneficial for increasing the robustness of the results. This confirms the critical importance of the dataset and the training strategies employed. The final version of the dataset²⁰ has been downloaded more than 8,000 times since its deposition in July 2021.

The highest-performing models were subsequently implemented and applied independently of the training set to images acquired since 2016 by various Arvalis, INRAE, and Hiphen phenotyping systems. The transition from ear detection (Figure 8.1a) to an estimation of surface density was made possible by integrating the sensor-to-crop distance measured by LiDAR or stereovision. The results obtained via image analysis were compared against visual field counts by Arvalis. The errors, measured by the RMSE, were 60 ears/m² for an average density of 550 ears/m² when comparing results per plot, noting that the sampled zones differed. Comparisons at the quadrat scale—that is, when the image is taken at the exact location of the count—showed an RMSE of 37 ears/m², which is of the same order of magnitude as the uncertainty associated with the visual method (Figure 8.1b).

► Digital phenotyping of mixed crops

In agroecology, the intercropping of cereals and legumes (notably lucerne) is considered an advantageous combination for enriching the soil with carbon and nitrogen while limiting the growth of weeds. This practice is however delicate to manage because if the alfalfa develops too rapidly it can smother the cereal crop. One avenue for improvement is the selection of alfalfa genotypes showing limited competitive ability with regard to the cereal. However, phenotyping of these mixed plots is a complex task to perform in the field through simple visual estimation. Therefore, the development of digital phenotyping methods is a promising route for the selection process. This requires the development of algorithms capable of distinguishing between mixed species within an image. This is an essential step to measure specific traits of interest that are difficult to estimate by hand.

The internship of Guillaume Studer (2021) initiated this approach with substantial annotation work, supplemented by the postdoctoral research of Tristan Dubos (2022) and existing datasets. A total of 6,000 images measuring 512 × 512 pixels was compiled and manually annotated, then used to train and evaluate deep learning models. These images feature a significant diversity of developmental stages, acquisition systems, and agrometeorological conditions, as well as various different cereal and faba bean species. Several model architectures and training strategies were tested: a U-NET architecture with class prioritisation via the cost function and different species distributions within the training sets (Studer, 2021), and a U-NET architecture trained on easily annotated pure culture images (approximately 8,000 images) with fine-tuning on a limited number of mixed-crop images (250) which are more tedious to label. This work was continued by Serouart *et al.* (2025a) within the framework of the AgroEcoPhen project of the PEPR 'Agriculture and Digital Technology'. The model, currently based on a SegFormer architecture, was evaluated for prediction on a batch

20. <https://zenodo.org/records/5092309>

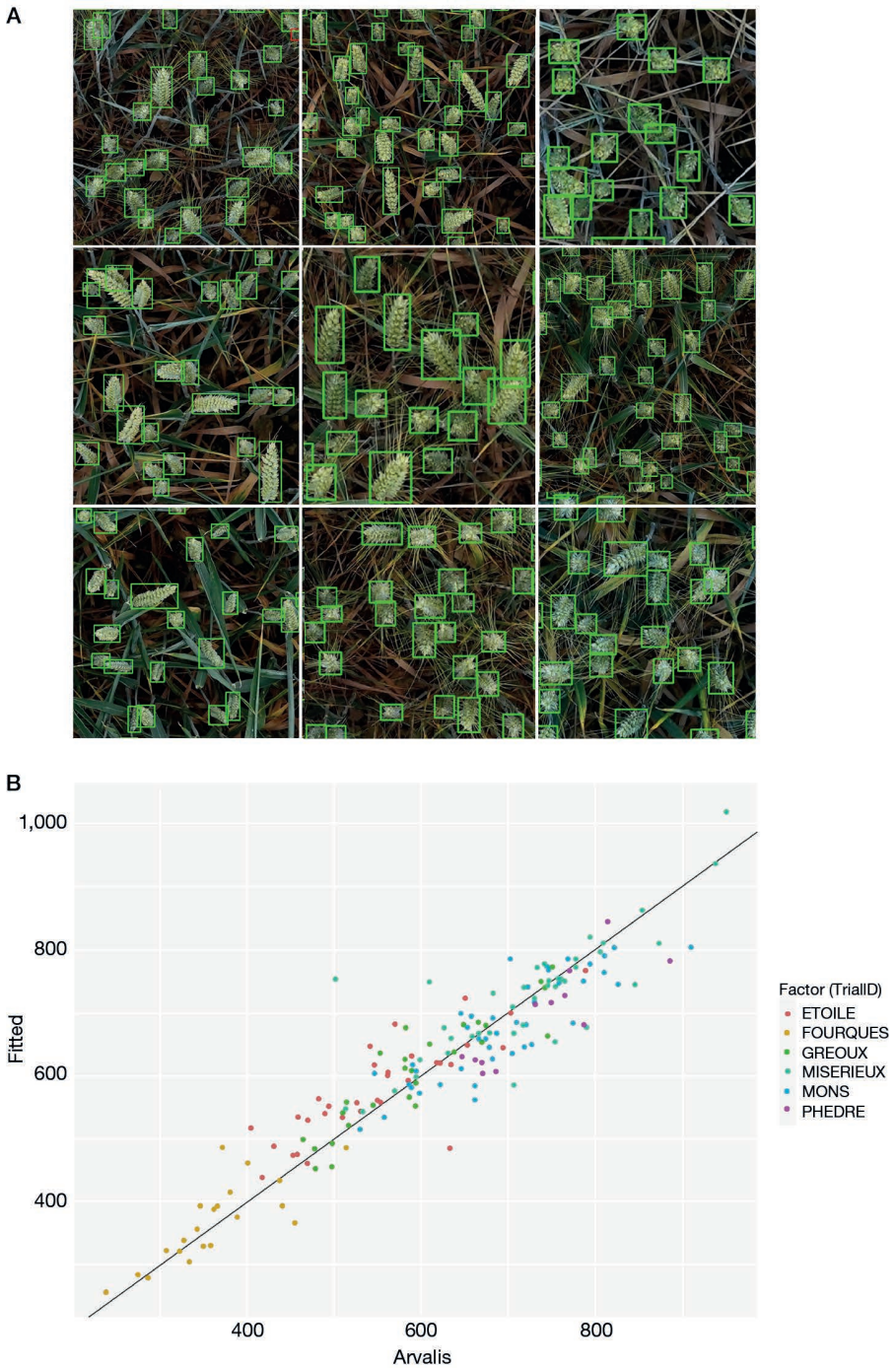


Figure 8.1. Estimation of wheat ear density through automated image segmentation. (A) Example of annotations from the 2021 Global Wheat Challenge (David et al., 2021); (B) automated counting via deep learning versus manual counting of wheat ears. Measurements conducted in 2023 across 5 Arvalis sites and 119 micro-plots at the scale of individual 0.25 m^2 quadrats. Source: Arvalis.

independent of the training phase (representing 30% of the complete dataset) with very satisfactory predictive performance: 0.91 for the IoU ('intersection over union', which quantifies the quality of the overlap between the manually annotated image and that generated by the model, where perfection = 1) and 0.96 for the F1-score (another measure of model accuracy that equals 1 if the model is exact).

Finally, a mixed-crop trial has been conducted since 2023 at Gréoux-les-Bains (in south-eastern France) by Arvalis, in collaboration with INRAE (Casdar Bbsocoul project). This trial, which associates a wheat variety with several alfalfa genotypes, was phenotyped by a robot, the *Phénomobile*, equipped with high-resolution RGB cameras synchronised with a flash. In 2024, data were acquired on 21 measurement dates. Each image was analysed using the developed segmentation model to estimate the total soil cover fraction for each species, as well as their respective green and senescent fractions. The temporal evolution of these traits shows the main phases of both crops: the growth and then senescence of the wheat; the growth and the regulation phases for the alfalfa (Figure 8.2). It also highlights differences in wheat development depending on the associated alfalfa genotype, thus paving the way for the use of this technique for larger-scale phenotyping within a varietal selection programme for lucerne genotypes adapted to intercropping.

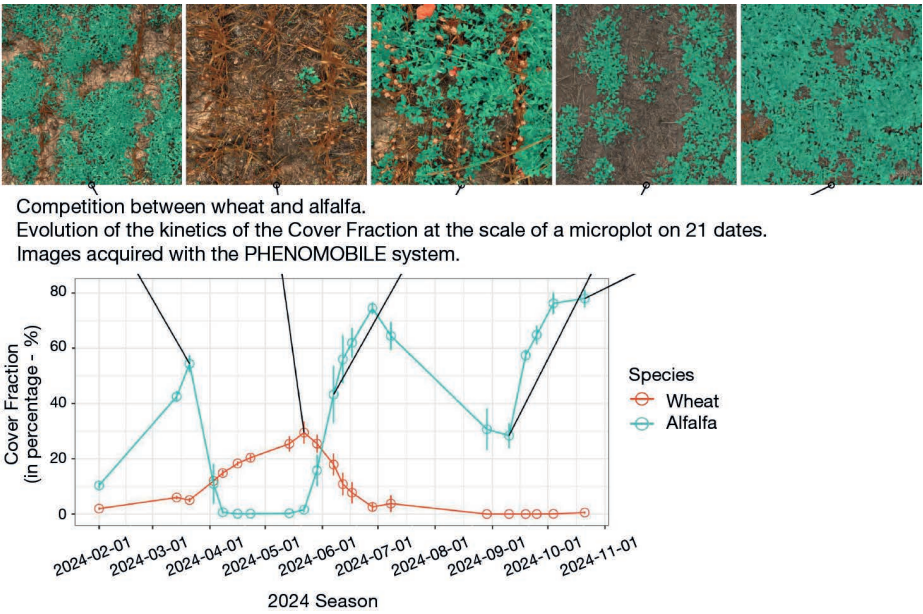


Figure 8.2. Application of the multi-species segmentation model to a trial combining perennial alfalfa with durum wheat. The growth of wheat and alfalfa can be monitored over time to identify the best combinations of genotypes and best practices. Source: Mario Sérouart, Arvalis.

►► Phenotyping 3D structure and leaf orientation to study intraspecific competition in maize

The capacity to increase yield by increasing sowing density depends on the ability of a species (or variety) to tolerate high density through leaf orientation or by modifying the leaf insertion angle. This is known as phenotypic plasticity. The spatial

organisation of maize plants within a field is one of the primary factors in agronomic performance. Depending on their arrangement, they intercept light differently, which influences biomass production and yield. Consequently, understanding the 3D structure of maize plots is a fundamental step in comprehending how stand architecture influences maize productivity.

In his doctoral research, Mario Serouart (2024) developed an innovative measurement method to characterise how plants respond to light competition, particularly through leaf orientation. This method relies on detecting the midrib of maize leaves in RGB images acquired in the field, then calculating the azimuthal orientation of the leaf relative to the row direction. The plant's adaptation to this competition is thus monitored dynamically through regular image acquisitions throughout the development of the maize crop (Serouart *et al.*, 2023).

However, the effects of stand structure on light distribution are not straightforward to determine. Individual leaf area or even the arrangement of leaves—via leaf angles—modifies light distribution within the plant. For this reason, a 3D numerical model (called Cornibu) simulating the architecture of maize plants was developed with adjustable parameters (Serouart *et al.*, 2025b). It is thus possible to recreate any maize canopy according to the foliar architecture, length and orientation specific to each variety and stand structure (Figure 8.3). From such a 3D reconstruction, it was possible to simulate the amount of light intercepted by the canopy, accounting for the weather and solar radiation specific to the latitude of the plot and the season. One can also simulate light quality, such as the red/far-red ratio (R/FR), which serves as an indicator of the shading a plant experiences from its neighbours and determines organ morphogenesis. In practice, the higher the shading, the lower this value.

The results of these simulations revealed significant differences depending on the hybrids grown and the sowing patterns (Serouart *et al.*, 2025b). Specifically, leaf positioning shows a strong predominance of leaves oriented perpendicularly to the row direction as intra-row competition increases. However, it appears that vertical leaf inclination is the primary architectural variable regulating light intensity and distribution. In this regard, plants with more erectophile leaves will result in increased canopy photosynthesis. Finally, the configuration of the sowing pattern plays a crucial role. Reducing the inter-row spacing systematically had a positive impact on yield, regardless of the density considered.

► Estimating architectural traits (vigour, structure) and production of fruit trees in the field

The two primary techniques used to phenotype fruit trees are RGB imaging—sometimes coupled with stereovision—and LiDAR. RGB imaging used alone is particularly effective for detecting or counting objects, whereas stereovision (often referred to as RGB-‘D’ for ‘Depth’) or LiDAR enables a 3D description of the trees (see Chapter 1).

While many papers evaluate fruit production based on RGB images (to count the fruits or estimate their size, Fu *et al.*, 2020), few have successfully accessed production potential via ‘floribundity’, which describes the abundance of flowers and their distribution across the branches. The Master’s research of Marie-Pia d’Argaignon (2022) enabled simple flower counting through the use of deep learning on images

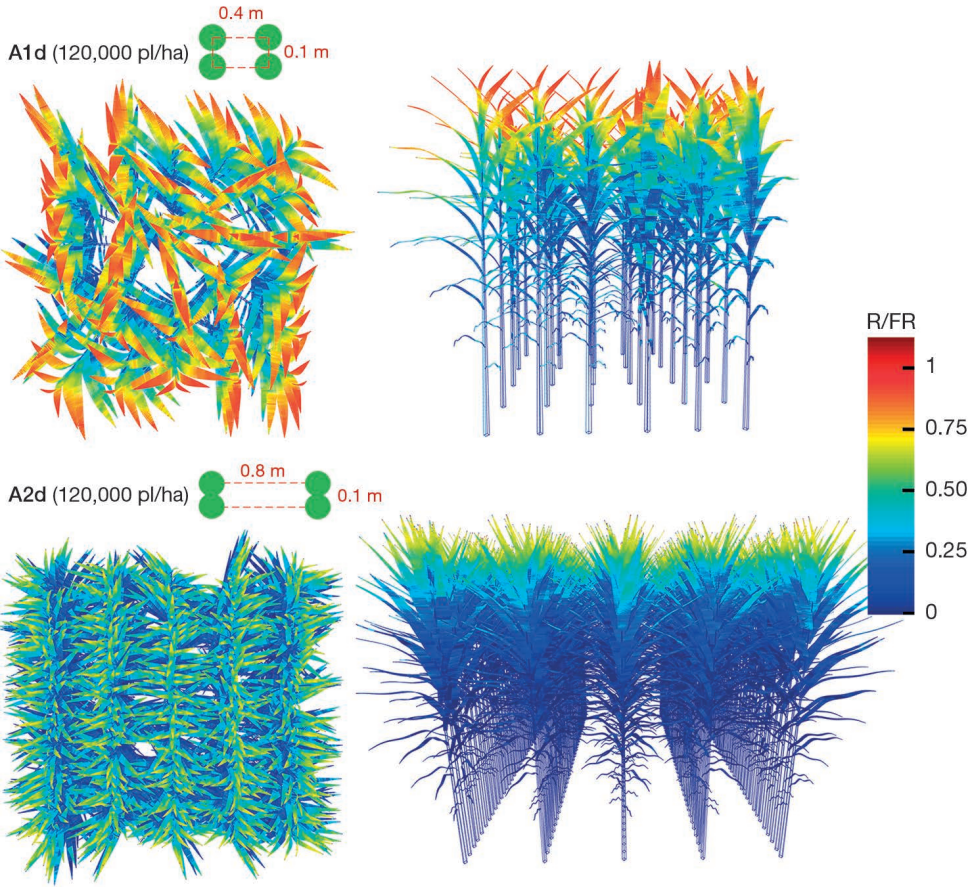


Figure 8.3. 3D simulations reveal that the red/far-red ratio (R/FR) decreases more rapidly with depth when maize rows are dense and closely spaced (bottom), leading to a more significant reorientation of leaves perpendicular to the row direction. Credit: Perspectives Agricoles.

acquired with the Literal pole. Despite satisfactory results on annotated images ($R^2 = 0.87$ between the automated method and visual counts on those same images), comparisons with visual scores assigned by orchard experts showed that field-based visual scoring of floribundity is not limited to calculating a simple index (number of flowers divided by the total branch size in pixels on the tree). It also accounts for the distribution of these flowers across the branches: the more homogeneously the flowers are distributed, the higher the production potential. Assuming that the distance between flowers increases more gradually if their distribution is homogeneous and their density is high, Marie-Pia d'Argaignon proposed to characterise floribundity by calculating the median value and the 10% and 90% percentiles of the distance from every flower to every other flower. She then used these values to classify and, therefore, score each tree (Figure 8.4). Significant differences between visual and digital scoring are still observed, primarily due to the difference in sampling between the two methods (a partial view of the tree via the Literal pole versus the overall assessment by staff in the field).

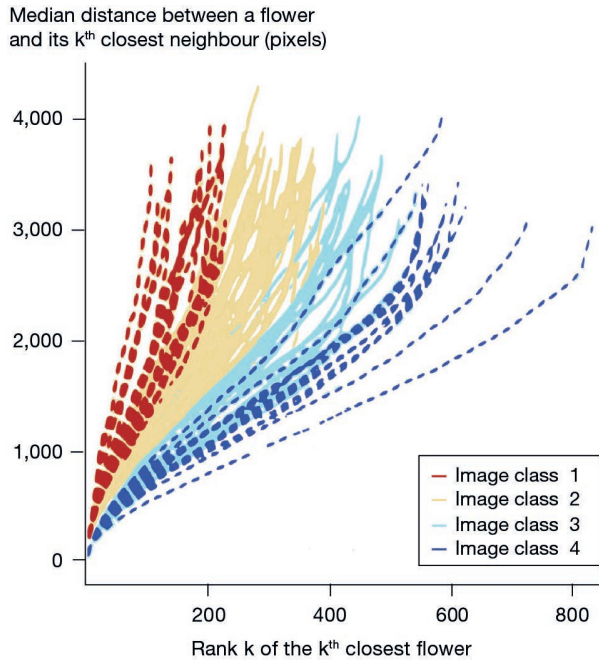


Figure 8.4. Establishment of a *Prunus* floribundity score using digital phenotyping: each curve colour is associated with a score ranging from 1 to 4. Source: based on the internship work of M.-P. d'Argaignon (GAFL Unit, EMMAH Joint Unit).

The work of d'Argaignon (2022), supplemented by the Master's internship of Julien Desforges (2023) and subsequently by the postdoctoral research of Khac-Lan Nguyen (2025), also focused on using field-based RGB imaging to characterise tree vigour (trunk diameter/circumference, pruning weight) using the Literal pedestrian tool or an autonomous robot (Philomene). Images are acquired in winter (when leaves are absent) and stereovision (a deep learning model) is used to calculate the distance from the sensor to the tree, as this varies from one acquisition to another. The processing chain requires a preliminary tree segmentation step, which is also performed using a deep learning method. The work of Khac-Lan Nguyen led to the development of a general method that functions on both the Literal (natural light acquisition) and Philomene (flash acquisition) by incorporating the RGB image and depth information to select only the tree in the foreground of the image (Figure 8.5) (see Chapter 1). The results are very satisfactory, with an overall F1-score of 0.92 on the test image set (F1-score represents the balance between correctly segmenting the woody parts while avoiding erroneous diagnoses; a perfect model would have an F1-score of 1).

Once the woody parts have been extracted, it is possible to calculate trunk diameter (and thus their circumference) (d'Argaignon, 2022; Desforges, 2023) or the total wood pixel area before and after pruning, which can be correlated to the 'pruning weight' (Nguyen, 2025) (Figure 8.6). The results show satisfactory performance, though they are sensitive to the spatial resolution of the images. Generally speaking, whether for 'floribundity' or trunk circumference, imaging results are more repeatable than measuring or scoring manually.

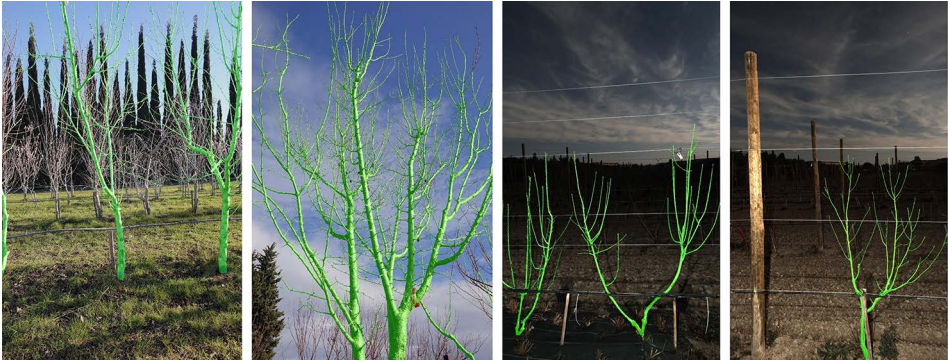


Figure 8.5. Example of segmentation (in green) of trees in the foreground of images acquired with the Literal pedestrian tool (natural light conditions) and the Philomene robot under semi-controlled conditions using a flash (images on the right). Credit: based on postdoctoral research results of Khac-Lan Nguyen, 2025.

Other research conducted in #DigitAg concerns the characterisation of the 3D structure of trees. Following the internship of Branthomme (2021), the doctoral thesis of Juan Pablo Rojas Bustos (2024) focused on characterising the 3D architecture of fruit trees at both the overall level (shape) and the fruit level (counting and sizing), using either terrestrial LiDAR (high point density, low throughput acquisition) or drone-mounted LiDAR (lower point density, high throughput acquisition). The targeted architectural traits were tree volume determined from the convex or alpha 'hull' of the 3D point cloud, height, 'Star' index (silhouette-to-leaf area ratio), crown size and crown eccentricity. The results show a sensitivity to point cloud density, particularly for traits susceptible to occlusions, which are less visible via drone (Rojas Bustos *et al.*, 2023). Fruit counting was performed exclusively with terrestrial LiDAR (using two resolutions, where the lower resolution allows for increased throughput). Manual annotation of point clouds is extremely tedious and difficult and does not give 100% accuracy. Consequently, this doctoral work also explored an approach to reduce the annotation task by using a Functional-Structural Plant Model (FSPM) to generate 3D apple tree 'mock-ups' and, from there, the corresponding point clouds. However, the results of the LiDAR method are disappointing compared with approaches based on RGB-D data (Bargoti *et al.*, 2017; Zine-El-Abidine *et al.*, 2021).

» Estimating plant physiological traits and stress

A series of studies within #DigitAg has focused on the characterisation and dynamic monitoring of the physiological state of plants under stress to determine the resistance and resilience traits of genotypes faced with such pressure. Most of these rely on infrared spectroscopy and chemometrics to identify the presence of symptoms, or on hyperspectral imaging techniques, which provide spatial information to, for instance, locate and characterise stress symptoms (see Chapter 1). Indeed, plant resistance reactions trigger modifications in physiology (leaf microstructure) and biochemistry that affect optical properties at specific wavelengths (Mahlein *et al.*, 2018). Dynamic monitoring and the use of spectral bands beyond the standard red, green and blue typically exploited in computer vision allow new information to be gleaned, such as the

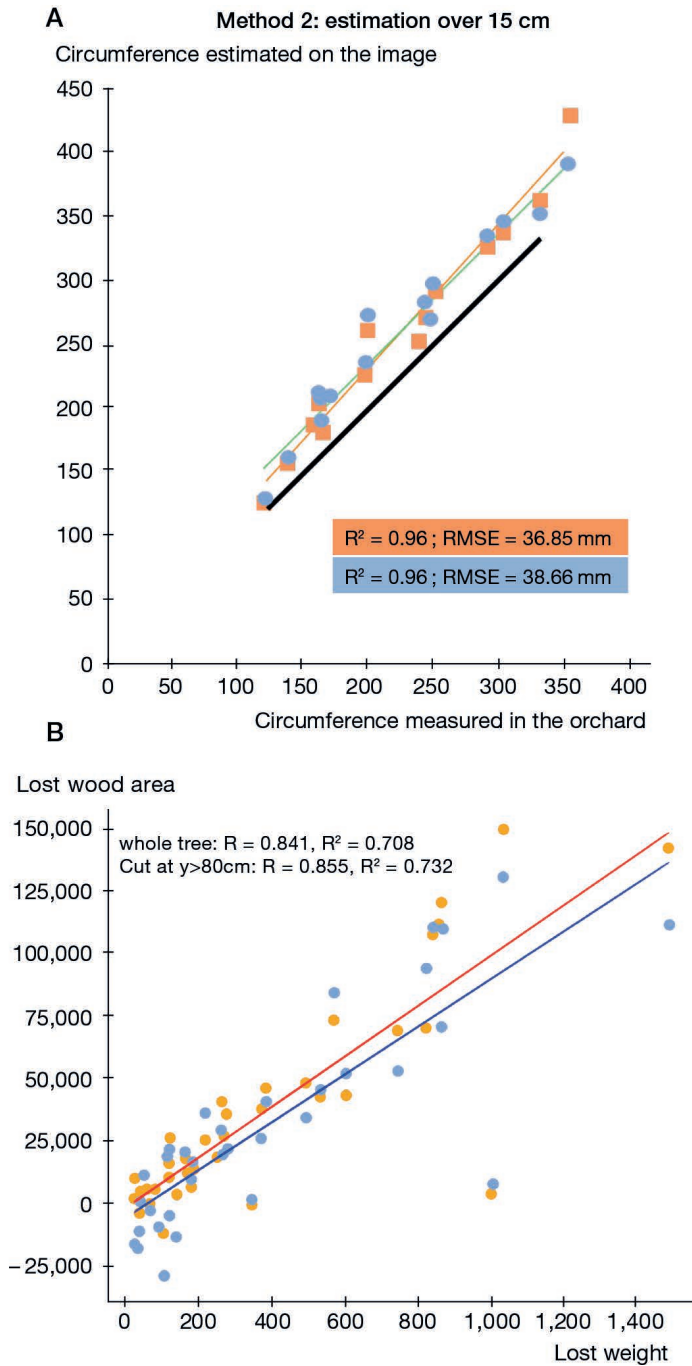


Figure 8.6. Evaluation of fruit tree parameters using computer vision: (A) measurement of trunk circumference by manual segmentation (orange) and automatic segmentation (blue); (B) correlation between pruning weight and the difference in surface area between two image acquisitions before and after pruning, by segmenting the entire tree or excluding the base of the trunk. Source: based on the postdoctoral research results of Khac-Lan Nguyen, 2025.

appearance of anthocyanins within necroses caused by wheat septoria, distinguishing these from senescence (Figure 8.7). In her doctoral thesis, H  lo  se Villesseche (2023) compared supervised and unsupervised approaches to characterise the dynamics of senescence. She demonstrated that knowledge of the biological process improves the performance of these methods (Villesseche *et al.*, 2022).

The implementation of these spectral technologies for field phenotyping remains difficult, as they are either costly (hyperspectral cameras) or delicate to deploy (distance from the measured object, lack of control over illumination conditions or the position of the object of interest, etc). Ryckewaert *et al.* (2021) developed an original method

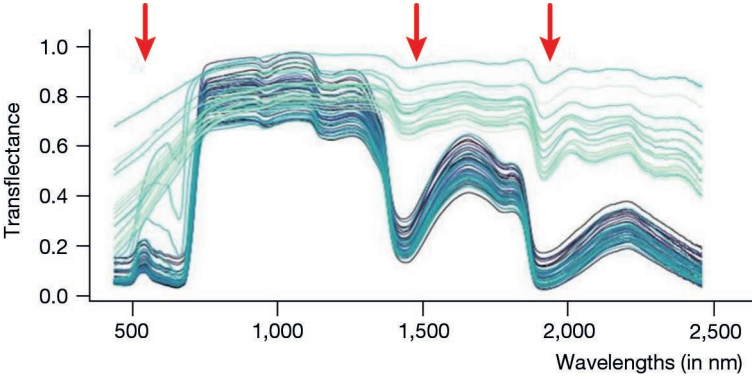


Figure 8.7. Raw spectra (from 400 to 2,500 nm) of an individual wheat leaf during senescence; the very dark blue curves were measured during the flowering period, while the lighter blue curves were measured at the end of leaf senescence. The red arrows indicate the main spectral ranges where signal modifications occur during senescence. Source: based on the work of Villesseche (2022; 2023).

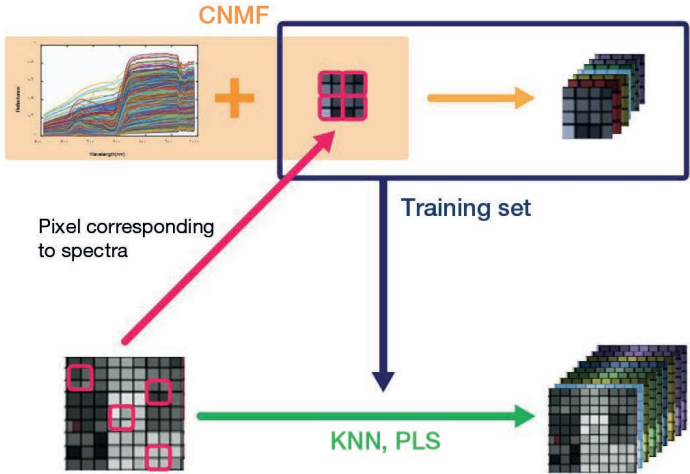


Figure 8.8. The Couple Nonnegative Matrix Factorisation (CNMF) method, proposed in Maxime Ryckewaert’s thesis (2019), is used to reconstruct a hyperspectral image from a panchromatic or RGB image and the spectral information associated with that image. The first step involves matching pixels between the hyperspectral image and the panchromatic or RGB image, in order to assign a spectrum to each pixel of the spatially resolved image, either using the nearest neighbour (KNN) method or the partial least squares (PLS) method.

to perform infrared spectroscopy measurements for the field phenotyping of water stress in maize under natural light. Having simultaneously collected RGB images and near-infrared spectral data, they developed a multimodal fusion method (pan-sharpening) allowing them to spatialise the spectroscopic data by using the spatially resolved RGB image, which is otherwise poor in spectral information (Figure 8.8). Finally, Sherif Bouzaouia (2024) proposed an innovative technology (biospeckle) as an alternative to hyperspectral methods (Bouzaouia *et al.*, 2024). This is based on the analysis of the statistical properties of polarised laser light, backscattered by the leaf and modified according to the plant's stress state (see Chapter 1).

» Conclusion

These use cases illustrate the transformations brought by the adoption of digital technologies in the field of agricultural research and development. They highlight several major trends: (1) the democratisation of field data acquisition tools via sensors mounted on robots, drones, or portable systems; (2) the performance of deep learning algorithms for analysing complex images; and (3) the importance of pooling data from diverse origins. They also demonstrate that the promises of high-throughput phenotyping are finally ready to materialise. The development of estimations for new traits—plant counting, disease quantification, competition against weeds, etc.—can indeed follow a similar approach. The quality and quantity of the variables thus generated pave the way for analyses of unprecedented depth, serving genetic improvement as well as the development of new plant protection products and the definition of innovative cropping systems. Direct uptake of the digital phenotyping tools presented in this chapter by farmers for diagnosis or crop management remains limited. It requires increased methodological robustness and a reduction in equipment costs, which still necessitate significant development effort to allow wider dissemination.

» #DigitAg doctoral theses contributing to Chapter 8

Bouzaouia S., 2024.	Multimodal optical imaging for the detection of stress in plants, PhD thesis. https://theses.fr/2024AGROM045
David E., 2021.	The challenge of robust trait estimates with Deep Learning on high resolution RGB images, PhD thesis. https://theses.fr/2021AVIG0733
Heidsieck G., 2020*.	Distributed Management of Scientific Workflows for High-Throughput Plant Phenotyping, PhD thesis. https://theses.fr/2020MONT066
Nguyen H.A., 2023*.	Connecting the dot between Crop Growth Models, Root Architecture Models, and High-throughput Root Phenotyping Platforms, PhD thesis. https://theses.fr/2023AGRO0055
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Chapter 9

Sustainable livestock farming systems

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The sustainability of livestock farming systems depends on being able to reconcile multiple dimensions to address growing societal concerns within a context of food sovereignty and climate change (Ducrot *et al.*, 2024). These concerns include land use, competition between animal feed and human food, environmental impact (climate, water, pollution, biodiversity), animal welfare, food security (One Health-One Welfare), the economic and social viability of the sector, as well as consumer confidence in response to international competition with variable regulations (Faverdin *et al.*, 2020). Agroecology is one viable way to address these concerns: better animal health, reduced inputs, lower environmental impact and increased biological diversity on farms to improve resilience and biodiversity (Dumont *et al.*, 2013). Practices are also changing in response to regulations (biosecurity, animal welfare, feed efficiency), all while preserving productivity levels that ensure the economic viability of livestock farming in a context of fluctuating prices. This affects all types of livestock farms, depending on the access animals have to the outdoors or on the plant resources found on the farm. To respond to these complex issues, digital technologies are increasingly providing livestock farmers with support. Individual animal identification, sensors, automation, decision support tools (DST) and other technologies can be used to monitor animals (health, behaviour, nutrition, production) and their environment more accurately. These tools also make it easier to monitor resources and impacts, irrespective of the type of farming system (Faverdin *et al.*, 2020; Brossard *et al.*, 2022). This use of digital technology to support livestock systems was one of the major challenges (Challenge 4: 'Sustainable animal production') of #DigitAg, the Convergences Institute for Digital Agriculture (see Chapter 12). The objectives of this challenge focused on the various aspects of livestock farming that could be improved with digital technology, whether this involves data collection, the use of models to integrate these data and support multi-criteria performance objectives, or even economic and social considerations. The 'animal welfare' dimension has gradually taken on a more important role in the research carried out by #DigitAg given the heightened awareness surrounding this topic in the 2020s. Given that livestock systems are based on multiple dimensions, the research carried out under Challenge 4 was interconnected with other research axes within the #DigitAg Convergences Institute, in particular: Axis 3, 'Sensors and data acquisition and management'; Axis 5, 'Data mining, data analysis, knowledge extraction'; and Axis 6, 'Modelling and simulation'.

Based on work conducted within the #DigitAg Convergences Institute, this chapter provides examples of the ways in which digital technology can improve the sustainability of livestock farming systems by improving productivity (while limiting environmental impacts), the promotion of animal welfare and support for pastoralism.

►► Monitoring and optimising performances while reducing environmental load

Performance monitoring, the example of cattle

Today, numerous tools are available that can monitor consumption (water, feed), production performances (weight, milk) and reproduction in animals in real-time to improve the management and productivity of livestock farming systems. For example, to be able to combine resource efficiency with economic performance, it is crucial to control water consumption (up to 150 litres/day for one cow²¹) and feed consumption (which accounted for 75% of the cost of pig farming in 2022; Cerfrance, 2023²²). Although there are existing tools that can help farmers better manage this consumption, the main challenge still has to do with the interoperability between these technologies, i.e. their capacity to communicate and run with one another. One such tool is the Internet of Things (IoT), a network that connects 'objects' (sensors, GNSS) to the internet, enabling the centralisation and continuous analysis of data. Activity sensors (accelerometers, cameras and associated algorithms) are a case in point: currently marketed for certain species, they can be used to detect when animals are in heat or have health problems, thereby optimizing reproduction and herd management. Some of the progress made by #DigitAg is listed below.

Performances: milk composition, body condition and weight

To be able to monitor animal performances more closely, milk quality indicators are measured (e.g. quantity and composition) using milk meters and other automatic measurement devices in the milking parlour. For several decades now, animals have been monitored using manual weighing and morphological measurements. In the past several years, three-dimensional (3D) imaging has been applied to livestock farming systems, especially ruminants, with the result that these measurements are now automated, as seen in several #DigitAg studies (see Chapter 1): the weight of cows between 700 and 800 kg has been measured within a margin of error of about 25 kg (Le Cozler *et al.*, 2019a and 2019b); indicators during growth (Le Cozler *et al.*, 2022) or during lactation (Xavier *et al.*, 2022) were monitored, while taking the animals' position into consideration to make the estimated values as accurate as possible (Tiercin *et al.*, 2024). This latter research also demonstrated that it was possible to estimate the animals' chemical composition (Xavier *et al.*, 2024).

21. Consommations d'eau en élevage : entre sobriété et résilience <https://idele.fr/detail-article/consommations-deau-en-elevage-entre-sobriete-et-resilience>

22. Observatoire de la production porcine 2024. <https://normandiemaine.cerfrance.fr/latelier/observatoire-production-porcine-2024/>

Estimating the amount of water consumed

To achieve better control over the amount of water animals consume, their water intake can be estimated using weigh-in water troughs and automated animal identification (RFID chips, collars or recognition using artificial intelligence), or by analysing changes in rumen temperature (Zitouni *et al.*, 2022). Based on the work of Moreau *et al.* (2008), the #DigitAg internship completed by Zitouni *et al.* (2022) showed that it is possible to determine the volume of water ingested by the animal using a weighing device as long as the initial temperature of the rumen and the water consumed are known. Although useful, it is necessary to have a reference value for the rumen volume and to take numerous temperature measurements (every two minutes) to be able to use this method. The approach developed by Nizzi *et al.* (2025) is based on the use of connected water troughs that recognise each animal through an RFID chip. The flow of water at the water troughs is recorded each time an animal drinks, and so it is also possible to track individual water consumption trends.

Monitoring feed intake

Precision (or tailored) feeding is on the rise in livestock farming systems, and is made possible by automation, sensors and tools that estimate the nutritional requirements. The goal is to adjust the ration quantity and composition to individual animals or small groups of animals so as to limit environmental losses and costs without compromising performances. By integrating individual data into nutritional models, it then becomes possible to optimise animal efficiency and reduce environmental impact.

These precision feeding distribution tools (connected feed troughs, concentrate dispensers) are not yet ready for use with large ruminants such as 'dairy breeds'. The Casdar Harpagon project demonstrates that, while the benefits of individualised monitoring and feeding are significant, the lack of repeatability in feed efficiency during lactation for the same cow limits the utility of an individual-centred approach within a European dairy system (Landais, 2024). However, this method may have value for large herds that can be divided into smaller groups of animals or for other types of dairy animals (sheep, goats).

Optimising feeding strategies, the example of pigs

Contrary to dairy cattle, precision feeding systems have already been shown to be highly effective in monogastric animals, such as pigs.

Innovative approaches to precision feeding

Sows have different nutritional needs based on their genotype, parity, prolificacy (number of piglets born), body condition (estimated by backfat thickness, BFT) and even housing conditions. Models have been developed to predict the daily nutritional requirements of each lactating and pregnant sow in an aim to fine-tune the dietary intake of each animal. These models require both farm-based data (such as reproductive performances) and individual data (such as the weight and BFT at insemination, and age). Large Canadian databases were used to validate these models (Gaillard *et al.*, 2020; Gauthier *et al.*, 2019) which show that performances are optimised and waste is minimised with frequent and tailored feed adjustments.

Another innovative approach involves using machine learning algorithms on data that has automatically been recorded by water trough sensors and automated feeding systems. These algorithms can accurately predict ($R^2 > 0.90$) the daily energy and lysine requirements of pregnant sows, thereby making it easier to implement a precision feeding strategy (Durand, 2023). Unlike previous models, historical data or individual characteristics are not needed.

Benefits of precision feeding strategies

Experiments were carried out in gestation rooms to compare the economic and environmental impacts of precision feeding versus conventional feeding. Adjustment of the daily lysine intake allowed a 25% decrease in the amount of lysine ingested, a 4% decrease in feed costs per gestation, and 18% and 9%, decreases in nitrogen and phosphorus emissions, respectively, without affecting the sow performances (weight gain and number of piglets) (Gaillard and Dourmad, 2022). A second experiment, carried out over three consecutive gestations, confirmed these results, showing improved body condition management and better nitrogen efficiency (Ribas *et al.*, 2024).

Finally, when energy and phosphorus were incorporated into these adjustments, an 18% decrease in lysine intake was observed without a negative impact on reproduction. The adjustment of phosphorus at the end of gestation made it possible to better meet the animals' dietary requirements, while limiting feed costs (Ribas *et al.*, 2025).

The contribution of digital tools to monitoring and precision feeding

Behaviour video analysis and artificial intelligence are promising alternative tools for automatically monitoring the physical activity of pregnant group-housed sows. A video analysis tool based on a deep learning algorithm was used to automatically detect the physical activities of sows (standing, lying down, sitting, eating, drinking) with an overall accuracy of 74% (Gaillard and Simon, 2024). If the robustness of these algorithms is improved, it will be possible to integrate this data into nutritional models to adjust the energy intake of sows in real time based on their activity level (Durand *et al.*, 2021).

► Promoting animal welfare using digital innovations

Animal welfare, a positive physical and mental state specific to each individual, fluctuates depending on the animal's perception of their situation. It remains a challenge to assess this state as it is quite complex and based on several criteria. Existing tools (Beep, Ebene, Boviwell, Welfare Quality) provide periodic assessments, although often for groups rather than individuals. Recent digital innovations make more continuous monitoring possible, either of individuals or groups, and facilitate the implementation of measures that will reduce the risks of distress in animals.

Digital tools to reduce the risk of distress

By automating certain tasks, the work of farmers becomes less arduous and gives them more time to do other things. However, certain tools such as automatic feed or water troughs, or free traffic flow for milking robots could result in competition between animals, or be a source of stress and injury, especially for subordinate individuals. While being able to act freely is beneficial to animal welfare, this competition is detrimental to it. To limit the problem, we could increase the number of devices, but this

solution remains costly. One alternative is to motivate animals to feed at a specific time using Pavlovian conditioning (Manteuffel *et al.*, 2009). For example, pregnant sows were given access to feed one at a time. Sixteen sows learned to recognise an individual sound signal (a human voice pronouncing three syllables), letting each sow know when it was time to feed (Blanc *et al.*, 2024). Each sow was first tested individually and responded to the correct signal almost 100% of the time, with a success rate of 72% when tested in groups. This system reduced fighting between the sows and thereby improved the animals' welfare. A similar system was tested in dairy cows for their access to the milking parlour, but results remain limited and the protocol will have to be adjusted.

The goal of other research, e.g. studies based on identifying sounds, is to mitigate common livestock problems such as piglet crushing (Chen *et al.*, 2021) and tail biting (Amichaud *et al.*, 2025).

Useful behavioural measures for detecting animal welfare problems

To be able to assess animal welfare, it is essential to continuously monitor the behaviour, health and emotional states of individuals. Digital technology has revolutionised this behavioural monitoring through the use of automated, continuous and tailored measurements, thereby overcoming the limitations of approaches based on group averages. Even though some tools are still under development, especially in terms of standardisation and high-sensitivity detection, these sensors (wearable or environmental) (see Chapter 1) can be used to collect high-frequency and/or large-volume data. Appropriate mathematical models and statistical analyses now enable this data to be better used to monitor animal behaviour and optimise livestock management (Nguyen-Ba *et al.*, 2020a; Taghipoor *et al.*, 2023).

For instance, Nizzi *et al.* (2022) and Lanthony *et al.* (2022) monitored water troughs and feeders using connected devices to identify the feeding order, animal replacements and hierarchy. In her thesis, Durand analysed video tracking with neural networks (such as YOLO) to identify the animals' physical activities and create 'daily time budgets' (average time spent between different activities across one day), while also detecting disruptions (such as limping, which increases the amount of time spent lying down). As an example, it is possible to detect a sow lying on her stomach or eating with 82–87% accuracy, compared with 47–53% for behaviours that occur less often such as sitting or drinking (Durand *et al.*, 2022). Projects now combine video and audio recordings to improve the detection of behaviours (The PEPR Agroecology and Digital Technology program, WAIT4 project; Gondret *et al.*, 2022).

Even though artificial intelligence can efficiently analyse this high-frequency data using supervised (targeted detection) and unsupervised (exploration of new traits) approaches, it is still crucial that ethologists are involved and use their expertise to validate and interpret these analyses (Riaboff *et al.*, 2021; Girardie *et al.*, 2023; Mauny *et al.*, 2025).

Detecting health problems using feed intake data

Feeding behaviour, especially the quantity ingested, is one of the early warning indicators of a decline in animal welfare status. In line with this, Nguyen-Ba *et al.* (2020a and 2020b) developed a model to characterise the response of an individual animal to a

generic perturbation and then later adjusted this model to the specific case of a perturbation caused by the ingestion of mycotoxins. The model is based on the hypothesis that, for each individual, a theoretical curve or expected feed intake profile exists; the trend of this curve or profile follows the same pattern based on age but with levels that are specific to each animal. When there are significant deviations in the quantities ingested compared with the theoretical curve, these are seen as potential warning signals of animal health or welfare problems.

» Digital technology to support pastoralism 2.0

Pastoral systems mostly rely on the grazing of natural spontaneous vegetation and implies that animals move from place to place depending on the characteristics of the terrain and infrastructures. This mobility requires varying degrees of human monitoring depending on the season. The goals of these systems (mostly concerning ruminants such as sheep, goats, cattle and camels) are the traditional goals as usual (e.g. production, reproduction, health and welfare), which are only profitable with low amounts of inputs. Performances, often quite low per hectare or per individual, must be assessed with regard to the resources utilised. This means that the use of digital technology in these systems comes with specific opportunities but also specific constraints.

Technological challenges in integration, production and maintenance

As these herds are mobile, some studies have used digital tools to monitor populations, such as devices on the animals themselves (tracking sensors) (Scriban *et al.*, 2024) or within pastoral communities (smartphones and specific applications). Intermediate configurations also exist, such as the use of sensors mounted on drones (Nungi-Pambu *et al.*, 2024) or the installation of stationary sensors at gathering points, such as watering holes or frequent herd transit areas. These devices must have a minimum of connectivity across a wide range of environments, which means that there must be a way to either locally integrate the data produced or to have access to reliable long-range telecommunications networks (Kriszt *et al.*, 2023). In some contexts, e.g. environments where human interventions are limited (especially for maintenance purposes), the energy autonomy of these devices is also a determining factor.

Moreover, pastoral management strategies are constantly being adjusted in response to the local dynamics related to animals, resources or multiple uses of this land. This variability leads to a vast diversity of uses and requirements regarding digital tools (Scriban *et al.*, 2024). Consequently, these tools must demonstrate both robustness and versatility.

Use-related challenges

Digital tools are designed to generate, process and send information that will be incorporated into livestock management strategies, and therefore must be based on a dedicated information system that is able to develop reliable and relevant indicators by combining this data with information from outside the livestock farming system. For pastoral farming, these information systems must not only be suitable for the connectivity challenges mentioned above but must also be able to incorporate information that is both heterogeneous (i.e. produced on different temporal or spatial scales) and complex (due to the diversity of the system's components) (Kalenga Tschingomba

et al., 2022; 2023). To be able to use this information in an efficient manner, simple and accessible tools need to be developed that are capable of combining diverse data sources with the knowledge and expertise held by the farmers (Deschamps and Jouven, 2025). One serious constraint has to do with the low level of detail offered by the available information: for example, only a few individuals are monitored among large herds, or the georeferenced data acquired for grazing land quality often has a low spatial resolution (Nungi-Pambu *et al.*, 2024).

For pastoral communities lacking experience or training in digital technologies, the changes brought about in the organisation of work are difficult to anticipate and support (Ferrari *et al.*, 2024). As a result, these populations may be reticent to adopt these technologies, especially when the methods used to assess their reliability and the benefits they have for managing livestock systems are not clearly defined. Thus, digital tools could be used at other levels, e.g. to produce reference data or to provide support for collaborations among the various stakeholders in the pastoral system. The tools could also take the form of models or simulators included in co-design approaches that can be used to assess the impacts of new practices (Laclef *et al.*, 2023). These approaches would directly involve farmers in discussions and experiments, which would then make it easier for them to adopt innovative practices, regardless of if they are based on the use of digital devices.

In conclusion, the challenges of combining digital technology and pastoralism

The reasons for integrating digital technology within pastoral farming practices are the same as for other types of livestock production: to improve the working conditions, to reduce the environmental impact, to improve animal welfare, and to maintain satisfactory zootechnical performances.

However, there are a number of limits associated with this integration that have to do with the inherently agroecological nature of these systems and their low intensification of production factors. On the one hand, for digital tools to be acceptable and viable, they must not only make a significant contribution to the principles of agroecology applied to livestock farming systems, and therefore have reduced environmental impacts (Huck *et al.*, 2024), but they must also improve efficiency without negatively affecting the economic profitability of the farm (Brossard *et al.*, 2022). On the other hand, given that each situation is different, combined with the geographical isolation of pastoral areas and the relatively modest economic weight of this sector, investments from industrial stakeholders able to provide suitable solutions are limited. This lack of structuring in the economic fabric slows down the dissemination of technological innovations designed to respond to the diverse range of contexts within pastoral systems.

Last, digital technology is not imperative for ensuring the sustainability of pastoralism or its ability to cope with major modern-day challenges such as climate change. However, it may play a key role, especially when used by the stakeholders involved with pastoralism who already use digital technologies in their private activities, in line with the use of digital tools by modern-day societies (see Chapter 11). The methods for integrating digital tools within pastoral systems may inspire the agroecological transition of other types of livestock farming systems, by promoting resilience based on profile heterogeneity and process diversification.

» Conclusion: the future of sustainable livestock systems

Sustainable livestock systems are increasingly relying on digital technologies to optimise productivity and animal welfare. Performance monitoring and precision feeding can increase the efficiency of farms, especially those with monogastric animals, while innovations in behaviour monitoring and stress management are opening new opportunities to address individual requirements. The integration of digital technology within pastoral systems is facing constraints stemming from their low-intensity nature and inherent diversity, even if they share the same goals as those found in other types of livestock farming systems. However, digital technology can still contribute to the agroecological transition, provided it is suitable for the specificities of pastoralism and championed by its stakeholders. The future lies in an integrated approach combining advanced technologies, artificial intelligence and knowledge of animal behaviour. This transition requires close collaboration between researchers, farmers and developers, making digitalisation a key lever for addressing the economic, environmental and societal challenges associated with livestock farming.

» #DigitAg doctoral theses contributing to Chapter 9

Danglot M. <i>in progress</i>	Feeding and reproduction strategies evaluated by modelling to optimize the production and reproduction performance of dairy cows as well as their welfare, PhD project
Cotil A., 2024*.	Modeling animal movement: study of Cucker-Smale equations and inference of interaction networks, PhD thesis. https://theses.fr/2024UMONS041
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Chapter 10

Observing, predicting and explaining food security

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Food security is defined as a situation in which “all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life” (FAO, 2006). This definition is based on four primary dimensions: food availability, economic and physical access, nutritional quality (including food safety and dietary practices), and the stability of these three dimensions over time (Barrett, 2010).

This chapter first describes the methods proposed and implemented to observe food security based on indicators at aggregated scales, namely territorial and national ones. It then presents the issues involved in predicting and explaining food security, which have been addressed within #DigitAg through a multidisciplinary framework, mobilising research in data science and artificial intelligence (TETIS), remote sensing (TETIS and AIDA), and economics (MOISA). The results of the various methods put into use and evaluated can support information services for the steering and management of agricultural activity. While this issue is crucial for many countries worldwide, this chapter focuses primarily on work conducted in the Global South and on the African continent, where food security remains a vital challenge.

►► How to measure food security

Food security results from the interaction of agro-environmental, socio-economic and biological factors: it is a complex concept to grasp. Consequently, there is no consensus on how to measure food security or which data to employ for this purpose. Assessing food security requires a multiplicity of indicators adapted to different scales of analysis (individuals, households, regions, countries).

At the individual level, one of the most widely used indicators is the Food Insecurity Experience Scale (FIES), developed by the FAO, which measures food insecurity based on self-reported experiences (Ballard *et al.*, 2013; FAO, 2022). Also, at the individual level, indicators such as calorie intake counts or anthropometric indicators—such as the prevalence of acute malnutrition (wasting) or chronic malnutrition (stunting) in children—allow the measurement of the biological effects of food insecurity (Unicef *et al.*, 2023). These individual surveys involve measurements and records and are very costly.

At the household level, ‘household surveys’, which are less expensive, are used as a fundamental source of information on food security (Carletto *et al.*, 2013; Jones *et al.*, 2013). Indicators such as the Household Food Insecurity Access Scale (HFIAS), Coping Strategies Index (CSI) and Household Hunger Scale (HHS) estimate the prevalence of food insecurity at the household level through a self-reporting method of lived experiences. Furthermore, indirect measures such as the Household Dietary Diversity Score (HDDS), the Food Consumption Score (FCS), or the proportion of spending on food in the household budget are often used to estimate both diet quality and economic accessibility to food (Swindale and Bilinsky, 2006).

Finally, at the regional or national scale, governments and international aid agencies tend to assess global levels of agricultural production and relate them to population size to obtain proxies for food availability, such as the Global Hunger Index (Von Grebmer, 2017). More precisely, the World Food Programme (WFP), the FAO and the World Bank provide food security indicators that extrapolate food consumption data collected through household surveys (Moltedo *et al.*, 2014). To populate these indicators at the regional and national levels, automated methods described in the following sections of this chapter can be mobilised to observe, predict and explain food security.

► Observing the components of food security through modelling and remote sensing

Since the 1980s, satellite imagery has been exploited within early warning systems to monitor vegetation growth anomalies at a regional scale, thereby allowing a better prediction of food crises. Since then, satellite data have expanded significantly in both quantity and quality (Tonneau *et al.*, 2019) and research progress has led to an expansion of the range of ‘essential agriculture variables’ (EAVs) derived from Earth observation data.

The TETIS and AIDA research units work on EAVs for food security, with a particular focus on the spatio-temporal characterisation of tropical agricultural systems. These systems, which are highly diverse and spatially and temporally dynamic, are characterised by small plot sizes, fragmented landscapes, a wide variety of cultural practices, frequent cloud cover that limits satellite observation and poor ancillary data. This necessitates the adaptation of methods developed for agriculture in the Global North and, quite often, specific developments (Bégué *et al.*, 2024). Thus, these research units develop original methods for identifying and extracting information layers—agronomic and landscape variables and indicators. They focus primarily on the ‘food availability’ aspect, particularly on agricultural production potential via the mapping of agricultural land use, the characterisation of production environments and the monitoring of land investments.

Mapping agricultural land use

In the absence of regular and exhaustive agricultural statistics in many countries, land-use mapping—cropland, crop groups or types, agricultural practices—is essential for evaluating the agronomic and environmental performance of cropping systems. Two examples of exploratory land-use mapping work are given below.

Mapping crop types in Madagascar

Numerous studies have highlighted the difficulties of remote sensing for small-scale agriculture, particularly in tropical zones (Lebourgeois *et al.*, 2017). One avenue for improvement, as yet little explored, is the combination of remote sensing data with expert rules or the modelling of spatio-temporal structures. Thus, in 2021, Arthur Crespin-Boucaud (Crespin-Boucaud, 2021) developed as part of his PhD work an original approach combining remote sensing and spatial modelling to improve the mapping of crop types in complex agricultural landscapes of the Madagascar highlands. The method is based on the joint use of high spatial resolution satellite images (SPOT 6/7) to characterise landscape structure, and high-frequency revisit time series (Sentinel-2, Landsat 8) to monitor land-use dynamics, combined with spatio-temporal rules expressing the strategies and practices of local farmers. The modelling of spatial dynamics uses a graph-based approach (Ocelet model; Degenne and Lo Seen, 2016). This approach is implemented in three stages (Crespin-Boucaud *et al.*, 2020) and results in the production of a map of mapping errors (omission or commission²³) for crop types. These errors are then corrected through the joint use of spatio-temporal rules and class membership probabilities. The integration of spatial rules does not show a quantitative improvement in classification results, but it reinforces the thematic consistency of the map, notably through better discrimination of rainfed crops and savannah zones (Figure 10.1). Thus, the integration into the Ocelet model of the logics and strategies of Malagasy farmers makes it possible to improve map quality relative to actual local conditions, thereby increasing its acceptability by territorial stakeholders and, ultimately, its use for local decision-making.

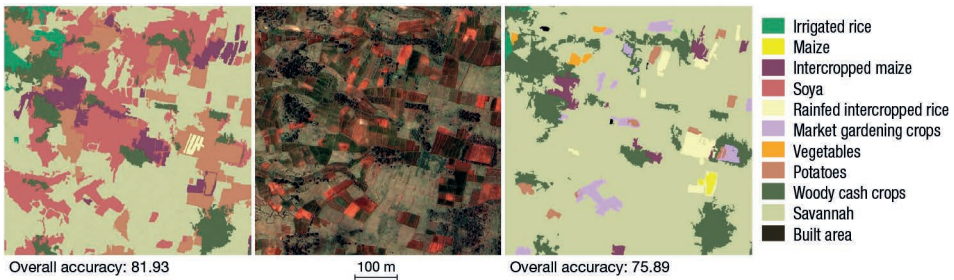


Figure 10.1. Comparison of mapping results with and without modelling for the same agricultural region in Madagascar. From left to right: satellite image classification, (areas coloured by type of land cover or crop), a Pléiades-type image (fine texture, visible plots), and a fusion of classification and modelling (the colours of the classification were corrected and smoothed by modelling, resulting in a pattern more consistent with the layout of crop areas [rice, maize, soya, vegetables, potatoes, etc.] and savannah areas). Source: Crespin-Boucaud (2021).

Mapping fallow land in Burkina Faso

In West Africa, mapping fallow land is essential for characterising the sustainability of agricultural systems and their contribution to food security. This is a difficult

23. Omission errors, when reference points for one class are allocated to another class; commission errors, conversely, when points from other classes are incorrectly assigned to a given class.

task, as yet not fully resolved at a large scale, because fallow lands are intermingled within the cultivated area, they have very different appearances depending on their age (Figure 10.2), and because their phenology follows that of the crops, synchronised by the rainy season. The doctoral thesis of Enzo Castro Alvarado (2023) explores three fallow mapping strategies based on supervised classification approaches, using Sentinel-2 image time series, rainfall data and an extensive database collected in the field at the plot scale between 2016 and 2021 at the Koumbia site in Burkina Faso.

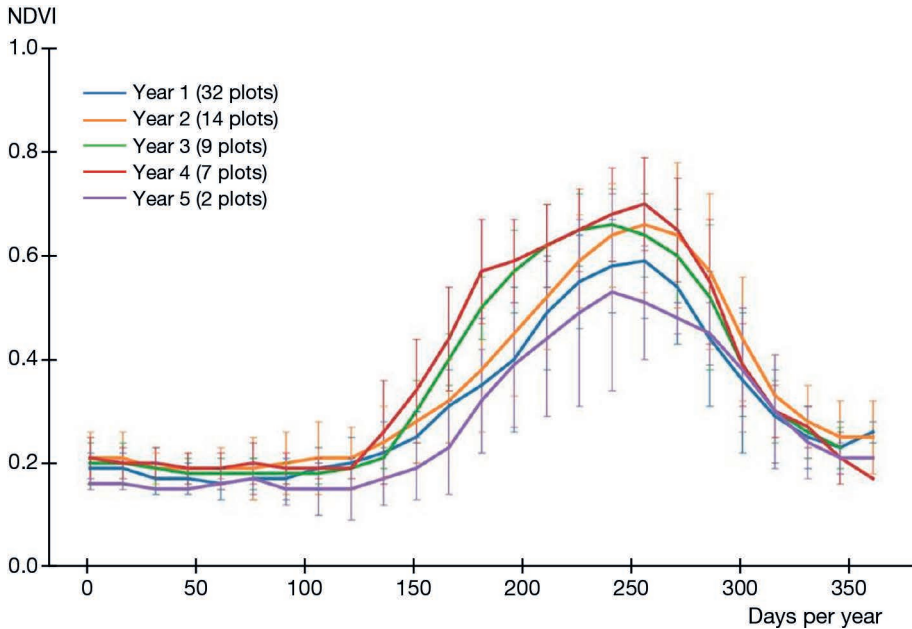


Figure 10.2. Mean Normalised Difference Vegetation Index (NDVI) profiles of fallow lands at different ages, calculated from pre-processed (gap-filled) Sentinel-2 data. Source: Castro Alvarado (2023).

The results show that (1) so-called 'traditional' machine learning methods do not allow correct detection, for a given year, of fallow surfaces under the soil and climate conditions of the study area (F1-scores < 0.20); (2) trajectory analysis, based on original methodological developments (Random Forest or TempCNN) to exploit image time series in their multi-year context (Castro Alvarado *et al.*, 2023), results in F1-score values for the 'inactive agricultural land' class between 0.75 and 0.92; (3) more explicit multi-year strategies, where the temporal analysis process is delegated to classification algorithms, were also tested and showed slightly improved results compared with direct annual mapping strategies, but with performance levels that remain moderate (mean F1-score of 0.44). The study concludes by emphasizing the importance of integrating multi-year spectral information into the learning process to describe fallow surfaces not by their current state (land cover), but by changes during the period following the start of the fallow period.

Although the practice of fallowing is tending to disappear in West Africa due to high pressure on land, the results of this study show that it remains integrated into

production systems in the Koumbia region, representing between 7% and 14% of the surface area depending on the year. This is valuable information for characterising production potential and for evaluating the sustainability of local agricultural systems.

Characterising production environments

In addition to a fine-scale characterisation of agricultural land use, characterising agricultural production environments is essential for targeted interventions, resource allocation and food security decision-making. However, existing methods for characterising production environments (for example, 'technological extrapolation domains') do not account for the high spatial and temporal heterogeneity of agricultural production environments characteristic of tropical agricultural systems. In the doctoral work of Habtamu S. Gelagay (2025), a spatialised and dynamic data-driven analytical framework was developed. It integrates the mapping of cultivated areas with the delimitation of 'agroecological spatial units' (ASUs) to characterise rainfed wheat production environments in Ethiopia (Gelagay *et al.*, 2025).

Initially, the mapping of rainfed wheat was carried out for two years, 2021 and 2022, using an ensemble machine learning approach alongside remote sensing and environmental data, and achieved an accuracy of over 90%. Subsequently, the ASUs were delimited using clustering approaches, taking into account short-term changes (annual ASUs for 2021 and 2022) and longer-term trends (ASUs developed from data aggregated over the 2016–2022 period). The clustering relies on key biophysical variables, notably climatic, pedological and topographical data, as well as vegetation indices derived from satellite imagery. Integrating the rainfed wheat cultivated areas with the ASUs made it possible to identify five main wheat production environments in Ethiopia (Figure 10.3), allowing for better targeting of future research and development activities to increase wheat productivity in the country.

Pixel-based ASUs	Object-based ASUs	Key features			Rainfed wheat area coverage	Logical name
		Altitude	Climate condition	Soil condition		
ASU 1	ASU 1	High	High	High	High	Prime highlands for rainfed wheat
ASU 4	ASU 5	Mid (Moderate)	High	High	High	Favorable mid-altitude regions for rainfed wheat
ASU 2	ASU 4	Mid (Moderate)	High	High	Mid (Moderate)	Emerging mid-altitude regions for rainfed wheat
ASU 3	ASU 2	None + Low	None + Low	Mid (Moderate)	None + Low	Low altitude rainfed wheat frontier
ASU 5	ASU 3	None + Low	None + Low	None + Low	None + Low	Low-altitude rainfed wheat void

None + Low

Mid (Moderate)

High

Figure 10.3. Characterisation of agroecological spatial units (ASU) for rainfed wheat in Ethiopia. Source: Gelagay *et al.* (2025).

Land tenure and food security

Land tenure plays a central role in food security. Without secure access to land and stable land governance, the production capacities of rural populations can be undermined (reduction in agricultural investment in plots, conflicts, evictions, etc.). In certain contexts, this access to land can be compromised by large-scale land acquisitions (LSLAs), often termed 'land grabbing', which are massive acquisitions of land by states or investors, primarily for agricultural production (83% of transactions correspond to agro-industries for food or biofuel production), but also for mining, tourism or conservation, reducing the resources available to local populations. According to the Land Matrix²⁴, an independent initiative for the census and monitoring of LSLAs at a global scale, mainly Africa is affected, accounting for over 40% of transactions. However, documenting LSLAs remains complex due to the opacity surrounding these land transactions and the lack of regulatory policy implementation.

To address this difficulty, the doctoral thesis of Yasmine Ngadi Scarpetta (2024) focused on the automatic and unsupervised detection of LSLAs using satellite imagery. A rapid and unsupervised method (named BFASTm-L2; Ngadi Scarpetta *et al.*, 2023) was developed to detect and date, within MODIS NDVI image time series, the breakpoint associated with the greatest magnitude of change. Compared with other change detection algorithms (BFAST Lite, EDYN and BFAST monitor), BFASTm-L2 proved particularly sensitive to seasonal changes and effective in highlighting agro-industrial LSLAs in Senegal. The contribution of LSLAs to the changes detected across the country (Ngadi Scarpetta *et al.*, 2024) was then quantified based on three spectro-temporal variables derived from the MODIS NDVI time series of each pixel (the magnitude of change, the NDVI ratio before/after change, and dissimilarity). Combined into a composite RGB image, these metrics allow the visualisation of the main drivers of change—climatic, natural and anthropogenic—in land use and land cover over the studied territory.

In addition to these remote sensing techniques, other approaches can also be used. These are described in the section below.

►► Analysing and predicting food security using AI methods and heterogeneous data

Machine learning (ML) and deep learning techniques can estimate key food security indicators such as the Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS), avoiding a sole reliance on costly and time-consuming household surveys. Artificial intelligence (AI) algorithms can integrate and analyse heterogeneous data, including satellite imagery, climatic data and socio-economic time series, to uncover hidden patterns and identify critical factors of food insecurity in diverse contexts. These models are capable of extracting relevant features from high-dimensional data, allowing granular insights into region-specific vulnerabilities. Furthermore, their adaptive capabilities permit continuous refinement as new data become available, making it possible to improve predictions in line with changing dynamics.

24. landmatrix.org

In his PhD work, Hugo Deléglise proposed and developed an original method called FSPHD (food security prediction based on heterogeneous data) based on machine and deep learning (Deléglise *et al.*, 2022). This approach provides food security predictions (FCS and HDDS) using publicly available data and AI methods (such as convolutional neural networks [CNN], recurrent neural networks [RNN] and random forest). The proposed approach was first applied to Burkina Faso (Deléglise *et al.*, 2022), then to two other African countries, Rwanda and Tanzania (Interdonato *et al.*, 2025), in order to explore different geographical and socio-economic contexts. The methodological details describing the multi-branch architecture, which relies on the implemented machine and deep learning models, are described in the second chapter of this book. Such an architecture allows heterogeneous data sources to be used to predict food insecurity situations.

The first version of the proposed approach relies on regression to predict the exact FCS and HDDS values in selected geographical units (municipalities). The second seeks to perform a classification task into three food security categories (high/medium/low) across various geographical environments. By predicting FCS and HDDS classes, we evaluate the robustness of the methodology and compare classification performance across different regions in Africa.

The experimental evaluation of FSPHD detailed in (Deléglise *et al.*, 2022) shows that the best performance (evaluated via R^2 for FCS and HDDS prediction) is obtained by integrating raster data (CNN branch) with seasonal and spatial variables (random forest branch), using fusion at the feature level. In this context, the feature extracted by the branches corresponding to the neural networks are concatenated and used jointly to obtain a single prediction of the target score. This technique proved more effective than an approach where each branch is used independently to obtain a different prediction, which are then fused via linear regression. Although the predictions obtained for this regression task are not yet precise enough for use in operational contexts, the R^2 values obtained for FCS (0.469) and for HDDS (0.434) are statistically significant, outperforming competing methods and thus demonstrating the advantages of integrating different AI techniques that incorporate a large number of heterogeneous data.

Figure 10.4 illustrates the distribution by municipality for 2018 of the FCS and HDDS criteria derived from the *enquête permanente agricole* (EPA) [continuous agriculture survey] and predicted by the best model. Despite the moderate predictive performance of the model, aggregating the predictions into three classes allows a fairly fine prediction of the distribution of municipalities with high, medium and low food security for both indicators used. Among the 318 municipalities considered in 2018, 66% are in the same class for HDDS (63% for FCS), 32% have a one-class difference for HDDS (34% for FCS), and only 2% are in opposite classes for the HDDS criterion (3% for FCS). The model thus classified the communes identically to the EPA survey in a majority of cases. Furthermore, the spatial distributions of the two indicators visible on the maps from the EPA are also observable on the prediction maps. The map produced by our model also allows some relatively subtle spatial specificities to be detected that are unique to each indicator. Finally, municipalities that were not monitored by the EPA in 2018 (shown in white on the maps in Figure 10.4) could be predicted by our model, with an obvious operational interest in compensating for survey gaps due to lack of time, limited funding or inability to access the area (conflict, climate) (Deléglise, 2021).

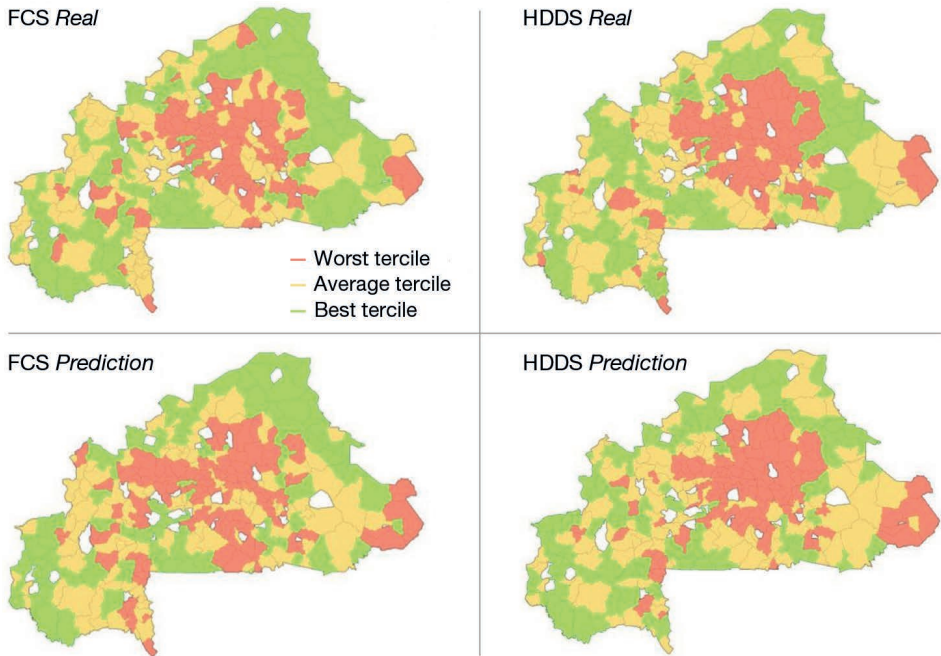


Figure 10.4. Spatial distribution of actual and predicted FCS (SCA) and HDDS (SDA), on average, by municipality in Burkina Faso, in 2018. Predictions are made using a feature fusion model that integrates raster data (CNN branch) and economic and spatial variables (Random Forest branch). Distributions are represented in three classes of equal frequency. Source: Deléglise (2021).

An extended and improved version of FSPHD was subsequently proposed, based on classification, which is more robust and better suited for producing food security maps based on the available data (Interdonato *et al.*, 2025). This new version was evaluated using different splits of the training and test data. The 'spatial split' combines spatial and temporal dimensions by selecting a percentage of municipalities (for example, 85%) for training and the remainder for testing, ensuring that the model is trained on separate geographical areas while preserving spatial data for testing. This allows the model's capacity to be evaluated across different geographical regions. The 'temporal split' divides data based on time, with the most recent data serving as the test set and prior data for training. Such an approach aims to evaluate the capacity of models to predict future outcomes based on historical data, as it simulates real-world forecasting scenarios. Spatial distribution maps of predicted and actual FCS classes are produced for Rwanda, Tanzania and Burkina Faso for both temporal and spatial splits. Regarding Rwanda, the proposed method shows an error in only one municipality for the temporal distribution and achieves a perfect prediction for the spatial distribution. Regarding Tanzania, prediction errors are more numerous. This is likely due to the more fragmented landscape and missing values in the population density rasters; similar observations are made for Burkina Faso. These maps clearly show how the proposed approach, using open data, can lead to the production of national-scale food security maps that are extremely close to actual maps, offering a tool that can truly support governments and NGOs in operational contexts.

►► Explaining food security through text mining

In addition to the data sources conventionally used for predictive models (satellite imagery sources described in the previous sections), it is also possible to exploit text sourced from various communication channels such as online articles or television news transcripts. These data offer real-time access to local and regional information and can be integrated as explanatory or predictive variables in analyses.

In #DigitAg, several studies led by the TETIS research unit have exploited textual data for explanatory purposes, based on the hypothesis that local media would have communicated about events preceding or accompanying food crises, thus providing explanatory value to predictive monitoring models (Ba *et al.*, 2022; Deléglise *et al.*, 2024). The proposed and developed processing chains integrate five major stages: (1) article collection, (2) automatic article classification, (3) spatialisation, (4) calculation of textual indicators, and (5) visualisation. Collection relies on targeted web

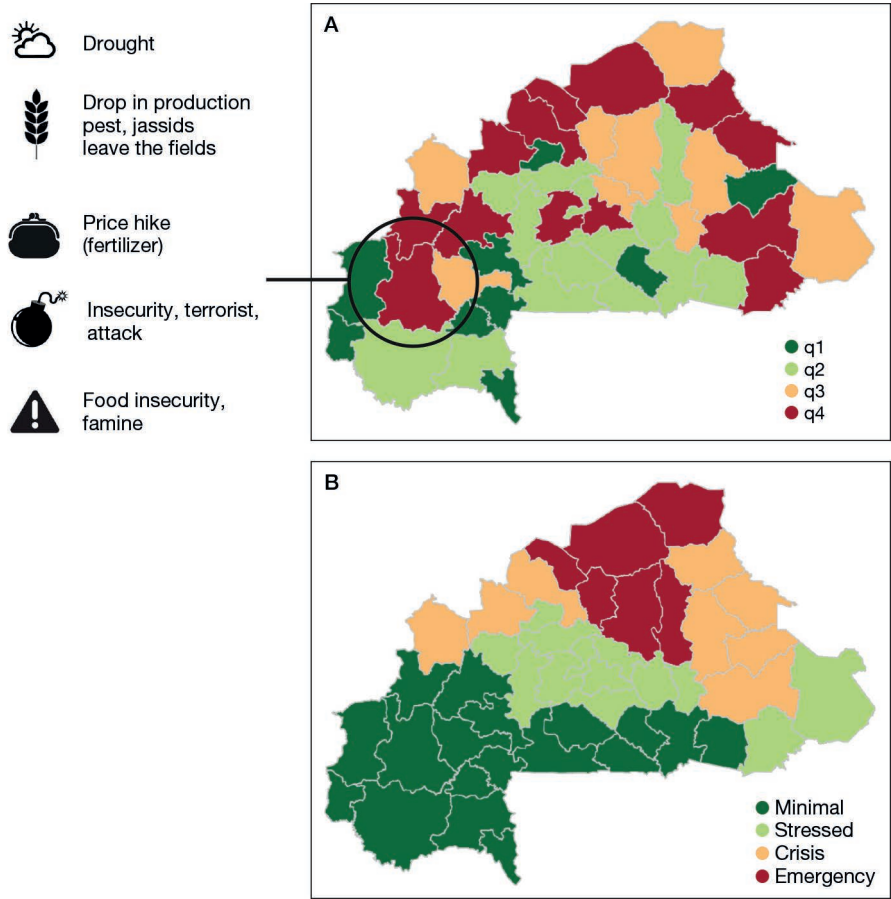


Figure 10.5. TXT-FS (Food Security indicator fully based on textual data) and IPC (integrated food security phase classification) values by province in Burkina Faso: (a) TXT-FS discretised by quantile; (b) IPC (as of 1 June 2022). Left: textual indicators from articles associated with Houet province. Source: Valentin *et al.* (2024).

crawling approaches based on online newspaper websites (for example, LeFaso.net). The selection of relevant articles is based on a semantic similarity threshold with a lexicon linked to food security (Ba *et al.*, 2022; Deléglise *et al.*, 2024) or on supervised classification models trained from annotated data (Valentin *et al.*, 2024). The spatialisation of articles is achieved through spatial named entity extraction models. In this context, language models derived from AI approaches, such as CamemBERT (a model for French), can be employed and adapted to our work.

Finally, an initial spatialised textual indicator, TXT-FS (food security indicator based on textual data), was proposed by Ba *et al.* (2022). This is based on the semantic similarity values of articles to the expert lexicon on food security. In the work of Valentin *et al.* (2024), this indicator was calculated for each type of food insecurity 'trigger': extreme climatic events, economic shocks and price instability, conflicts, land tenure issues and decline in agricultural production (Figure 10.5). The spatialised representation of these indicators highlights areas where the media communicate on food security and identifies the risk factors involved. These works point out, however, the limitation of these media sources alone, with coverage often being low in rural areas. Finally, it should be noted that alternative sources such as YouTube videos transcribed into textual data can also be used to predict food insecurity (Ba *et al.*, 2022) or to analyse agricultural practices in more detail (Maxim *et al.*, 2025) and provide explanatory information.

» Conclusion

This chapter provides an overview of the methods proposed across several #DigitAg projects within a multidisciplinary framework to observe, predict and explain food security. The research summarised in this chapter combines several types of approaches and data sources, such as remote sensing and modelling methods for observation, or Artificial Intelligence (AI) approaches integrating satellite imagery and other open-access data sources for prediction. Furthermore, these approaches are supported by economic expertise to define and interpret the data and indicators.

Finally, data science and AI approaches, alongside methods for modelling and analysing textual data, can provide an essential explanatory component for decision-makers wishing to integrate results into an operational service. Future prospects could involve integrating new data sources, provided certain bottlenecks are overcome, such as the inherent complexity of data access and acquisition or the multilingual aspects that must be carefully considered. For example, data from radio broadcasts may contain particularly important complementary information about the African continent, which could be exploited if such technical and scientific barriers were addressed.

» #DigitAg doctoral theses contributing to Chapter 10

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Part 4

Reflective analysis and outlook for the Convergences Institute

Chapter 11

A Perspective on the #DigitAg ‘Sud’ Challenge: Digital Agriculture in the Global South

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The ‘Sud’ Challenge of #DigitAg incorporates research on the digitalisation of agriculture in Global South countries, a term designating countries with a low GDP per capita, mostly described as ‘developing countries’. Digital technology is often presented there as an indispensable lever for agricultural modernisation, and the transformative narrative focuses on the creation of a digital service delivering on multiple promises: rural inclusion, productivity gains, access to information, knowledge and markets, financial inclusion and traceability. This chapter analyses certain digitalisation dynamics at work in the agricultural systems of these countries, from the dual perspective of public policy and stakeholder appropriation. Several research projects conducted in Africa and Latin America within the framework of #DigitAg are mobilised for this analysis and cited as references, mainly PhDs and Master’s degrees linked to field projects.

In these countries, the digital service offering is highly diverse, and sector stakeholders (local start-ups, NGOs, telecom companies, financial platforms, cooperatives, agricultural processing companies, public agencies, Big Tech) do not always operate with the same objectives, timescales or resources. Faced with this flurry of activity, which the national public policy instruments studied here attempt to regulate, the observation of a relative failure of digital applications specifically dedicated to agriculture is becoming apparent. Many struggle to move beyond the framework of the projects that funded them, due to a lack of users, a viable economic model or suitability for local practices (Paget *et al.*, 2025a). The recommendation is often to respond through co-design and capacity building, but without always questioning the relevance of the tool or its place within the production systems.

To better understand this apparent paradox, this chapter also proposes an analysis of the appropriation of digital tools by stakeholders in agricultural and food systems. The objective is to place the tools and services back into their contexts. The approach followed is based on an objective observational approach, without favourable or critical preconceptions about digital technology. It endeavours to document supply and usage dynamics and reflexively analyses experiments, remaining attentive to inequalities of access without taking them as an exclusive analytical angle. Indeed, beyond the

real digital divides (access, skills, infrastructure), the research is based on the empirical observation of a definite appetite among agricultural stakeholders for digital tools, driven by the rapid spread of mobile phones, the adoption of digital financial services (mobile money, i.e. a bank account in one's SIM card) and the expansion of access infrastructure (network, energy) (Paget *et al.*, 2025b).

The chapter is based first on a comparative analysis of public policies in West Africa and Latin America where, faced with numerous initiatives and a multiplicity of actors, public authorities have produced public action instruments to guide and support innovations. It then presents six case studies from contrasting agricultural value chains in Sub-Saharan Africa. An entry point via value chains allows us to understand, through historical comparison (before-after) and by case, a diversity of agricultural issues at the scale of production, value chains and markets, relationships between actors, and territorial interconnections.

The analysis is structured around a four-point reflective sequence (Figure 11.1). It sought to determine the real value of a digital tool in agriculture: is it useful, usable, used and sustainable? This logical chain, often neglected, is nevertheless fundamental, as it allows a better justification and guidance of investments, including those from the state and donors. Usefulness first requires a thorough understanding of the agricultural system concerned. As Bateson (1972) points out, information is “a difference that makes a difference,” hence the question: Does the digital tool generate information that truly makes a difference and offers added value in its context of application? The question of usability then examines whether this information has the capacity to transform practices. Does the information produced concretely allow stakeholders to act differently? Only after these two conditions have been met is a solution worth developing – with the imperative that it should not be too far removed from capabilities and uses, and should not widen inequalities between users, so that the tool can be used. Sustainability constitutes the ultimate challenge: how can we ensure the tool's longevity beyond the ephemeral cycle of the projects that fund the majority of agricultural applications in the Global South?



Figure 11.1. Analytical approach, applicable *ex ante* or, as in this article, *ex post*.

By combining qualitative and quantitative field diagnostics, institutional analysis, and interpretation frameworks inspired by value chain economics and political sociology, we propose here a critical but constructive reading of the challenges of the digital agricultural transition in the Global South. The aim is to promote a digital technology that is useful, usable, used and sustainable, serving the objectives of empowerment, sovereignty and the sustainability of agricultural production. We shall follow a critical analytical framework that focuses upstream of digital developments and at the core of practices and contexts. These observations analyse the public policies supporting digital agricultural development, revealing the disruptions that lead to the failure of numerous digitalisation initiatives in the Global South.

» West Africa and Latin America: digitalisation policies in the agricultural sector

Since 2015, across varied agro-socio-economic contexts, the digitalisation of agriculture has become a public policy issue in both West Africa and Latin America. #DigitAg has thus endeavoured to support the publication of comparative public policy analyses (Le Coq *et al.*, 2024). Public authorities are positioning themselves by initiating policy-definition processes that promote, guide and seek to regulate ongoing developments. While situations remain heterogeneous across different countries and regions of the world, several points of convergence are emerging in both the narratives and the instruments deployed.

A digital transition driven by a modernist sector narrative and technical ministries

Promoters of the digital transition rely on a modernist rhetoric to address agricultural challenges, be these economic (increased productivity and competitiveness), social (food security, education, civic and financial inclusion) or environmental (optimisation of inputs, adaptation to climate variability, etc.). Two major narratives currently structure digital development in agriculture: (1) digital technology as a lever for the capacity building of producers, through knowledge exchange, advice, training or peer-to-peer learning; (2) digital technology as a tool for facilitating economic exchange, market access, price negotiations and the simplification of financial transactions.

In West Africa, the voluntary and massive adoption of mobile phones by agricultural producers, connected to expanding internet networks, fuels a tech-driven vision of ending rural isolation. Telephones are perceived as a means of reaching farmers and promoting networking. Digital services, from the most basic (calls) to the most technical (geolocation, trusted third-party platform), are considered tools that can contribute to the structuring of value chains, a better connection of producers to markets, product traceability and, more broadly, sector growth. Promoting technical innovations, policy orientations favour a digital transition that is inclusive of small-holders—the pillars of West African agriculture—who are often less well-endowed with capital and digital skills.

In Latin America, the use of digital technologies in agriculture has developed strongly with the spread of mobile phones, GPS and specific agricultural applications. Their promotion is also part of a tech-driven vision through the promotion of 'Agriculture 4.0' or '5.0', centred on precision agriculture and primarily adapted to farms with the most capital, notably those in agribusiness. However, under the impetus of international donors, cooperation agencies or administrations in charge of rural development, initiatives are emerging to encourage a more inclusive digital transition serving family farms.

The prioritisation of the digital transition has been driven mainly by ministries of telecommunications or science and technology, which were the first to formulate policies in this field. Consideration by ministries of agriculture is more recent. On both continents, the analysis of public policy documents reveals three trends regarding the digitalisation of agriculture. Some countries adopt a general digital agenda with no

explicit mention of agriculture (Ecuador, Guatemala, Peru and Argentina). Others integrate specific guidelines for the agricultural sector into their overall digital agenda (Senegal, Costa Rica, Chile, Mexico). Finally, some countries have a sectoral policy for the digitalisation of agriculture promoted by their ministries of agriculture (Benin, Ivory Coast, Brazil, Colombia, Uruguay).

A diversity of policy instruments serving the digital transition in agriculture

To implement a digital transition for agriculture, States deploy four types of public action instruments. Their implementation is funded and orchestrated in part by States and delegated to agencies, either through their own funding or by contracting conditional international loans from international financial institutions. Certain actions are also delegated to public partners, primarily bilateral cooperation agencies. These agencies then contract with NGOs, associations and private actors for their implementation.

These instruments fall into four categories: (1) Normative: Legislation on data protection and digital identification. In West Africa, these instruments pave the way for better financial inclusion and improved traceability—for instance, within the framework of the European Union Deforestation Regulation (EUDR) and globalised value chains; (2) Organisational: The creation of multi-sector committees to coordinate the implementation of rural connectivity policies or to combat the digital divide; (3) Incentive-based: investments to improve rural connectivity, integrating digital infrastructure and roads in West Africa, with priority given to promoting a digital service ecosystem based on start-ups. In Latin America, these funds are national and based on digital hub strategies, whereas in West Africa they are linked to international cooperation (e.g., World Bank, GIZ); (4) Capacity building through acquired skills: training stakeholders in the use of products and services, included either as a component of the previous instruments or as the subject of *ad hoc* programmes.

» Agricultural value chains and digitalisation: utility and adoption

In this context, how are stakeholders in agricultural and food systems actually taking up digital technology? Among several possible entry points, we have chosen that of agricultural value chains, viewed as systems of interdependent stakeholders (Figure 11.2). These chains are defined by specific practices, power dynamics, organisational forms and territorial constraints. This choice allows us to explore what digital technology transforms—or fails to transform—in the relationships between producers, intermediaries, processors, technical operators and institutions.

A value-chain approach allows for the exploration of two major digital narratives: knowledge exchange and market access. In theory, digital technology intervenes to address dysfunctions or to strengthen links deemed strategic²⁵. The PhD and Master's research within #DigitAg is based on several field studies incorporating value chain analyses (Table 11.1).

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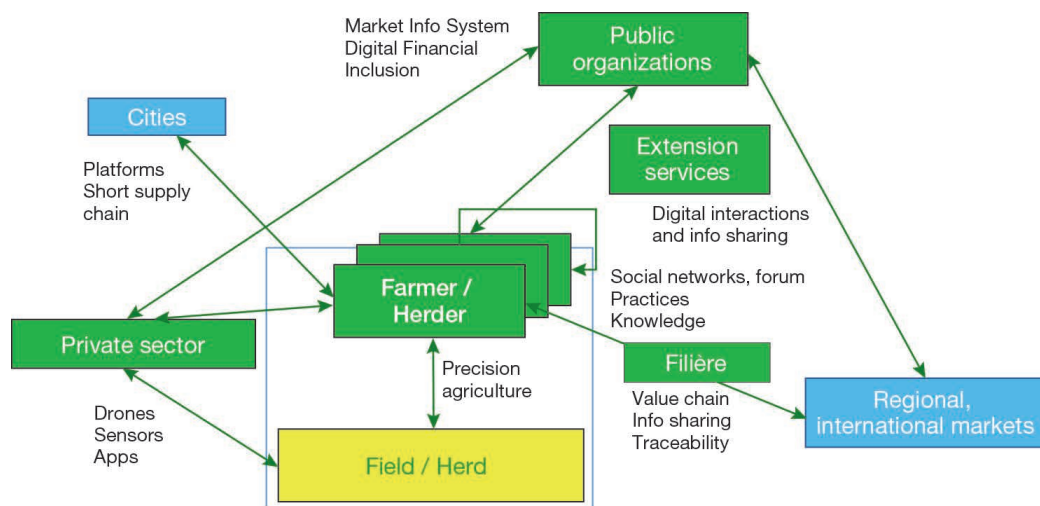


Figure 11.2. Systemic view of the stakeholder system, indicating possible digital objects and functions in a generic value chain.

Table 11.1. Value chains of agricultural sectors and their digitalisation

Context	Key Challenges	Organisational Level	Digital Tools	Constraints
Market Gardening (Benin)				
Peri-urban, short cycles, high connectivity	Market access, price information, technical advice	Informal, independent smallholders, competitive	Calls, WhatsApp, mobile money	Poor structuring fragmented and dispersed information
Dairy (Senegal)				
Agro-pastoral zone, regional and national markets	Collection, traceability, quality, perishability	High; via an industrial actor (<i>La Laiterie du Berger</i>)	QR codes, mobile money, milk collection monitoring, digital accounts (inputs)	Limited network coverage, animal mobility, digital illiteracy
Cocoa (Côte d'Ivoire)				
Export sector, commodity	Traceability, producer income	Long, structured supply chain; multinationals and State control (<i>Conseil café-cacao</i>)	SMS, traceability applications, mobile money	Low producer bargaining power
Rice (Republic of the Congo)				
Local sector, single outlet	Price information of limited use, meteorological services	Monopsony, captive buyer (brewery)	Dedicated application (rarely used)	Limited network coverage, few smartphones

Table 11.1. (next)

Context	Key Challenges	Organisational Level	Digital Tools	Constraints
Mango (Senegal)				
Seasonal export and national market	Yield estimation, information asymmetries, pre-harvest contracting	Independent producers	PixFruit/SoYield apps: yield assessment (Smartphone AI)	Difficulty in converting new information into a competitive advantage
Rabbit (Burkina Faso)				
Emerging national sector	Structuring, technical advice, marketing	Association (<i>Cercle des cuniculteurs</i>)	WhatsApp, social media	Self-management, geographic dispersion

Analysing agricultural value chains to evaluate their digitalisation potential

In the light of these findings, our approach aims to document, in a comparative manner, what works, what is repurposed, what is abandoned, and for what reasons. By varying the value chains and contexts, we seek to account for the concrete conditions surrounding the emergence, adoption and sustainability of digital tools. The six cases presented here capture this diversity.

In three value chains (market gardening, dairy and cocoa), the work of the *Fracture numérique* (Digital Divide) project (funded by the Ministry of Europe and Foreign Affairs France), supported by Master's degrees and a PhD funded by #DigitAg, involved observing and analysing stakeholders and their use of digital tools. The two other case studies (rice and mango), also based on #DigitAg funded work, represented cases of *ex ante* analysis (identifying dysfunctions and bottlenecks to be resolved) or prospective analysis to assess the utility of a digital application and its expected effects for producers.

In the peri-urban areas of Benin, particularly around the city of Cotonou and certain southern regions, market gardening is a key activity for urban food security. It operates through short cycles with perishable products and an informal, adaptive organisation. Producers often operate on a small scale, on the margins of structured value chains, using direct sales circuits or a limited number of intermediaries (Figure 11.3). In an environment that is relatively well-connected, digital technology appears as an accessible lever to improve access to price information, limit post-harvest losses, streamline financial transactions, and support the dissemination of technical advice.

The dairy value chain in the Ferlo pastoral zone of northern Senegal is based on mobile and transhumant livestock farming, practised by rural communities far from urban centres and poorly served by digital infrastructure. *La Laiterie du Berger* a central private actor that structures the producers (Figure 11.4), seeks to ensure regular milk collection and supplies numerous urban markets, some of which are distant (Dakar). It has implemented innovative digital systems to organise collection, monitor payments via mobile money, and identify herders through QR codes. These solutions, designed to support the dairy's development, nevertheless face significant constraints: irregular

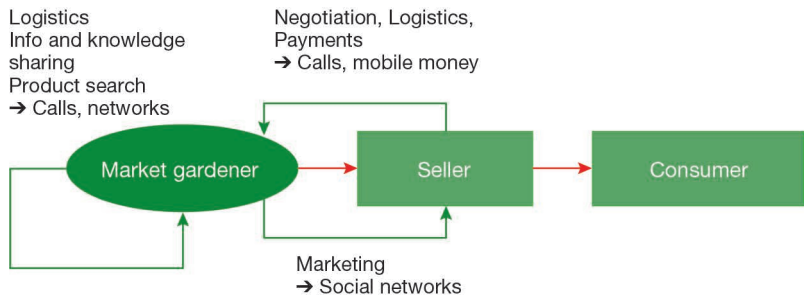


Figure 11.3. Market gardening in Benin and digital potential.

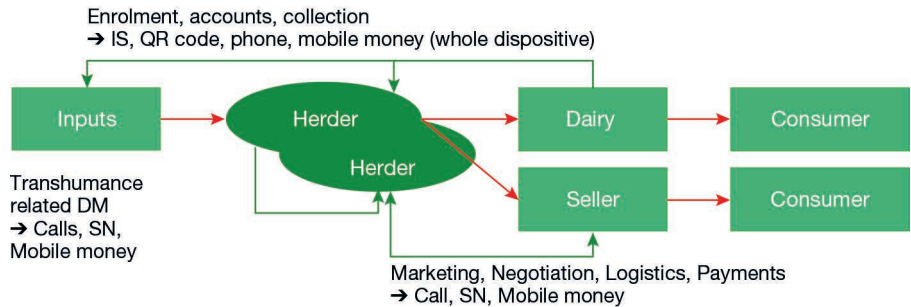


Figure 11.4. The dairy sector in Senegal and digital potential.

network coverage, low levels of equipment, and limited digital literacy. However, the tools deployed by the dairy have improved collection precision, secured the supply chain, and enabled targeted solutions to address milk quality issues.

In Ivory Coast, the world's leading cocoa producer, the sector relies on family-run production integrated into an export chain that is relatively structured by the State, yet marked by weak integration between producers and downstream actors. These producers sell their output to '*pisteurs*' (collectors) or cooperatives without stable contractual relationships (Figure 11.5). The potential of digital technology lies in a dual challenge: (1) for the State, its institutions (CCC – *Conseil Café-Cacao*, coffee-cocoa council), and downstream actors (exporters, cocoa processors and the European Union), strengthening product traceability to prevent the purchase of cocoa from deforested areas (EU Deforestation Regulation, EUDR); (2) for producers, securing their income and accessing technical support services. With connectivity varying

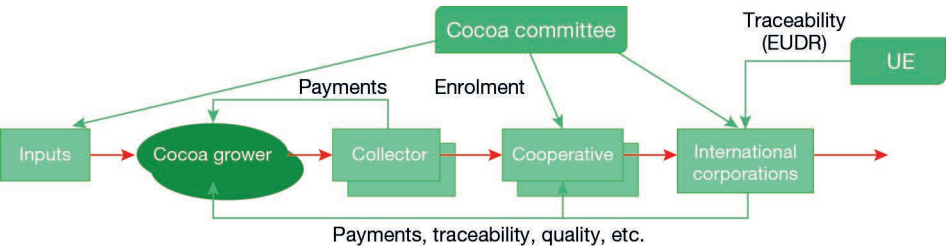


Figure 11.5. The cocoa sector in Côte d'Ivoire and digital potential.

by region, digital technology could contribute to the dissemination of solutions for persistent agronomic challenges (disease, declining soil fertility) and the simplification of numerous financial transactions.

In these varied contexts with promising digital potential, what are the realities of adoption, and has digital technology created inequalities?

Analysing digitalisation and its effects: technology appropriation in value chains

Digital technology is a well-known generator of inequality. Digital divides are observed at several levels: (1) the motivation to engage, (2) the type of access, (3) the capacity to use, and (4) actual usage (Van Dijk, 2013). This framework served as the starting point for this study on the appropriation of digital technology by arable and pastoral farmers. It was supplemented by the Technology Acceptance Model (TAM), derived from psychology (Davis *et al.*, 1989), which allows a detailed analysis to be made of the prerequisites for digital adoption (Box 11.1).

Box 11.1. The rice value chain in the Ruzizi Plain, eastern Democratic Republic of Congo (South Kivu): from an R&D project creating apps to a reflective analysis on their value

The #DigitAg-labelled PhD thesis of Cadeau Rushigira (2023) was conducted as part of a digital agricultural development project that included the creation of new applications. It initially focused on the appropriation of a smartphone app (price information system and weather service) intended for rice producers in eastern DRC. Very quickly, the PhD project was refocused towards an *a priori* analysis of the value of such an application and the conditions for its acceptability, based on the Technology Acceptance Model (TAM).

Field surveys revealed that over 80% of the rice produced in the region is purchased directly by a local brewery. While this guarantees a stable outlet, it severely limits the usefulness of a price information system for producers (Rushigira *et al.*, 2023). In this context, incentives to adopt a digital tool are lessened. The study also highlighted very poor network coverage, low literacy, almost non-existent access to smartphones, a very low level of acceptability regarding digital tools, and low trust in weather information received from unknown sources. This work illustrates the importance of addressing the questions of utility, usability and actual use upstream, before committing to digital development. It also underscores the limits of techno-centric approaches in environments where the material, economic and organisational conditions are not met.

A huge appetite for digital tools was observed, with a predominance of basic mobile phones being used, driven by expanding infrastructure and the spread of solar power. These basic phones are the cheapest and most practical due to batteries which can last up to a week. They enable voice calls and financial transactions via mobile money services. In agriculture, usage here is reserved for peer-to-peer exchanges (calls) to obtain diverse information—such as the resource status or prices—or to assist in negotiations and payments (Atindehou, 2022). Smartphones are also becoming more widespread and are used for instant messaging applications (Nacambo, 2020), social

media and video platforms. This leads to more advanced usage, such as marketing agricultural products through photos and videos or exchanging information within groups of varying sizes, forming a ‘virtual community’ through these apps (Box 11.2).

Box 11.2. The case of the *Cercle des cuniculteurs* in Burkina Faso: using digital tools to institutionalise a community of practice and develop an emerging value chain (Alexandre, 2023)

The *Cercle des cuniculteurs* is an association of rabbit producers in Burkina Faso. This community began to take shape in 2017 when a core group of Burkinabè rabbit farmers created a WhatsApp group to facilitate their exchanges. As the rabbit sector was not structured at the time, the group aimed to compensate for the lack of dedicated services. Informal but structuring rules of use were defined (concerning themes, language and message formats). By 2019, the community had grown to include over 250 producers. However, the limits of digital interaction soon became apparent: saturation, moderation issues, rule-breaking, and the dilution of learning objectives in favour of a market-driven logic. A small group of highly committed producers decided to form an association to address the broader challenge of structuring the value chain. They carry out activities both upstream and downstream: lobbying, knowledge sharing, bulk purchasing, and market creation. Key decisions, such as setting up relay points in various neighbourhoods, demonstrate the community’s strong local roots. This case illustrates both the contributions and the limitations of a WhatsApp group—created at low cost and managed with complete autonomy by local actors—in facilitating the flow of knowledge and the institutionalisation of a community of practice, followed by an emerging value chain.

Digital tools and services serve multiple functions: intermediation, financial and documentary dematerialisation, task automation, knowledge mediation, facilitating producer-consumer or supplier-business relationships, and strengthening peer-to-peer partnerships. Most of these functions can be performed through a simple phone and generic applications. An important observation is the predominance of generic tools—those not developed for agriculture but applied to the sector as an extension of everyday digital practices (Certeau, 1990). Few tools specifically designed specifically for agriculture are used individually by the family farmers surveyed. Frugal (low-tech) approaches, based on existing tools, therefore seem highly relevant as a first entry point into digital practices. Even when services and systems are more complex and defined by actors at other links in the value chain (such as in the dairy sector), the interface accessible to producers remains simple—a QR code, an SMS, or an audio message (Ferrari *et al.*, 2024). For instance, beyond commercial relationships in the dairy sector, mobile phone use further helps to secure agro-pastoral farming practices by allowing information-gathering on the state of distant pastures, enabling crucial decisions regarding transhumance dates. Mobile money services, which streamline financial exchanges and link producers to various financial services (savings, credit), are now widespread across all value chains, particularly for payments.

Certain divides are being mitigated (Figure 11.6); the low digital literacy of heads of farms can be offset by intra-family solidarity and intergenerational learning driven by children. In a society where knowledge is traditionally passed from elders to the

young, the relationship is reversing: children are becoming digital mediators, assisting their parents with phone use. In the cocoa sector, 64% of children report regularly helping their parents in this way.

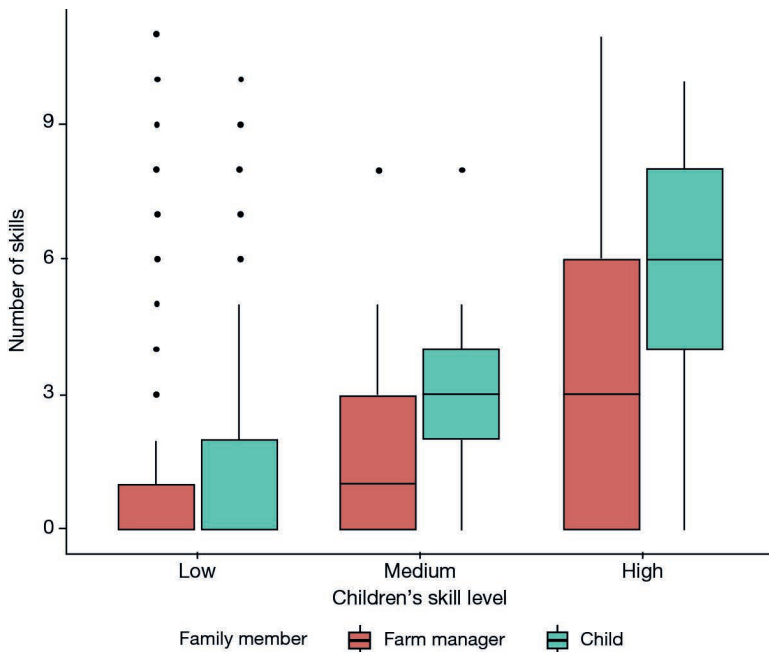


Figure 11.6. Intergenerational digital skills development in the cocoa sector in Côte d'Ivoire: joint progress by farm managers and their children in eleven digital uses: sending or reading voice and text messages, taking photos or videos, joining, creating or administering groups, searching for and communicating information, buying or selling products, and learning online.

Effects of dependency on these services are emerging, though they remain largely unmeasured except through stakeholder testimony: *"The phone is my business; I cannot do without it."* There is a strong motivation to adopt digital tools and a near-impossibility of turning back—abandoning the phone is not an option despite significant recurring costs (Paget et al., 2025). In the monitoring of the use and effects of the PixFruit application, developed for the mango value chain, experiments after three years show a very limited impact on reducing information asymmetry regarding orchard yields, contrary to initial hypotheses. Although the asymmetry is real, other determinants come into play in the relationship between producers and collectors, specifically regarding trust and power dynamics (Box 11.3).

In the context of highly organised and strictly regulated value chains that ensure fixed-price sales (rice, cocoa), the individual use of digital tools for production or chain operations seems less likely to stimulate producer-led 'innovation niches'. The forms and challenges of digitalisation vary significantly depending on the value chain's influence on the national economy (stakes, organisation) and the complexity of the issues to be resolved. In the case of cocoa, while financial transactions between producers and collectors are becoming dematerialised, the challenge of 'zero deforestation' (EUDR regulation) can only be resolved through action by the State and its institutions.

Box 11.3. The PixFruit case. Developing an application for the mango value chain in Senegal: design, evaluation and transfer—towards the challenge of sustainability

A major obstacle to structuring the mango value chain in Senegal is the lack of reliable, factual or predictive advisory tools for production. Producers are often unaware of their annual yield and struggle to sell their entire harvest, leading to significant losses. Meanwhile, buyers and exporters find it difficult to anticipate their supply, and local authorities and researchers lack the data necessary to develop adapted agricultural policies and research (Sarron *et al.*, 2023). Within the mango sector, work funded by #DigitAg (Sarron, 2019) enabled the development of proofs of concept aimed at overcoming some of these obstacles. In consultation with sector stakeholders, researchers developed a decision support tool (DST) called PixFruit (renamed SoYield® upon its transfer to the private sector). This tool estimates orchard production using smartphone images of trees, analysed via artificial intelligence and agronomic models. The objective was to estimate harvests reliably and in advance to facilitate negotiation and contracting. After three years of deployment (2020–2023), although several obstacles to adoption were identified—capacities, access and trust (Alexandre *et al.*, 2023)—a major challenge lies in the producers’ inability to use this information for negotiation. The DST might therefore be more useful to the producer organisations (POs) emerging in the study area. These organisations could estimate the consolidated yields of their members and negotiate large volumes with exporters. This intermediary role for POs appears all the more relevant as traditional orchard owners have very limited financial resources and low digital skills, complicating the use of a sophisticated smartphone application. This case underscores the importance of conducting an *ex ante* evaluation to test hypotheses regarding the utility and potential users of an application.

This requires the implementation of a dedicated information and geolocation system in partnership with private service companies. The increasing complexity of digital tools therefore goes hand-in-hand with the organisational models and specific challenges of each value chain; the gradient of tools observed aligns directly with the rationale and ultimate goals of digitalisation.

► Conclusion

The digitalisation of agriculture in the Global South cannot be considered without accounting for digital habits and situated realities. Contrasting agricultural, economic, technical and social contexts determine the forms of appropriation, the effects produced, and the tools used. These observations mirror findings from similar studies in the Global North (OECD countries). Nevertheless, certain commonalities emerge: the centrality of the mobile phone and the use of generic tools such as voice calls, mobile money and instant messaging. Primarily, simple support for the deployment of high-quality infrastructure and affordable handsets appears indispensable.

The cases studied reveal a reality that defies standard conclusions—such as the perceived necessity of user-centred design or the simple need for capacity building. Digital tools specifically designed for the agricultural sector are, in many instances, used less than general-purpose tools that have become successfully established in the daily lives of producers. This does not reflect a rejection of digital technology;

quite the opposite. It demonstrates a genuine, often pragmatic appropriation based on simplicity, habit, networks and trust, within an environment still largely shaped by oral tradition and mutual understanding—synonymous with proximity and power dynamics. The most flexible and familiar tools are the ones most widely adopted.

Beyond access, a sequential approach is required as a prerequisite for application development. It must cross-reference value chain diagnostics—to understand the economic and organisational rationales of production systems and thus the capacity of information to make a difference (Is it useful?)—with territorial analyses sensitive to the dynamics of access, connectivity, and the structuring of local innovation ecosystems (Is it usable?).

In the future, design efforts should stem from the digital practices of users, the organisational gaps observed within value chains, and expressed needs—particularly regarding networking and the simplification of information flows—rather than technical projections aimed at maximising usage probability. This implies recognising the social and economic value of existing tools—imperfect but flexible—analysing their functions within social and economic interactions, and imagining digital services that link to and facilitate them rather than seeking to replace them. Digital innovation must be designed in connection with available skills, local forms of organisation, and the capacity to maintain services over time (Paget *et al.*, 2025b). This vision does not preclude advanced digital developments by stakeholders with greater resources, as shown by *La Laiterie du Berger* in Senegal, but the interface for the producers must align with their habits and capacities. Such an approach moves away from the burdensome task of capacity building in a way that breaks with existing habits, instead supporting genuine capacity growth while limiting the widening of inequalities.

Several research avenues emerge from work focused on family farming in the Global South: the sustainability of developed tools, the role of the State versus the private sector in funding and maintenance, the design of frugal and differentiated tools based on the user, and the role of digital technology in agroecological transitions. Digital technology must not be an end in itself, nor a technocratic response to complex problems. It can partially fulfil its promises—food sovereignty, social inclusion, and the sustainability of agricultural systems—provided it is integrated into a coherent set of adapted supports and practices. Thinking about agricultural digitalisation in the Global South means, first and foremost, recognising habits as they are, with their limits and strengths, and designing digital tools that do not precede usage, but extend its logic.

► #DigitAg doctoral theses contributing to Chapter 11

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* #DigitAg theses that address the chapter's theme but are not cited in it. In addition to these theses, #DigitAg has included around twenty theses based in the Global South (theses whose titles appear in italics in the list of theses in the appendix).

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Chapter 12

The architecture of interdisciplinarity: an experiment in institutionalising an interdisciplinary scientific community at #DigitAg

Jongheon Kim, Karine Gauche

The #DigitAg Convergences Institute was established in 2017 under the *Instituts Convergences* programme of the French National Research Agency (ANR), with the mission of structuring a scientific community around the challenges of digital and sustainable agriculture. This programme aimed to foster the emergence of high-level research hubs capable of addressing major societal challenges by mobilising interdisciplinary expertise and promoting a dynamic of convergence between scientific fields. #DigitAg thus brings together laboratories specialising in agronomy, digital sciences, economic and social sciences, modelling and environmental sciences. Its objective is to respond to the profound transformations in the agricultural sector through interdisciplinary research that is locally anchored and user oriented.

From its inception, #DigitAg displayed clear intent to foster disciplinary hybridisation, which is considered a necessary condition for addressing the complexity of agricultural, ecological and digital transitions. This aligns with ongoing reflections on the configurations of ‘interdisciplinarity in action’ (Weingart and Stehr, 2000; Frodeman *et al.*, 2010; Barry and Born, 2013). This ambition was notably reflected by introduction of incentive schemes—PhD and postdoctoral grants, internal calls for projects, and cross-cutting events—encouraging collaboration between laboratories from historically distinct fields, such as technology and engineering sciences, life and environmental sciences and the humanities and social sciences. The challenge was twofold: to structure an emerging research field—digital agriculture—and to train a new generation of researchers capable of integrating scientific knowledge with professional practices and technical innovations.

This chapter will analyse how the support mechanisms implemented by the institute have contributed to the progressive construction of an interdisciplinary community around #DigitAg. This structuring dynamic is part of a perspective where interdisciplinarity is not limited to a simple addition of skills, but entails the formation of research collectives capable of developing shared objects and stabilising epistemic compromises (Jasanoff, 2004). While interdisciplinarity is widely promoted in institutional discourse, its effective implementation requires specific conditions—institutional

recognition, the academic legitimacy of hybrid objects, and arbitrations between disciplinary and goal-oriented logics. In this sense, this chapter aims to highlight the mechanisms and configurations that have enabled the emergence and consolidation of these collaborative practices within #DigitAg.

►► Method, data collection and analysis

The analysis is primarily based on internal data provided by the management of #DigitAg. This database, updated as of 24 April 2025, lists all funded or labelled projects, giving the title, abstract, disciplines involved, challenges and research axes according to #DigitAg's own classification, host units, supervisors, type of funding (funded, co-funded, labelled), and type of project (Master's, PhD, postdoctoral). We extracted projects between 2017 and 2024, excluding those started in 2025. It should be noted that the abstracts analysed are those submitted at the time of funding validation or project labelling. They therefore reflect initial intentions, targeted problems, and planned collaborations, rather than the actual results of the work carried out. The rationale for this methodological choice is our interest in the research themes supported by #DigitAg, as well as the scientific supervision arrangements (notably interdisciplinary co-supervision), which are generally defined at the start of the project and vary only marginally thereafter. In this sense, the data used allow us to capture the institute's strategic orientations regarding interdisciplinarity and to identify the structuring dynamics of the research networks that have emerged with its support.

To conduct a systematic analysis of the projects funded or labelled by #DigitAg, we employed two complementary tools. The CorText Manager web platform (Breucker *et al.*, 2016) was used to produce co-occurrence maps, contingency matrices crossing textual variables and metadata (such as keywords or host units), and to apply the Epic Epochs method, which analyses the temporal evolution of themes. In parallel, the open-source software IRaMuTeQ (Ratinaud, 2009) was used to perform a hierarchical descending classification analysis (Reinert, 1983) to identify homogenous lexical classes from the project abstracts. The integration of these two approaches allowed us to cross-reference semantic structuring, disciplinary relationships and temporal dynamics to better understand the concrete forms that interdisciplinarity takes within the research supported by the institute.

►► Structuring through support mechanisms

Support mechanisms

In contrast to other mechanisms aimed at incentivising interdisciplinarity—which are often based on funding collective projects or structuring undergraduate and Master's level training programmes (Greef *et al.*, 2021)—#DigitAg made the strategic choice to support Master's, doctoral, and postdoctoral projects as the primary lever for structuring its scientific community. The originality of this choice lies in the emphasis placed on the co-supervision of doctoral and postdoctoral researchers, conceived as a central vehicle for establishing connections between researchers of varying statuses and from distinct disciplines. This multi-level support allows young researchers to be anchored in long-term, evolving and progressively hybrid trajectories, which are conducive to the consolidation of an interdisciplinary stance and the emergence of transversal skills (Pohl *et al.*, 2010).

The Institute employs three types of mechanisms: full funding, co-funding (50% #DigitAg, 50% from another source), and labelling, which is accompanied by a one-off grant of 3,000 euros. While the first two constitute the most strategic levers for strengthening interdisciplinarity and guiding the institute's scientific direction, the latter is designed to increase #DigitAg's visibility and broaden the scope of the digital agriculture community. This diversity allows the level of commitment to be adjusted based on opportunities and institutional backing. According to the data, #DigitAg has supported a total of 249 projects, including 136 PhDs and postdoctoral fellowships. Among these, 76 were co-funded, while the others fall under the more flexible category of labelling.

Distinct interdisciplinary configurations

Drawing on the classification system currently used by the ANR (French National Research Agency), #DigitAg categorises disciplines into three broad groups: Science and Technology (ST), including engineering sciences, mathematics and computer science; Life and Environmental Sciences (LES), comprising agronomy, biology, and ecology; and the Humanities and Social Sciences (HSS), encompassing economics, sociology, and law. Based on this classification, the #DigitAg leadership distinguishes between two forms of interdisciplinarity: simple interdisciplinarity, involving disciplines within the same group, and extended interdisciplinarity, associating disciplines from different groups (Table 12.1)

On the one hand, simple interdisciplinarity appears relatively common in general research practices: researchers frequently cross the internal boundaries of their field, often implicitly, by integrating concepts, methods or tools from neighbouring disciplines. On the other hand, collaborations involving extended interdisciplinarity prove more demanding, both organisationally and cognitively, and necessitate greater efforts to articulate heterogeneous epistemic frameworks (Bertrand, 2012; Deffontaines and Hubert, 2004).

Table 12.1. Number of PhD and postdoctoral research projects by interdisciplinary approach

	N	Monodisciplinary	Simple interdisciplinarity	Extended interdisciplinarity
PhD + Postdoc	136	57 (41.9%)	21 (15.4%)	58 (42.6%)
Funded PhD + Postdoc	18	6 (33.3%)	2 (11.1%)	10 (55.6%)
Co-funded PhD + Postdoc	58	0 (0%)	17 (29.3%)	41 (70.7%)
Labelled PhD + Postdoc	60	51 (85.0%)	2 (3.3%)	7 (11.7%)
Funded PhD	2	2 (100%)	0 (0%)	0 (0%)
Co-funded PhD	55	0 (0%)	17 (30.9%)	38 (69.1%)
Labelled PhD	52	43 (82.7%)	2 (3.8%)	7 (13.5%)
Funded postdoc	16	4 (25.0%)	2 (12.5%)	10 (62.5%)
Co-funded postdoc	3	0 (0%)	1 (33.3%)	2 (66.7%)
Labelled postdoc	8	8 (100%)	0 (0%)	0 (0%)

In this regard, #DigitAg established an organisational structure intended to foster interdisciplinarity. Among all the projects analysed, 64 (representing 25.7%) involve extended interdisciplinarity. This proportion rises to 42.6% when considering only PhDs and postdoctoral research projects and reaches as high as 67.1% among projects co-funded by #DigitAg, illustrating the structuring effect of targeted funding on interdisciplinary outreach. Furthermore, co-funded projects show the highest rate of extended interdisciplinarity (70.7%), making them the primary lever for promoting interdisciplinarity within the institute. Conversely, labelled projects, which receive more symbolic and less structured support, remain predominantly monodisciplinary (85%). A significant number of these projects are led by LES units and involve more targeted or exploratory technological approaches, such as sensor optimisation or the study of physiological processes. In these instances, labelling appears to play a priming role, preparing certain disciplinary research for a potential scaling up towards more integrated configurations.

Among PhD and postdoctoral projects, the most frequent combination is that of ST and LES (41 projects), followed by the ST-HSS pair (11) and the LES-HSS pair (6). This pattern demonstrates the central role played by science and technology in the dynamics of disciplinary crossing within #DigitAg, as well as their capacity to circulate between different epistemic worlds. More broadly, these results confirm that the nature of the funding directly influences the scientific architecture of the projects, conditioning not only their interdisciplinary scope but also their potential for epistemic and organisational reshaping.

Interdisciplinary trajectories

#DigitAg's support across all levels—Master's, PhD, and postdoctoral—combined with the ten-year duration of the programme, has fostered a degree of stability in academic pathways, which is an essential condition for the development of interdisciplinary research. Indeed, the decisive role of long-term horizons in an interdisciplinary career has been highlighted by several studies (Barry and Born, 2013). This stability is reflected in the evolution of certain trajectories: five students who completed a #DigitAg-funded Master's degree went on to pursue a PhD within the institute, and one of them then went on to do postdoctoral research, also supported by #DigitAg (in a different laboratory). The five Master's projects were initially aligned with a single research axis. However, at the time of the doctoral project submission, an interdisciplinary opening materialised through the addition of a second axis, broadening the scientific scope. For example, a Master's project initially focused on modelling in plant protection led to a PhD that also integrated another scientific axis, moving towards the design of metrological tools intended to support agroecological practices. Similarly, another Master's study on digital usage in agricultural organisations was extended by doctoral research employing data analysis techniques to study the transformation of agricultural value chains within the framework of the digital transition. These evolutions reflect a process of hybridisation, which requires an extended timeframe to unfold.

Parallel to this, the literature highlights a broad consensus: a solid disciplinary foundation is an indispensable prerequisite for conducting credible and scientifically legitimate interdisciplinary research (Bühler *et al.*, 2014; Sedooka *et al.*, 2015). In a context marked by rapidly evolving knowledge and increasing specialisation—particularly in

public research—young researchers face a dual challenge: namely, building recognised expertise in their anchor discipline while progressively broadening their horizons towards other fields. This tension between disciplinary deepening and interdisciplinary openness characterises the career paths of researchers in training. To address this issue, it becomes essential to create institutional environments that simultaneously support the consolidation of disciplinary expertise and the supervised exploration of the interfaces between disciplines (Weingart and Stehr, 2000; Haider *et al.*, 2018).

► Interdisciplinarity in the making

Scientific structure and thematic cross-cutting

Interdisciplinarity within #DigitAg is not merely a desired scientific orientation; it constitutes a structuring principle of the organisation of research. This is notably shown through interdisciplinary co-supervision, detailed above, but also by the very architecture of the scientific programme. Rather than relying on traditional disciplinary themes, #DigitAg adopted a matrix structure combining scientific axes and socio-technical challenges (Figure 12.1). This encourages researchers to move beyond their disciplinary investigation frameworks to integrate a broader reflection ranging from knowledge production to tangible usage in the agricultural sector (Joly *et al.*, 2015).

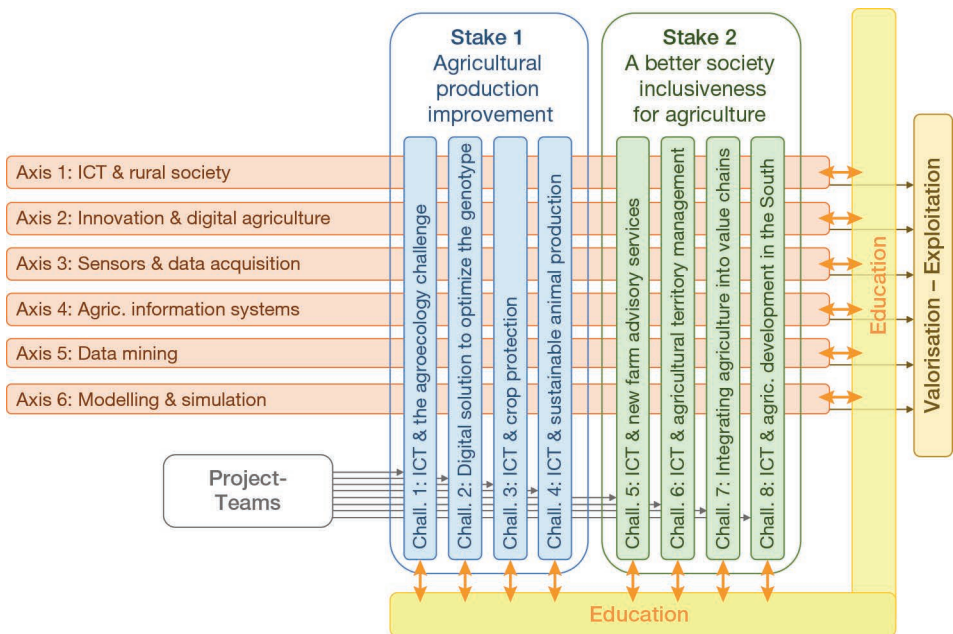


Figure 12.1. Organisation of #DigitAg based on scientific axes and major challenges. Source: #DigitAg.

The six scientific axes of #DigitAg are divided into two main groups. On one side, two axes with a broad, systemic focus address digital innovation in rural society and innovation processes in agriculture. On the other, there are four more techno-scientific axes, centred on sensors and data acquisition, information systems, knowledge

extraction and modelling and simulation. To this are added eight challenges, defined according to major agricultural topics (sustainable production, value chain enhancement, regional management, etc.) in which digital technologies are expected to play a transformative role. This dual structure encourages researchers to formulate their projects according to a transversal logic—both interdisciplinary and ‘application-oriented’—which fosters concrete links between approaches, methods, and objects of study (Gibbons *et al.*, 1994).

Analysis of the funded projects shows that this structuring is not merely formal: it is reflected in the research practices themselves. As illustrated in Figure 12.2, obtained from a co-occurrence analysis performed on the CorText platform using the abstracts of all projects supported by #DigitAg (Master's, PhD, postdoctoral), the scientific axes do not function as isolated compartments. Using automatic n-gram term extraction, this analysis identifies the key concepts of the projects and their co-occurrence network with the stated axes. It reveals a strong interconnection between the axes, showing that projects simultaneously address several issues and help to identify areas of thematic convergence. This dynamic suggests that researchers are led to step out of their disciplinary comfort zones to engage in interdisciplinary exchange and co-construction (McNair *et al.*, 2015).

For example, concepts such as *livestock farming systems*, *agroecological systems* and *environmental conditions* appear as nodes recurrently linking axes 3, 4 and 5, suggesting that research is not limited to compartmentalised domains (such as animals, the environment or data), but tends to combine them within an integrative perspective. Similarly, the numerous links between *agricultural practices*, *digital tools*, *innovation system* and *food systems* reveal constant porosity between axes 1, 4 and 6. The resulting map thus shows that the scientific axes function more as spaces of convergence than as lines of separation, supporting an organic interdisciplinarity anchored in research objects and methodologies. In other words, interdisciplinary co-supervision mechanisms encourage supervisor-researchers to dialogue beyond their disciplinary comfort zones by prompting them to build bridges between heterogeneous knowledge and practices.

In short, the structuring of #DigitAg appears to promote an interdisciplinarity of integration (Klein, 2010), which does not simply juxtapose disciplines but brings them into dialogue through shared analytical frameworks. The very design of the scientific programming instruments—axes, challenges, co-supervision—participates in a process of institutionalising interdisciplinary collaboration, by offering researchers practical tools for bringing together diverse areas of expertise to address common problems.

Forms of hybridisation and interdisciplinary convergence

Lexical groupings and thematic classes

Figure 12.3, derived from a lexical analysis using the Reinert method (Reinert, 1983) and generated with IRaMuTeQ software, highlights cross-cutting thematic groups within the abstracts of the PhD and postdoctoral projects supported by #DigitAg. Each class brings together textual segments sharing lexical regularities, revealing zones of content-based interdisciplinarity that transcend organisational structures such as axes, disciplines, or units. Among the six identified groups, we chose to analyse groups 5

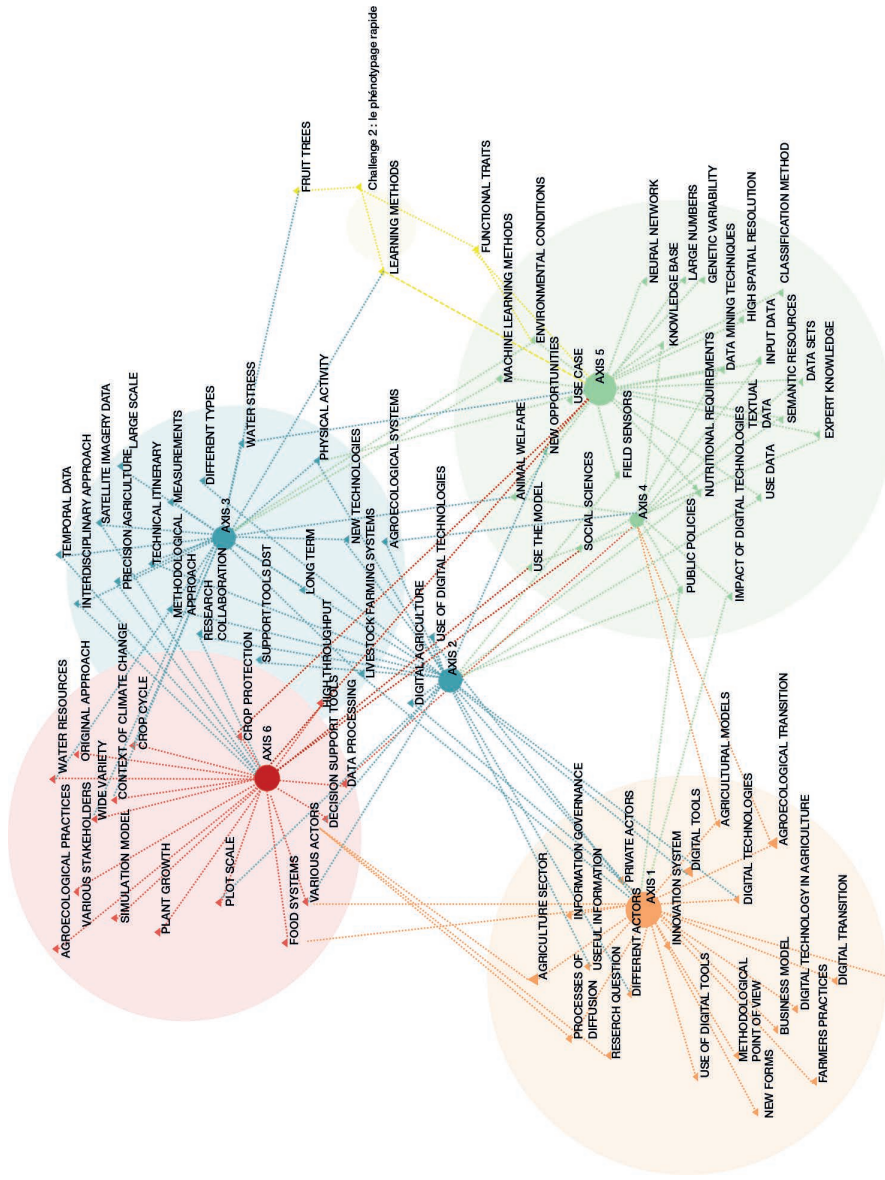


Figure 12.2. Network analysis between scientific axes and central terms in #DigitAg research. Source: Figure generated with CorText. This figure and the following ones are based on bibliometric analysis the authors performed based on language abstracts and technical terms in English.

and 6 in greater detail, as they embody two contrasting and particularly representative forms of the interdisciplinarity promoted by #DigitAg: one anchored in socio-ecological and participatory dynamics (Group 5), and the other in the challenges of digital governance and socio-technical innovation (Group 6). Together, these groups illustrate the diversity of interdisciplinary configurations present within the institute.

These groups should be viewed in relation to #DigitAg's scientific architecture (Figure 12.1). While four axes (Axes 3 to 6) are primarily focused on technological development—sensors, information systems, data extraction, etc.—and thus constitute the instrumental backbone of agricultural digitalisation, the other two (Axes 1 and 2) are by definition oriented toward transversal and systemic issues. It is precisely these two axes that are most heavily employed in Groups 5 and 6. Their interdisciplinary scope is not only established in conceptual terms but also institutionally supported: #DigitAg management has strategically promoted them as essential to ensuring a responsible, equitable and socially anchored digital transformation. Furthermore, it is significant that over time, these two axes have become twice as involved in projects as #DigitAg's management had originally anticipated, given the circumstances, attesting to a tangible structuring effect of #DigitAg's scientific programming instruments.

Group 5 is structured around keywords such as *agroecology*, *biodiversity*, *ecosystem* and *participatory*. It is supported by research units such as SELMET, AbSyS, MOISA, and SENS, and intersects Axis 6 (modelling), Axis 1 (ICT and the rural world), and Axis 3 (sensors). Projects in this class are associated with Challenges 1, 8, and the Cross-cutting Challenge (methodological challenge on “precision farming methods and digital

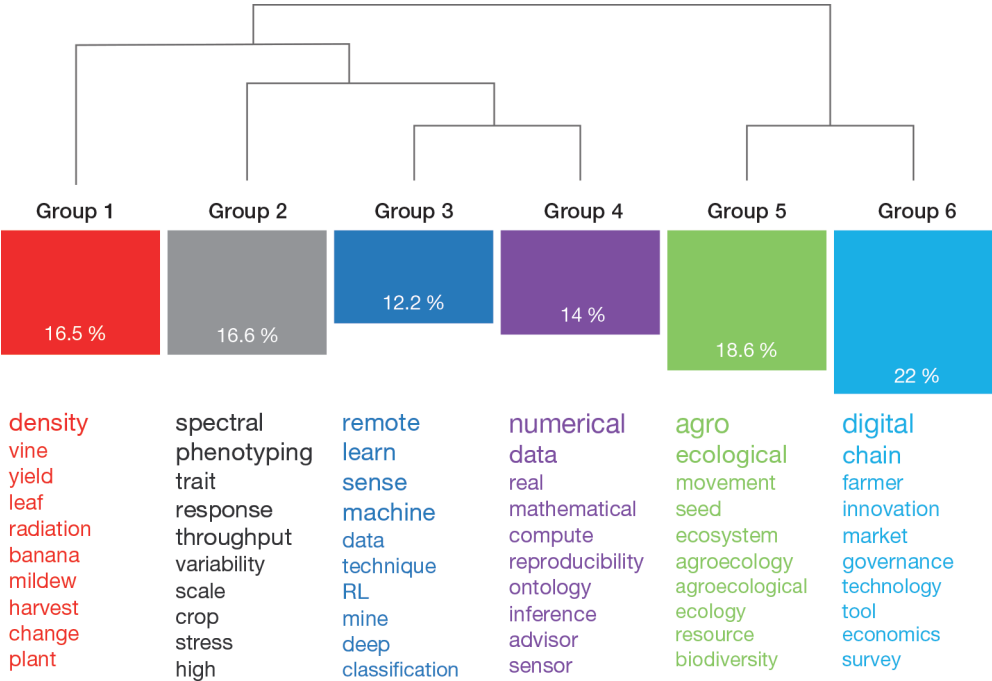


Figure 12.3. Lexical analysis using Reinert's method. Source: figure generated using Iramuteq and redrawn by the authors.

agriculture”). Here, we observe an interdisciplinarity oriented toward the co-construction of knowledge and the consideration of ecosystemic and social dynamics, combining ecology, modelling, HSS, and technology. Group 5 thus illustrates an ‘upward’ (bottom-up) interdisciplinarity, anchored in regional areas and usage.

In contrast, Group 6 is centred on terms such as *digital*, *chain*, *farmer*, *blockchain* and *policy*. It mobilises units from the humanities and social sciences (MOISA, INNOVATION, MRM), but also technological units like ITAP, and crosses Axes 6, 5, and 2, around Challenges 5, 7, and the Cross-cutting Challenge. This configuration reflects an interdisciplinarity oriented toward governance, digital infrastructure and integration into agricultural value chains. Here, the encounter between HSS and digital engineering is structured by challenges involving regulation, traceability and agricultural services.

These two examples illustrate how interdisciplinarity at #DigitAg is not limited to a formal principle but unfolds in real-world spaces for interdisciplinary collaboration, where disciplines intersect around shared challenges, bringing together diverse knowledge, tools and objectives.

Temporal evolution of themes

Figures 12.4 and 12.5 reveal a notable evolution in the themes addressed by the projects supported by #DigitAg. Both were produced using the CorText platform, based on an automatic n-gram extraction (groups of two to five words) applied to the full set of project abstracts funded or labelled by the institute (Master's, PhD, postdoctoral). These analyses allow an exploration of how scientific priorities evolve over time and how they are distributed among the research units.

Figure 12.4, produced using the Epic Epoch method, retraces the temporal evolution of salient terms extracted since 2018. During the initial years (2018–2020), most projects were characterised by concepts stemming from precision agriculture and digital technology, such as *high spatial resolution*, *decision support tools*, *sensor data* or *digital agriculture*. This reflects #DigitAg's initial orientation towards technological infrastructure and agricultural production management tools. However, from 2020 onwards, a shift is observed. Notions such as *agroecological transition*, *agroecological systems*, *public policies*, or *animal welfare* became more prominent, indicating a progressive broadening of scientific concerns towards social, ecological and territorial challenges. In parallel, the rise of *learning methods* or *data processing* attests to a growing interest in artificial intelligence methods, which enhance analytical capacities without eclipsing the new thematic dimensions.

Figure 12.5 allows the spatialisation of this transformation. It displays the statistically significant associations (using the chi-squared test) between the extracted n-grams and the research units, distinguishing between two periods. In the graph on the left (2017–2019), the dominant terms—*digital agriculture*, *decision support*, *data sets*—are heavily concentrated within technological units such as ITAP, TETIS, and MISTEA. This confirms an initial period marked by instrumental and technological expertise. In contrast, the graph on the right (2020–2023) shows a significant semantic redistribution: terms related to agroecology—*agroecological practices*, *transition*, *systems*—are now present in agronomical units (SELMET, AGIR), but also in historically technological units such as ITAP or LIRMM. This semantic hybridisation indicates an interdisciplinary percolation of these themes, moving beyond traditional institutional divisions.

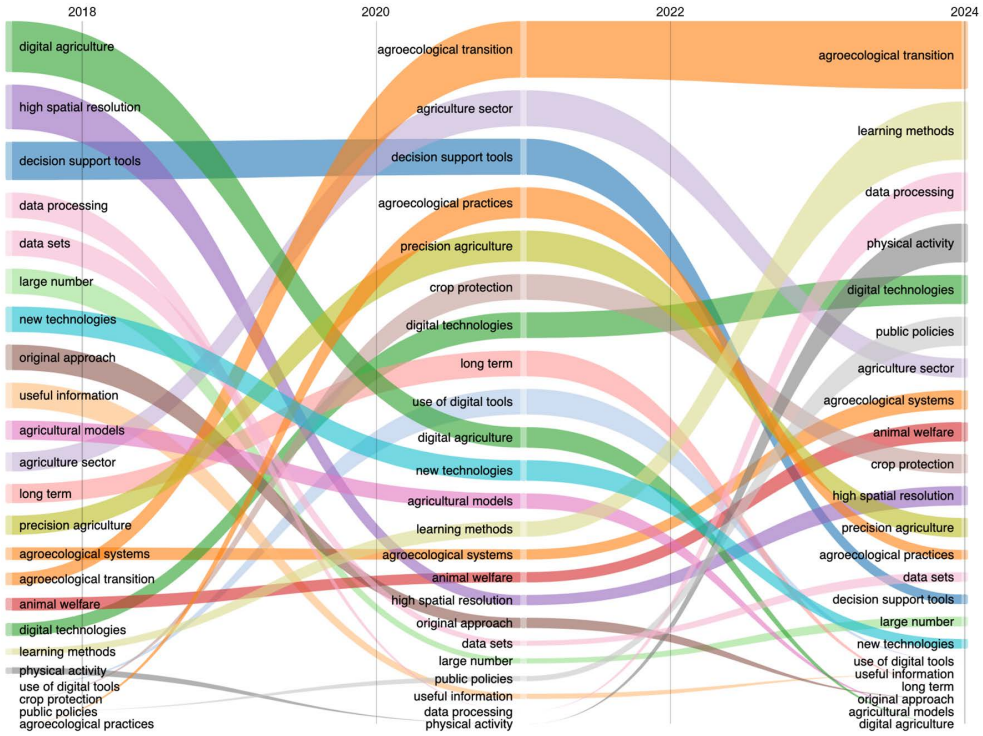


Figure 12.4. Epic Epoch analysis. Source: figure generated with CorText.

It would be premature to conclude that there has been a complete reorientation of #DigitAg's scientific agenda towards agroecology. The increased presence of agroecological terminology does not necessarily guarantee substantial engagement, as highlighted by several studies discussing the risk of 'discursive greenwashing' (Lyon *et al.*, 2015). Nevertheless, the increasing frequency of these terms, their diffusion into traditionally technology-focused units, and their integration with digital themes suggest a shift of conceptual frameworks. These transformations could reflect a progressive broadening of research horizons, potentially facilitated by the interdisciplinary mechanisms established by #DigitAg. Rather than a radical shift, what is perhaps happening is the emergence of a productive interdisciplinary dialogue, supported by public policies, notably France 2030. On the one hand, the spread of agroecological concerns would signal not merely a rhetorical effect, but the initial stages of a gradual and contextualised reorientation of scientific priorities at the intersection of production, sustainability and governance. On the other hand, this dynamic is part of a broader movement where research funding, since 2020, has tended to concentrate on transition-related challenges, thereby reinforcing the alignment between #DigitAg's internal transformations and the strategic orientations of national research policies.

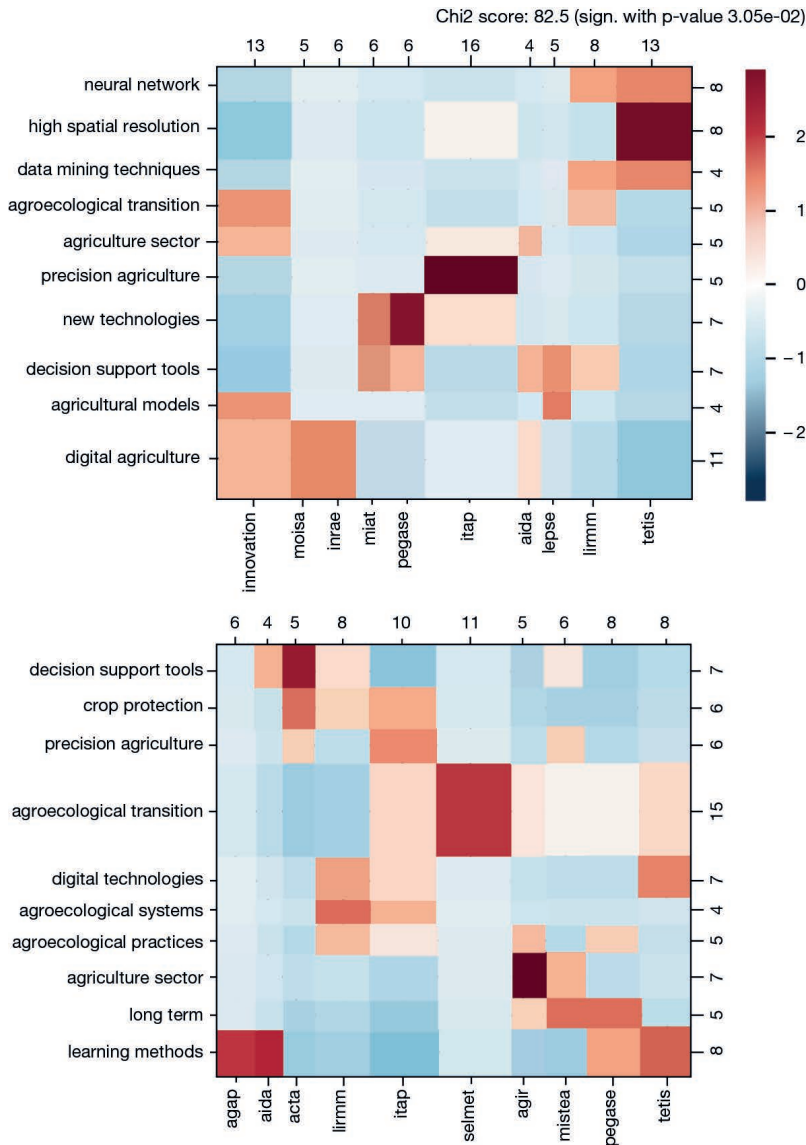


Figure 12.5. Spatialisation of significant semantic associations between n-grams and research units (top: 2017–2019; bottom: 2020–2023). Source: figure generated with CorText.

» Conclusion

The analysis of the mechanisms implemented by the #DigitAg Convergences Institute demonstrates that it is not merely a research support programme, but indeed an institutional laboratory for experimenting with the practical conditions of interdisciplinarity. By mobilising varied instruments—multi-level funding, co-supervision, matrix structuring and strategic project selection—#DigitAg has contributed to the emergence of a scientific community capable of working at the crossroads of agronomical, technological and social knowledge.

Far from imposing a uniform model, #DigitAg has fostered the emergence of diverse interdisciplinary configurations; these are often hybrid, sometimes unstable, yet always anchored in shared research objects. The growing prominence of extended interdisciplinarity, particularly in co-funded projects, attests to the structuring power of the institute's targeted intervention. Similarly, the semantic evolution of projects and the progressive redistribution of themes reflect an organisational plasticity that permits dialogue between technical innovations, regional transformations and societal challenges.

However, this dynamic remains subject to several underlying tensions. The increasing demand for disciplinary specialisation, the institutional fragility of certain early-career trajectories, and the persistent asymmetry between disciplines in academic arbitrations continue to limit the transformative scope of interdisciplinarity. These obstacles necessitate constant vigilance in the design of support mechanisms: simply decreeing interdisciplinarity is insufficient; the concrete conditions for its practice, recognition and legitimisation must be established.

For the years ahead, the challenge is twofold. On the one hand, it will involve consolidating achievements by maintaining a balance between interdisciplinary outreach and disciplinary anchoring, particularly for researchers in training. On the other hand, it will be necessary to support the evolution of the research objects themselves, notably concerning agroecological and digital transitions, by ensuring that thematic hybridisations are accompanied by genuine methodological and epistemic hybridisations. The established mechanisms must remain sufficiently flexible to accommodate the transformations of the agricultural, technological and scientific worlds, without losing sight of the central objective: to make interdisciplinarity not a mere slogan, but a situated, collective and sustainable practice.

In this sense, initiatives such as #DigitAg are drafting the blueprint for an original institutional model, where interdisciplinarity becomes a vehicle for scientific structuring as much as a lever for transforming research practices. The challenge is now to sustain these experiments, to document their long-term effects, and to draw lessons from them for other contexts where the complexity of the stakes necessitates moving beyond disciplinary boundaries without compromising disciplinary rigour.

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Chapter 13

The emergence of new digital models: towards accessible and responsible digital agriculture

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Digital technology in agriculture was initiated through precision agriculture and precision livestock on large-scale holdings. Digital agriculture corresponds to a wave of increasingly diversified new digital solutions. However, adoption rates remain low, and concerns are being raised about the risks and impacts of digitalization. The interdisciplinary approach of #DigitAg—linking, among others, technology-focused researchers with specialists in usage (human and social sciences)—has led to an exploration on how to better align digital technologies with the expectations of various forms of agriculture. This is the theme of this chapter which is organised according to three perspectives: (1) responsible approaches, (2) facilitated access to technologies, and (3) data governance.

► A necessary shift in stance: the contribution of ‘responsible research and innovation’

Early 2020s: adoption remains low

Adoption rates for digital technologies vary significantly, depending on the digital literacy of farming communities and the accessibility of digital agricultural services (Piot-Lepetit *et al.*, 2023). In France, despite a substantial framework of research and innovation support through public policy measures, the diffusion of digital tools within agriculture remains limited. Bellon-Maurel *et al.* (2023) summarizes the results of the ‘Agrinaute’ survey published in 2022. Despite high connectivity levels on farms (95% have internet access), the most widely adopted tools are those offering immediate benefits—in terms of work comfort or ergonomics—and strong interoperability. Examples include geolocation and navigation (GNSS) and smartphone applications for professional use (both used by 50% of farmers, with weather apps being the most prominent). A more recent study by the *Cour des comptes* (the French Court of Audit) involving over 1,000 farmers highlights that in 2023–2024, 34% had acquired digital applications and technologies, while 14% had purchased connected or autonomous agricultural machinery (Cour des comptes, 2025). In robotics, adoption primarily

concerns milking robots; indeed, 18,000 milking robots were in operation on dairy farms in 2023 (up from 10,000 in 2018), whereas only 600 robots were used in crop production (up from approximately 100 in 2018²⁶).

To better understand adoption levels and the obstacles encountered, l'Institut Agro (Montpellier) established the *Observatoire des usages de l'agriculture numérique* (French Observation Centre of Digital Agriculture Adoptions²⁷), co-funded by #DigitAg and the AgroTIC Chair (Bellon-Maurel *et al.*, 2023). This observatory conducts surveys among manufacturers and users of digital technologies, producing reports and infographics either for specific technologies (such as smartphones or satellites) or by agricultural sector. According to the observatory (Lachia *et al.*, 2021), the primary barriers to adoption are a lack of training, tool complexity and high costs. Nearly 60% of surveyed farmers indicated that difficulty of use and price are obstacles, particularly in low-margin sectors.

The adoption of these tools is heavily influenced by the characteristics of the holding and the digital maturity of the farmer, but also by relationships with upstream and downstream partners. For instance, nearly 75% of arable farms are equipped with digital traceability systems to satisfy downstream partners and regulatory requirements. However, the adoption of these tools does not necessarily mean they will be used. For example, only 20% of farmers equipped with yield monitoring tools actually use them for yield mapping or variable-rate fertilisation.

The risks are identified

The 2010s abounded with techno-optimistic approaches that paid little attention to the unanticipated, and sometimes controversial, consequences of agri-food system digitalisation (Lajoie-O'Malley *et al.*, 2020). However, the risks associated with the digitalisation of agriculture must not be overlooked. An initial synthesis of these risks, drawn from a relatively critical body of social science literature, was conducted by Bellon-Maurel *et al.* (2022), who categorised them into four types: (1) hindrances to the ecological transition of agriculture, (2) reinforcement of inequalities and power dynamics, (3) loss of sovereignty, and (4) increased vulnerabilities.

More recently, Saucède and Pardo (2024) analysed social science research on digital agriculture through the concept of 'transformative power'. They identify four 'blind spots' regarding the transformative impact of digital tools. Firstly, digital technologies often convey mainstream visions and tend to marginalise alternative trajectories (Eastwood *et al.*, 2019) tailored to different user needs (Schnebelin *et al.*, 2021), potentially leading to a technological lock-in that obstructs the agroecological transition. Furthermore, digital technology acts as a mediator, altering the connections between actors in socio-technical networks—particularly regarding power and dependency—or between the farmer and their holding or livestock (Eastwood *et al.*, 2019; Martin *et al.*, 2022). Additionally, digital tools can transform individual identities through their effects on practices (Martin *et al.*, 2022), decision-making (Eastwood *et al.*, 2019), or farmers' skills. Finally, digital technology is intrusive; the transformations it triggers are profound and extend beyond the activities it seeks to optimise. Consequently, digital technology may generate new forms of exclusion or vulnerability, such

26. <https://agrotic.org/observatoire/2023/05/16/usages-des-robots-en-agriculture-2023/>

27. <https://www.agrotic.org/observatoiredesusages>

as the marginalisation of smallholders, agricultural workers or alternative models, thereby reinforcing technological lock-in, a loss of farmer autonomy, or even a loss of sovereignty involving data risks (data confiscation, cybersecurity).

One way to mitigate the risks identified above is to commit to a Responsible Research and Innovation (RRI) approach, in order to develop and disseminate ethical and inclusive digital technologies and services.

Reducing risks through a shift in stance: Responsible Research and Innovation

The concept of Responsible Research and Innovation (RRI) was developed in the early 2000s under the impetus of René von Schomberg, a Scientific Policy Officer at the European Commission Directorate-General for Research and Innovation (DG RTD), specifically in the Governance and Ethics unit (Temri, 2018). On the one hand, RRI is based on the necessity of considering societal expectations and values when steering technological development. On the other, it integrates the responsibility of researchers to anticipate the potential consequences of these technologies at an early stage in the innovation process. Four dimensions characterise Responsible Research and Innovation (Stilgoe *et al.*, 2013): inclusion (involving as many stakeholders as possible throughout the process); anticipation (identifying the risks associated with the innovation and the effects it is likely to produce); reflection (requiring researchers and innovators to reflect on their own approach and the associated ethical, societal, and political consequences); responsiveness (activating the capacity to reorient the innovation trajectory by mobilising knowledge produced during the process). Originally developed for controversial technologies, the RRI concept has prompted an increasing body of work within digital agriculture (Bellon-Maurel *et al.*, 2022a).

This approach was introduced into #DigitAg through the doctoral thesis of Boris Biao (2022), which focused on innovation within AgTech companies that design and market digital agricultural solutions. Biao studied innovation governance in these companies to find the degree of responsibility of digital agricultural innovation. He demonstrated that while these innovation processes are indeed open, they are only partially responsible. These processes focus on exploring ideas with high technological potential and only occasionally integrate user needs. Thus, while there is potential for responsible innovation, current practices are far from ideal (Biao *et al.*, 2023; Chapter 6).

In parallel, an interdisciplinary group of #DigitAg researchers at INRAE explored this subject to identify the characteristic features of an RRI approach applied to the development of digital tools for agroecology (Bellon-Maurel *et al.*, 2022b). The authors drew on the four pillars of RRI to adapt the design of digital technologies for agroecology across several levels of Gliessman's scale. Their analysis highlighted four key issues and two axes of tension—or trade-offs—which served to define a framework for selecting and steering research aimed at developing ethical and inclusive digital technology in agriculture.

An application of RRI for digital agriculture: the OccitANum living lab

In 2020, #DigitAg set up OccitANum, an experimental framework to put RRI into practice, aiming to foster the deployment of digital agricultural technologies tailored

to farmers' needs and agroecological principles. This project, OccitANum²⁸, brought together a dozen living labs across the Occitanie region, covering seven sectors (arable farming, livestock, arboriculture, viticulture, market gardening, beekeeping, and local food) and a dozen coordination sites (Bellon-Maurel *et al.*, 2023). The living lab approach relies on collectives of diverse stakeholders (agricultural development agencies, farmers, AgTech firms, researchers, etc.) who collaborate on a complex subject—in this case, digital technology to encourage agroecology and local food systems—to co-construct pathways for progress. Within OccitANum, three such pathways were pursued:

- Improving information on the costs and benefits of digital technologies across the three dimensions of sustainability. Environmental assessment was the focus of Clémence Huck's PhD, which developed and applied a method based on life cycle assessment (LCA) (Huck *et al.*, 2024). Human and social assessment—evaluating the impact on the user—was the subject of Mauro Florez's postdoctoral research, developed a framework with the help of an interdisciplinary panel, in response to the lack of existing evaluation methods (Florez *et al.*, 2024).
- Co-designing tailored digital systems with users. Two ergonomists supported this action by analysing digitalised activities on the farm to understand and improve human-machine interactions. Technologies included assistance with machine operation, robotics and data registration in farm information management software—the latter being the subject of Clément Zind's doctorate. Moreover, we also studied the process established by OccitANum to identify farmers' needs and include them as early as possible in the design of digital technologies (Larbaigt *et al.*, 2024).
- Accelerating capacity building for actors in the agricultural ecosystem (farmers, advisors, etc.) for both digital technology and agroecology, using innovative educational and experimental frameworks. The MobiLab was created in OccitANum to raise awareness about the use of digital tools in agriculture (it will be described later in this chapter). Another initiative concerning agroecology was the launch of a new research theme on On-Farm Experimentation (OFE) supported by digital tools. OFEs, conducted by farmers alongside advisors and researchers, aim both to address farmers' agronomic questions (concerning new practices, varieties, etc.) and to generate formalised knowledge. Supporting OFE with low-cost digital solutions facilitates and secures data collection. This approach was launched at the OFE2021 conference (Lacoste *et al.*, 2025) and is the subject of a foundational position paper (Lacoste *et al.*, 2022). It is also being implemented in Africa, for example with the Soyield application, developed during Julien Sarron's doctoral work and used for data entry (Alexandre *et al.*, 2023). Other educational tools to support skill development among farmers and advisors have been produced within #DigitAg. For instance, #DigitAg funded the textbook *Le numérique en agriculture : des technologies aux applications* [Digital technology in agriculture – from technologies to applications] (Brun and Le Gall, 2025), which clearly describes available technologies and implementation examples. Furthermore, regarding agroecology, a serious game called Erosion t-Tool, was created in a 'phygital' format (hybridising physical and digital elements) during Laurie Dunn's #DigitAg postdoctoral research, to help farmers understand the benefits of collective erosion management.

28. Funded by the Banque des Territoires (under the 'Territories of Innovation' programme) and the Occitanie region.

► Facilitating access to and mastery of technology: the role of open-source and high-low-tech solutions

As one of the difficulties identified in the adoption gap is that tools are not fit for purpose, initiatives have been launched to develop low-tech and low-cost systems, often in collaboration with farmers. This chapter draws on a series of studies conducted and funded within the framework of #DigitAg and OccitANum, which concretely explored how participatory, frugal, and open approaches could foster broader technological ownership among stakeholders in the agricultural world.

The challenge: high-low-tech as a means to democratise digital technology

Making innovations more accessible, adaptable, and highly useable can remove the economic and technical barriers to adoption. In practical terms, this means designing low-cost tools that are transparent in their operation and involve farmers throughout their development.

These frugal digital tools are termed ‘high-low-tech,’ a concept proposed by MIT (Bellon-Maurel *et al.*, 2022a, p. 83) to denote a hybrid approach. It combines elements of high-tech (digital) technology with the core principles of low-tech: simplicity, frugal design, robustness, accessibility (self-build), and repairability. This involves integrating electronic components—such as sensors, wireless communication, and embedded intelligence—into a tool while maintaining full control over costs, manufacturing, and maintenance.

Simon Moinard, manager of the AgroTIC MobiLab (see below), explained the growing enthusiasm for DIY (Do-It-Yourself) in agriculture: “Based on listening and exchange, these [DIY] approaches help to democratise digital technologies in agriculture and explore new pathways by gathering the expectations of the profession. Low-tech, or ‘Do-It-Yourself’, is deeply rooted in agricultural culture. Farmers are accustomed to building their own tools, tailored to their specific needs.”

Participatory and open-source approaches

Several initiatives stemming from #DigitAg and OccitANum illustrate how these principles are put into practice. The flagship example is the AgroTIC MobiLab, an itinerant FabLab that travels through the Occitanie region countryside to engage with farmers (Ducanhez *et al.*, 2025). Through demonstrations and games, it aims to raise awareness and allay concerns about digital technology (Valloo *et al.*, 2025). Several steps are involved. First frugal digital technologies are showcased at local events, followed by the organisation of workshops. Participants can then build the sensors they require, learn the basics of Arduino programming, or operate connected tools. The reproducibility of the suggested low-tech tools is ensured by the use of standard electronic components, open-source Arduino code, and the sharing of generated knowledge (guides, videos, etc.) on the website²⁹. Between 2019 and 2024, the MobiLab trained 1,300 people.

29. mobilab.agrotic.org

Three low-cost (costing a few dozen euros) and low-tech innovations issued from the MobiLab are particularly noteworthy (Figure 13.1): *Coup de pouce* (Helping Hand): a 3D-printed robotic finger that can remotely trigger an irrigation pump in response to a simple SMS; AgroCam: a small, connected field camera that automatically takes a daily photograph of the plot to monitor crop growth and detect malfunctions; Pilow-Tech: an irrigation management system consisting of soil moisture probes linked via LoRa radio to an internet gateway, which sends an SMS alert to the farmer, indicating the optimal time to stop surface irrigation.

Admittedly, these systems may be less robust or less precise than industrial versions; however, their accessibility and repairability pave the way for large-scale adoption among small-scale farmers.



Figure 13.1. (a) The MobiLab (© Marie-Caroline Fiocca); (b) the AgroCam (© Simon Moinard, 2024).

Other co-design projects have been conducted by various research teams as part of action-research.

The Hub'IS project (digital technology for managing an irrigated system in Tunisia) mobilised an interdisciplinary team of researchers specialising in sensors and social sciences alongside irrigation associations using a living lab approach. During a series of workshops, participants identified priority needs (in this case, soil moisture monitoring) and subsequently co-developed open-source wireless sensors to manage drip irrigation (Vandôme *et al.*, 2023). This technology served as the foundation for the PilowTech probes mentioned above. In his Master's degree work, Louis Haegi (2024) provided feedback on these PilowTech tools by three viticulturists in Hérault, France. The results were mixed—ranging from very passive use to the deep integration of data into irrigation management—thereby highlighting the importance of ongoing support to ensure successful technological adoption. Technical issues were also noted, such as battery failure and imprecise calibration; these were to be addressed in a new version of the probes as part of an iterative design process.

Finally, the doctoral research of George Aboueldahab (2023) explores the open-source frameworks used by farmers' organisations (such as *L'Atelier Paysan* and *CoopCircuits*)

to share knowledge and digital infrastructure through principles of pooling, empowerment and cooperative governance. His work also illustrates the reluctance of these organisations to engage with digital tools. The action research he conducted to build an open-source knowledge-sharing tool for a movement involved in landrace seeds could not be completed. Indeed, the development project failed to reach a consensus due to fears regarding the risk of grabbing of these seed resources by the agro-industry.

Conclusion: Low-tech as a double-win entry point

Low-tech and open-source solutions not only address the major barriers to digital adoption—specifically cost and technical complexity—but also foster a broader social shift. Field feedback demonstrates a collective upskilling: individuals are inventing new tools (such as connected fence alarms) and sharing their experiences with peers, sometimes fostering the emergence of informal ‘agricultural maker’ groups. Farmer empowerment is thus strengthened: rather than being mere users, they become co-designers, inventing tools better tailored to field realities.

However, challenges remain in this route: the reliability of low-tech systems, their maintenance by non-specialists (i.e. farmers), and the long-term viability of open-source communities are critical issues. Furthermore, while farmers’ autonomy regarding hardware is enhanced, the question of data sovereignty remains. This is the subject of the following section.

► Data: ensuring sovereignty and equitable governance

Facilitating data access and guaranteeing sovereignty

Over two decades of agricultural digitalisation, the key challenges have evolved. Initially, the issue was to resolve technical hurdles (sensors, databases, etc.), followed by the development of connectors (Application Programming Interfaces or APIs, interoperability, etc.). Today, data-related issues can no longer be sidelined, whether these concern access, trust, or sovereignty (Brun *et al.*, 2016).

Access can be facilitated through data integration platforms for agricultural applications, designed to manage heterogeneous data sources (sensors, machinery, satellite imagery, meteorological services, and farm management information systems). Data access fosters open innovation, as demonstrated by Mathieu Rajaoba’s PhD work (2022), which analysed the role of agricultural data in the emergence of digital agriculture during the 2010s through an examination of data exchange platforms and farmer consent management. This period was indeed marked by promises of services leveraging agricultural data, but also by concerns regarding value sharing. The benefit of accessing agricultural data during ‘hackathons’ dedicated to creating innovative services has also been proven: the HackTaFerme event, organised in 2019 on farms in Gers Department by ACTA with #DigitAg support, illustrates this, as it led to the founding of the start-up Assolia (Brun *et al.*, 2022).

The concept of data sovereignty dictates that data producers retain control over how their data is used (Chapter 7). The European Commission addressed farmers’ anxieties regarding data usage by highlighting the need to provide “guarantees regarding data sharing, sovereignty, and security in order to build trust.” The European Data Act establishes harmonised rules on fairness in data access and use. The strategy chosen

to strengthen data sovereignty is the development and deployment of federated data ecosystems. Consequently, in agriculture, a three-year project initiated in 2025—the CEADS (Common European Agricultural Data Space)—aims to facilitate the secure, transparent and responsible sharing, processing and analysis of agricultural data.

Legal, regulatory and governance challenges related to data sharing

Despite these advancements, the question of data usage rights for agricultural data—particularly those generated by machinery—remains ambiguous. In 2022, Laura Tomasso addressed this subject in her #DigitAg doctoral thesis in law. Conducted prior to the European Data Act, this research drew upon existing initiatives: the Data-Agri charter, proposed in 2018 by agricultural unions, and the Multipass project concerning agricultural consent (Lauga *et al.*, 2023). Due to their diverse nature (heterogeneity, level of processing, etc.), agricultural data are not covered by a single set of regulations. Consequently, stakeholders must rely on contracts (soft law) to govern the access and use of the data they generate (Tomasso, 2024).

Furthermore, while the Data Act enhances safeguards (user access rights, fair pricing principles and dispute resolution bodies), these elements must be translated into practice. This is especially critical given the rapid growth of artificial intelligence (AI), which uses agricultural data to create services. The European AI Act imposes obligations based on the risk level of digital agricultural tools (transparency sheets for low-risk advisory tools and external audits for high-risk tools, such as integrated farm management or livestock management systems), which will inevitably constrain agricultural data governance frameworks.

Finally, two other risk factors concerning data exchange must be integrated: firstly, the issue of cybersecurity, which is addressed by the Cyber Resilience Act, imposing security and update obligations on all connected devices sold within the EU, including those used in agriculture; and secondly, the international nature of data flows associated with agricultural products. This necessitates navigating data governance frameworks that vary across jurisdictions, even within the EU, thereby hindering data fluidity.

Adapting public policy to digital evolution

Policy measures aimed at fostering digital inclusion in agriculture are multifaceted: obligation of rural connectivity, subsidies for farmers' digital equipment, deployment of digital public goods (data), infrastructure and, crucially, the development of farmers' skills (Piot-Lepetit, 2023)—a fundamental requirement for an inclusive transformation. Regarding the latter, it is recommended to employ practical, tiered approaches—progressing alongside the user's adoption level—as illustrated by the participatory methods described above. These aim to instil a basic digital culture and raise awareness of data-related issues and cybersecurity. However, providing support for farmers remains difficult: everywhere in the world, there is a shortage of digital trainers, and the ministries of agriculture, regulatory bodies and advisory services are themselves at varying stages of digital transformation.

Furthermore, the discrepancy between technology development cycles (often measured in months) and policy-making timelines (generally measured in years) creates mis-alignment issues, complicating policy coordination. Institutional capacity to adapt to digital change varies considerably across Europe, resulting in implementation

environments that are sometimes inconsistent. For instance, Member States interpret the digital greening incentives of the CAP differently (Bellon-Maurel *et al.*, 2023), leading to uneven adoption pathways (Piot-Lepetit *et al.*, 2023). To address this challenge, flexible and scalable regulatory approaches that evolve alongside technology and ensure policy coherence are essential.

» Conclusion

Through the French Observation Centre of Digital Agriculture Adoption at Institut Agro, #DigitAg possesses a vital tool for monitoring the spread of digital technology across value chains and identifying key bottlenecks. Research efforts must now focus on overcoming these barriers while mitigating identified risks of digitalisation. Consequently, in the early 2020s, #DigitAg realigned its vision, its scientific programming, and its operations to commit more deeply to digital technology that serves agroecology and small farmers, seeking alignment with the RRI framework.

The progress achieved extends beyond academic output: a new innovation initiative, OccitANum, was launched to work more closely with the farmers, evaluating technologies in use or co-designing them with farmers. This initiative enhances skills by leveraging high-low-tech and open-source solutions. It enabled the implementation of pioneering approaches such as the MobiLab— the only mobile FabLab of its kind in the world—and the digitally-assisted OFE approach, launched in Montpellier in 2021. Furthermore, within #DigitAg, data-related issues (access and governance) have been the subject of academic research in law, social sciences and economics. These efforts aim to advance models that facilitate data access while guaranteeing sovereignty. Collective data governance models, such as data cooperatives, offer promising avenues for ensuring both inclusion and data sovereignty.

This chapter also demonstrates how #DigitAg and OccitANum have fostered the emergence of interdisciplinary approaches rooted in field realities, blending engineering with the humanities and social sciences through co-construction with stakeholders. These examples show that producing open, frugal and user-friendly agricultural technologies requires both scientific openness and a deep grounding in the practices and knowledge of end-users. This innovation pathway can complement the more traditional AgTech route, which remains advantageous for farmers who do not wish to engage in digital DIY projects. The objective is not to oppose these approaches, but to recognise the diversity of farmer profiles and expectations—as clearly demonstrated by Schnebelin *et al.* (2021)—and to offer different pathways for digital engagement.

» #DigitAg doctoral theses contributing to Chapter 13

Aboueldahab G., 2023.	Pooling knowledge through digital sharing: Challenges and opportunities for the agroecology movements, PhD thesis. https://theses.fr/2023UMOND004
Biao B., 2022.	Is innovation in smart agriculture responsible?, PhD thesis. https://hal.science/tel-03986147v1
Huck C., 2025	Assessing the environmental impacts of digitalisation in agriculture: application of comparative life cycle assessment on current farming practices, PhD thesis. https://theses.fr/s353522

Martin T., 2023.	The Barn Sentinels. Robotisation of milking and a new division of labour in French dairy farming, PhD thesis. https://theses.fr/2023MON30021
Rajaoba M., 2022.	The politics of agricultural data. An inquiry into digital innovation and platformization in French agriculture, PhD thesis. https://theses.fr/2022UPSLM060
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Conclusion

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The objective of this volume was to present the ten years' (2017–2026) research outputs of the #DigitAg Institute community, funded by the France 2030 Convergence Institute programme. It has endeavoured to illustrate the various facets of this institute in terms of knowledge creation, tool development and methodological innovation. The objective was not to be exhaustive as an attempt to present #DigitAg work in its entirety would have resulted in either an oversized volume or a frustratingly superficial overview. Instead, these chapters provided an opportunity to consolidate essential research around shared subjects of study, whether methodological or thematic. Other academic works (doctoral theses and post-doctoral research) that contribute to these subjects but could not be cited here are listed in the appendices.

Furthermore, beyond the academic outputs supported by the work of PhD and Master's students, and post-doctoral researchers, #DigitAg has introduced several initiatives to increase the visibility of student research outside the immediate academic community. These include the *T-tAg* webinars, where two students present their findings, and the #DigitAg digital showcases. These showcases allow volunteer doctoral and post-doctoral students to present a facet of their work through web-based demonstrators (such as simulators, serious games, or quizzes). A full list of the *T-tAg* webinars and digital showcases (with access links) is provided in the appendices.

►► Academic, applied and procedural advances

Methodological progress in digital sciences and technologies primarily concerns data acquisition, featuring the development of new sensors—largely optical—and novel processing methods (specifically those based on artificial intelligence) to obtain new data at a large scale (Chapter 1). Chapter 2 focused on agricultural big data: massive, diversified data sets from proximal or remote sensing imagery and connected objects. This field is currently shifting towards new paradigms—moving from traditional statistics to artificial intelligence (deep learning)—and, crucially, towards integrative solutions that jointly leverage multiple data sources. Chapter 3, dedicated to data and knowledge management and integration, presented the diversity of approaches used to structure, interconnect and exploit agricultural data and knowledge. Technical and scientific challenges are emerging due to the rapid growth in data volume, complexity and heterogeneity, establishing interoperability as a key priority. Finally, Chapter 4 provided a broad panorama of new forms of modelling driven by innovative methods - notably based on artificial intelligence - and data sources. The current challenge is to operationalise these models to make them usable for the farmers and agricultural advisors.

New insights into the transformations induced by digital technology in agriculture were provided by the humanities and social sciences across three chapters. The first (Chapter 5) dealt with agricultural digitalisation as both a process and an innovation ecosystem, concluding that RRI approaches are necessary to achieve greater convergence with the SDGs. Numerous empirical contributions resulting from farmer surveys were then highlighted in Chapter 6. The diversity of uses identified encourages a link between digitalisation and greening, focusing on the plurality of digital systems supporting the agroecological transition. Finally, the last contribution (Chapter 7), which views digital tools as intermediation instruments, based its analysis on the gaps between promises and observed realities. It concluded that governance of digital agriculture must be both inclusive and transparent.

In Chapters 8, 9, and 10, three application themes (plant phenotyping, sustainable livestock farming and food security) illustrated how digital technology can improve characterisation, monitoring, and decision support processes at different scales (from the plant to the regional level) and for various stakeholders (breeding companies, conventional or extensive livestock farmers, and public policymakers). Other themes, such as crop protection or precision farming, could also have served as illustrations, given the extensive work conducted on these subjects within #DigitAg.

Finally, the last three chapters, which were more reflective, considered how #DigitAg has functioned and evolved, thereby representing procedural advancements in how research is conducted at the interfaces between disciplines, and between research and the field. Chapter 11, presenting digital agriculture in the Global South, acts as a ‘mirror’, prompting us to reflect on how technology is deployed in the Global North. We have much to learn from ecosystems of the Global South: are the drivers of adoption perhaps the same in both contexts? Chapter 12 addresses interdisciplinarity—embodied by the word ‘convergence’—, a constitutive feature of #DigitAg. It shows how various mechanisms (funding, joint supervision, matrix structuring) have been set up to enable the emergence of a scientific community with an interdisciplinary awareness, and outlines that a balance between disciplinary specialisation and interdisciplinary collaboration must be struck to make interdisciplinarity a sustainable collective practice. Chapter 13 illustrated the introduction of the RRI framework into #DigitAg—an emergent property of the interdisciplinary convergence between the humanities and social sciences (HSS) and digital sciences, which has shifted perspectives and research of both fields around the question: what kind of digital technology for agroecology?

The question of “responsible digital technology for responsible agriculture”—and thus of agricultural digitalisation that supports the agroecological transition—rapidly emerged from interdisciplinary discussions within the institute to become a core research hypothesis: “Can digital technology accelerate the agroecological transition?” By framing the question this way, #DigitAg prompted researchers to examine their contributions to agroecology in its broadest sense (close to FAO’s definition), encompassing not only bio-technical aspects to reduce the production environmental footprint and but also social aspects to foster farmer autonomy. Consequently, while precision farming—which contributes to the first level of agroecology on the Gliessman scale—was a prominent subject when the institute was first established, it later gave way to more inclusive approaches e.g. participatory co-design of low-cost

digital tools. These integrate the goal of reducing inputs with that of increasing farmer autonomy. Subjects previously unseen in agriculture, linking digital technologies with system redesign, multiplied during the second phase of #DigitAg: animal monitoring in grazing systems, simulators for highly diversified agroecological market gardening systems, and the monitoring of intercropping. The new systems established by #DigitAg and associated projects for co-innovation with farmers (OccitANum, MobiLab) have, for their part, helped ensure the social and agroecological relevance of the research. Participatory research thus appears to be a vital pathway for the institute's future.

► Outlook: new tools and new horizons

While the goal of building an interdisciplinary community—with a higher level of mutual understanding among researchers and the cross-integration of research problems—has been achieved, this ten-year programme has also witnessed the birth of new approaches. These include endogenous developments in agriculture, such as the participatory element in the design of digital solutions, as well as the integration of exogenous factors, of which generative artificial intelligence is the best example. Furthermore, the strong connection with the Global South, driven by the involvement of CIRAD, provides inspiring research avenues, as in these contexts these are shaped by more challenging bio-technical and socio-economic constraints (resource scarcity, complex stakeholder networks and food systems, actor capacity, etc.).

Future prospects are taking shape around these three directions and their intersections: artificial intelligence, participatory methods, and interactions with the Global South (Figure C1).

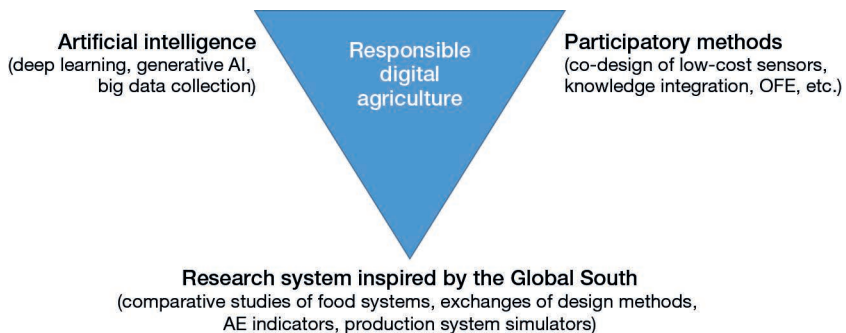


Figure C1. The outlook for #DigitAg, based on three pillars: AI, participatory research and research inspired by the Global South.

These directions are in perfect alignment with major agencies such as the FAO, which convened a hundred experts in April 2025 to discuss AI and digital technology for smallholders—and the Digital Transformation Accelerator (the CGIAR 2025–2030 programme³⁰). They will enable the formation of strategic alliances and will foster fundamentally interdisciplinary research, continuing the vision initiated by #DigitAg a decade ago.

30. <https://www.cgiar.org/cgiar-research-portfolio-2025-2030/digital-transformation/>

Appendices

► #DigitAg PhD theses

Theses whose titles appear in italics in the list are theses based in the Global South.

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► #DigitAg postdoctoral research projects

- Arouna K., 2022-2023, Value of information, digitalization of agriculture and pesticide use, Center for Environmental Economics, Montpellier, UMR MOISA.
- Blancaneaux R., 2024-2026. *Scaling-up agroecological market gardening through digital technologies*, UMR MOISA, MRM.
- Cheraïet A., 2022-2023, *Development of innovative solutions combining biocontrol and agricultural equipment: a further step towards precision spraying in viticulture*, UMR ITAP (Chapters 1 and 4, digital showcases).
- Dubos T., 2022-2023, *Deep4mix: using deep learning to monitor vegetation species dynamics in mixed crops*, UMR EMMAH, LIRMM, UMR AGIR (Chapter 8).
- Dunn L., 2022-2023, *Transitool: a companion tool to assess step-by-step agroecological transition of a cash crop farm*, UMR AGIR, Montpellier Research in Management, Unit MIAT (Chapter 13, digital showcases).
- Faucher M., 2023-2025, *Co-design, adaptation and dissemination of high-low-techs to understand and support water management in the agro-ecological transition*, UMR AbSyS, UMR G-Eau.

Florez M., 2023-2025, Evaluation of human costs and benefits of digital technologies in farms, UMR ITAP (Chapter 5).

Guillot-Pelliet R., 2025-2026, Analysis of the business models and financial trajectories of digital agriculture organisations in France, UMR AGIR (Chapters 6 and 7)

Kalboussi N., 2018-2020, OPTI-REUSE (Digital Platform for the optimisation of water and nutrient resources in agriculture, including treated waste water reuse), UMR ITAP (Chapter 4).

Kim J., 2024-2026, Construction and Impacts of interdisciplinarity in the Digital Agriculture Convergence Lab, UMR MOISA, UMR ITAP (Chapter 12).

Latchoumane L., 2024-2026, Time series analysis of hyperspectral images for early diagnosis of septoria symptoms in durum wheat, UMR AGAP, UMR ITAP.

Lee S. H., 2018-2025, PLANT HEALTH (*Plant disease monitoring in crowdsourced image streams*), UMR AMAP (Chapter 1).

Lee-Cruz L., 2023-2025, Integration of heterogeneous data for simulation of livestock-wildlife contacts, UMR TETIS, UMR SENS (Chapter 4).

Marescot L., 2021, Integrative ecological modelling of Senegalese locust management, UMR CBGP.

Martin T., 2023-2025, Co-evolution between labour market and agricultural robotics, UMR Innovation (Chapters 6 and 13).

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Nguyen K.-L., 2024-2025, High-throughput phenotyping of fruit tree genetic diversity for better adaptation to climate change, UMR EMMAH, UMR AGAP (Chapters 1 and 8).

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Pérution Kihli G., 2025, Reasoning on Data in Agronomy and Agriculture, LIRMM (Chapter 3).

Raffaillac T., 2022-2023, Co-design of participatory simulations of MAS models for multi-actor decision support, UMR SELMET, UMR SENS (Digital showcases).

Ryckewaert M., 2020, Detection of vine water stress by optical instrument, UMR ITAP (Chapters 1 and 8).

Sandonis-Pozo L., 2025, A hybrid approach to combining biophysical modeling and remote-sensing derivatives model 3D canopy architecture in vineyards for differential management, UMR ITAP, UMR TETIS.

Smolinski J., 2024-2026, Determinants, modalities and value of data sharing by farmers and SMEs in blockchains for transparent and sustainable food supply chains, UMR MOISA, UMR TETIS (Chapter 7).

Syed M. A., 2024-2026, Development of a machine learning framework for the prediction of food security indicators at country scale from heterogeneous data, UMR TETIS, UMR MOISA (Chapter 2).

Tarraf B., 2022-2023, Added value of farmers' weather IoT stations and ensemble weather forecasts to provide local advice on water management integrating uncertainty, ACTA, les instituts techniques agricoles, UMR MISTEA (Chapter 4).

►► Digital showcases

The #DigitAg digital showcases bring together demonstrators derived from the application of selected doctoral and post-doctoral research results. Examples of digital tools developed by the community's research teams are also presented. These tools were built by a specialised technical team in close collaboration with the researchers.

AgroforestAR

Laetita Lemière, Projet GAIA (Generative Artificial Intelligence for Agriculture)

An augmented reality agroforestry system

This augmented reality application enables the visualisation of agroforestry systems, facilitating their design by accounting for the interactions between trees and crops. Its purpose is to optimise ecosystem services and enhance protection against climate hazards.

Download the APK application directly from the Play Store and the App Store.

AIDMOIT

Rodrique Kafando, UMR TETIS

Quickly find localised and dated documents on specific topics

A generic tool for building thematic corpora that takes into account spatial and temporal factors. Based on a thematic keyword, a geographical area and a time period, a corpus of documents is collected from the web. The quality of the retrieved documents is ensured by an artificial intelligence approach that automatically assesses the relevance of each document to the theme.



<https://aidmoit.hdigitag.fr/>

Anemone

Olivier Gauriau, ACTA, les instituts techniques agricoles

Mapping for pathogen prediction

The tool is a visualisation interface for our pattern-based machine learning models. It allows users to select sets of plots (by year and geographical location) on which our models were trained to predict the incidence of certain pathogens. The tool then allows us to visualise the importance of agronomic and meteorological variables assigned by our models in their predictions, providing us with useful information on the factors that have had the greatest influence on the development of the diseases under study.



<https://anemone.hdigitag.fr/> QR CODE

Apex Vigne Territoire

Léo Pichon, UMR ITAP

Visualising the vegetative growth of vines across the region

The Apex Territoire showcase application enables the visualisation of observations collected using the Apex-Vigne mobile application.

ApeX-vigne is a free mobile application developed by the Institut Français de la Vigne et du Vin and the Institut Agro to monitor the evolution of grapevine vegetative growth and estimate water stress levels. It is based on the apex method, a simple technique for characterising grapevine vegetative growth. By observing the tips of the shoots, known as the apices, this method is commonly used in vineyards by technicians, particularly in the mediterranean region, where an early cessation of growth is often linked to significant water stress levels.

ApeX territoire provides a geolocated visualisation of apex growth indicators and a spatio-temporal analysis of the growth observed within vineyard plots. This showcase application allows users to add, update, share, and export summaries of their observations. The application is designed for use on computers, mobiles, and tablets.

Download the apk application directly from the play store and the app store.

Cartogame

Léa Courteille, UMR LISAH, UMR TETIS

The cartographic representation of uncertainty for decision-making

Uncertainty is a part of our daily lives, whether it concerns weather forecasts or journey times, and we integrate it into our decision-making without even realising it. However, when it affects decision support maps, such as soil maps or biodiversity maps, uncertainty can discourage the user and compromise the use of the data. We invite you to step into the shoes of a planning stakeholder, who must make land-use decisions under uncertainty based on soil quality maps. You will be able to see to what extent uncertainty hinders your decision-making and how different cartographic representations of the same information can influence it.



<https://cartogame.hdigitag.fr/>

Crop2ML/CyML

Cyrille Mindingoyi, LEPSE

A metalanguage and a translator to make crop models accessible and facilitate their understanding and reuse by non-computer scientists

Designed for biologists, the Crop2ML/CyML web application enables them to explore and understand crop models shared on major international platforms and to reuse them for their own purposes, without needing any programming skills.



<https://crop2ml.org/#/Home>

GRI

Boris Biao, UMR MOISA

The test to measure your company's impact

"Innovation must generate more benefits than negative impacts." This tool is designed for companies keen to measure the impact of their innovation in just a few minutes. Join the movement—take the test!



<https://gri.hdigitag.fr/home>

PastoFutur

Thibault Raffaillac, UMR SELMET, UMR SENS

A serious game to explore the complexities of sustainable livestock farming

Manage your land to ensure the health of your sheep whilst preserving biodiversity and limiting soil erosion. This strategy game, based on multi-agent simulations, invites you to tackle the challenges of sustainable livestock farming and reflect on current environmental issues.



<https://pastofutur.hdigitag.fr/>

TechnodoseViti (la juste dose)

Anice Cheraïet, UMR ITAP

Determine the dose of plant protection product to be applied based on the characteristics of the vegetation and the sprayer used

Depending on the sprayer type and the evolution of the structural characteristics of the vegetation, the application determines the appropriate dose of the product and makes it possible to compare several technological scenarios integrating different sprayers and dose application rationales. Scenarios are compared in terms of input savings. The input data include the plot, date, risks regarding plant protection efficacy, and the sprayer used.



<https://technodoseviti.hdigitag.fr/>

Transitool

Laurie Dunn, UMR AGIR, Montpellier Research in Management, Unité MIAT

A serious game to raise awareness about soil erosion

You are a farmer. The aim of the game is to successfully limit erosion across your entire farm without compromising the operational viability of the holding. To achieve this, you will use action cards of varying costs to activate different crop and plot management levers.



<https://transitool.hdigitag.fr/>

T-tAg webinars

These sessions, started during the Covid-19 period, allow volunteer doctoral and post-doctoral researchers to present their research work for approximately twenty minutes. These short presentations provide an opportunity for a discussion session with the participants. The T-tAgs can be found as replays on the #DigitAg YouTube channel: <https://www.youtube.com/@digitaglab>



» HAL collection

This collection provides access to all publications from the #DigitAg community that have been uploaded to the HAL platform. This long-term platform ensures that these resources remain visible.



<https://hal.inrae.fr/DIGITAG>

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ACTA	French agricultural technical institutes	https://www.acta.asso.fr/en/
UMR AGAP	Agap Institute (Genetic Improvement and Adaptation of Mediterranean and Tropical Plants)	https://umr-agap.cirad.fr/en
UMR AGIR	Joint research unit AGroecology - Innovations - Ruralities	https://eng-agir.toulouse.hub.inrae.fr/
UPR AIDA	Research unit Agroecology and sustainable intensification of annual crops	https://ur-aida.cirad.fr/en
UMR AMAP	Joint research unit botAny and Modeling of Plant Architecture and vegetation	https://amap.cirad.fr/en/index.php
CEE-M	Center for Environmental Economics of Montpellier	https://www.cee-m.fr/
UMR EMMAH	Joint research unit Modelling Agricultural and hydrological systems in the mediterranean environment	https://umremmah.fr/eng
UMR G-Eau	Joint research unit Water Management, Actors, Territories	https://www.g-eau.fr/en/
UR GECO	Research unit Fonctionnement écologique et gestion durable des agrosystèmes bananiers et ananas	https://ur-geco.cirad.fr/
UR HortSys	Research unit Fonctionnement agroécologique et performances des systèmes de culture horticoles	https://ur-hortsys.cirad.fr/
UMR IATE	Joint research unit Ingénierie des Agropolymères et Technologies Emergentes	https://iate-montpellier.fr/
IES	Institut d'Electronique et des Systèmes	https://www.ies.umontpellier.fr/
UMR Innovation	Joint research unit Innovation	https://umr-innovation.cirad.fr/en

UMR ITAP	Joint research unit Technologies and Methods for the Agriculture of Tomorrow	https://eng-itap.montpellier.hub.inrae.fr/
Lacodam	Large scale Collaborative Data Mining	https://team.inria.fr/lacodam/fr/
LEPSE	Laboratory for Plant Ecophysiology under Environmental Stress	https://eng-lepse.montpellier.hub.inrae.fr/
LIRMM	Laboratory of Computer Science, Robotics and Microelectronics of Montpellier	https://www.lirmm.fr/lirmm-en/
MIAT	Unité de Mathématiques et Informatique Appliquées de Toulouse	https://miat.inrae.fr/
UMR MISTEA	Joint research unit Mathématiques, Informatique et STatistique pour l'Environnement et l'Agronomie	https://mistea.montpellier.hub.inrae.fr/
UMR MOISA	Montpellier Interdisciplinary center on Sustainable agri-food systems social and nutritional sciences	https://umr-moisa.cirad.fr/en
MRM	Research unit Montpellier Research in Management	https://mrm.edu.umontpellier.fr/en/
UMR PEGASE	Joint research unit Physiology, Environment, and Genetics for the Animal and Livestock Systems	https://eng-pegase.rennes.hub.inrae.fr/
UMR SELMET	Joint research unit Mediterranean and Tropical Livestock Systems	https://umr-selmet.cirad.fr/en
UMR TETIS	Joint Research Engineering and Territories	https://umr-tetis.fr/
UMR SENS	Joint research unit Savoirs, Environnement, Sociétés	https://www.umn-sens.fr/

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The financial support provided to the Convergences Institute facilitated the development of mutual understanding between research teams and the creation of a truly interdisciplinary community in digital agriculture—a pioneering initiative both in France and abroad. This strong community continues its exchanges and networking activities within a learned society, which will remain active beyond the conclusion of the France 2030 funding.

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For 10 years (2017-2026), the #DigitAg Convergences Institute conducted research on digital agriculture, the result of the transformation of agriculture through digitalisation, bringing together an interdisciplinary community of researchers from various French research and higher education organisations (INRAE, CIRAD, Institut Agro, University of Montpellier, INRIA, ACTA, AgroParisTech).

This book describes the tools and methods developed, covering the entire data chain: from sensors to satellite imagery, including data processing, artificial intelligence, and decision support systems. Their uses for phenotyping, sustainable livestock farming, and food security are detailed. The book also explores the impacts of digitalisation on farmers' practices, ecosystems, and agricultural models in France and in the Global South.

Interdisciplinarity is at the heart of this reflection: how did this community manage to bring together such diverse expertise? How did this approach contribute to rethinking the agriculture of tomorrow? This book provides concrete answers to these questions, drawing on a decade of collaborative research.

This book is intended for students and researchers, and anyone interested in methodological advances in digital science and technology in agriculture.

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