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WORLDWIDE CROP PRECISION AGRICULTURE ADOPTION: 2026 UPDATE

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Abstract.

Robotics, machine vision, and drone spraying have attracted much attention in recent years. But the technologies introduced in the 2000s and earlier, such as yield monitors, guidance, variable rate technology (VRT), and digital imagery continue to advance worldwide, more on large mechanized grain and oilseed farms. This update summarizes the census estimates and adoption surveys with statistically reliable random sampling resulting from our review, from 24 countries. Within-country and farm size breakdowns are reported when available.

Global navigation satellite systems (GNSS)-based guidance and GNSS-dependent systems, such as section control, continue to be widely used in mechanized agriculture. In the USA, 85% of agricultural retailers working with field crops used GNSS guidance (manual or autoguidance) in their custom fertilizer and pesticide application services in 2025. The USDA estimates that 70% of large-scale family farms and 52% of midsize family farms used GNSS guidance in 2023. In Japan, 32% of farmers used GNSS guidance in 2024. The EU has a high proportion of smaller and mixed farms, and in 2023, 15% of farmers used GNSS guidance, with 9% using autosteer systems and 12% using sprayer boom section control. In Denmark specifically in 2025, 33% of farms covering 74% of farmland used RTK GNSS guidance, and 31% of farms managing 66% of farmland used sprayer boom section control.

Use of variable rate fertilizer technology, introduced in the 1990s, has increased only modestly in recent years. In Australia, 30% of cropland used VRT fertilizer in 2025. In the USA in 2025, 84% of agricultural retailers offered VRT fertilizer application, but only a modest percentage of US farmers use those services. The USDA estimates that 12% of crop farms used VRT application (for fertilizer, seeds, or pesticides), although adoption rates were higher for large (45%) and midsize (32%) family farms. In 2025 in Japan, roughly 6% of farmers used VRT fertilization and 8% used VRT or targeted pesticides; in the EU in 2023, VRT was used by 11% of farmers.

Input applications using uncrewed aerial vehicles (UAVs, drones) have increased quickly. Industry sources suggest that one third of agricultural land in China is managed with UAVs. In 2024 about 20% of crops in Japan were managed with UAV pesticide applications. In 2024,

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27% of US agricultural retailers offered UAV application services, mostly pesticide spraying, with 8% of the retailers' market area treated in 2025. Even in the EU, where UAV applications are tightly regulated, roughly 4% of farms in the southern EU used UAV applications. This is similar to the 4% adoption rate on US farms in 2023.

Robots are also starting to be used in countries with mechanized agriculture and high labor costs. By the end of 2024, there were almost 350 companies worldwide developing arable farm robots, and at least 70 crop robots were commercially available. In 2025, the CropLife/Purdue survey showed 8% of agricultural retailers used robots for crop scouting or soil sampling. Robotic weeding was offered by 4% of US agricultural retailers. In France, over 800 farms used crop robots in 2023. In the EU overall, 6% of farmers used field robots (mostly for weeding) in 2023.

Keywords.
adoption, guidance, robotics, UAV, variable rate technology, remote sensing, yield monitor.

Introduction:

Since the beginnings of precision agriculture in the 1990s, a stream of technologies has been developed and commercialized. Among those technologies, farmers and agribusinesses have selected those that they find the most useful. Some of the recent introductions have been spraying with uncrewed aerial vehicles (UAVs), machine vision herbicide targeting and robotics, but adoption continues for the precision agriculture (PA) technologies from the 1990s, such as yield monitors, variable rate technology (VRT) and global navigation satellite systems (GNSS) guidance. Each technology introduction often follows a now familiar "hype cycle" (Chandra and Collis, 2021; Fenn and Raskino, 2008) with each innovation lauded initially, later criticized as its limitations become known and eventually finding its place as standard practice somewhere or in the dustbin of failed innovations. The speed and pattern of adoption differ from place to place and the technologies selected vary depending on local economics, type of farming, and many other factors. Many studies have tried to identify reliable factors driving adoption and predict adoption rates, but beyond a decisive role for the economic benefits of the technology in long run adoption patterns (Tey and Brindal, 2012), PA adoption remains difficult to anticipate. This creates planning challenges for farmers, agribusinesses, entrepreneurs and policymakers. In many cases it is even difficult to know with any certainty what is being adopted where. Inventors and companies promote their technology, often with exaggerated claims and overstated adoption estimates. Many poorly designed on-line surveys with unrepresentative samples and unsubstantiated blog posts can create misinformation that obscures the facts. The first step in understanding PA adoption is a better understanding of what is actually being used by farmers and agribusinesses. The objective of this study is to provide an update on which precision agriculture technologies are being adopted in key geographic areas. The methodology focuses on national statistics based on representative samples from robust statistical designs. The results of this study will be useful to PA researchers, technology entrepreneurs, agricultural policy makers, farmers and agribusinesses.

National adoption estimates are crucial to understanding global precision agriculture because more localized estimates can be difficult to interpret from a distance. There are some statistically robust surveys for PA adoption in certain localities (e.g. states, provinces, counties), but heavy use of a given technology on a certain type of farm in a specific area may be an indicator of a broader trend or may be driven by purely local factors. Generalizable data on PA technology adoption is collected in only a few countries (e.g. USA, Canada, EU countries, UK, Australia) and because of budget and personnel constraints most of them collect this data only intermittently every few years. In most cases, this data is collected by the national ministry of agriculture or the national statistics agency.

One main issue for all adoption studies is the widely varying definitions of "precision agriculture". For example, the International Society of Precision Agriculture (ISPA) defines PA as: "…a management strategy that gathers, processes and analyses temporal, spatial and individual plant and animal data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production" (ISPA, 2024). The ISPA definition is quite broad in the sense of including both crop and livestock but narrowly focused on spatial and temporal management. By contrast, the Eurostat manual for the 2023 Integrated Farm Survey (IFS) defines PA strictly for crop production with a focus on use of spatial and temporal data in management: "……the application of modern information technology to gather, process and analyze multisource data of high spatial and temporal resolution for decision making and operations in the management of crop production" (Eurostat, 2026c). This source comes to some very different conclusions about which technologies are worthy of attention. For example, the 2023 IFS includes data in its PA module on band application of pesticides and soil sampling, which are technologies that predate the precision agriculture era and have been used widely in USA and Canada for decades. The IFS has a separate subsection on machinery for livestock management capturing some technologies that are included in the ISPA definition of PA for livestock. This includes sensors for health and welfare monitoring, and milking robots. In a study of PA in northern India, PA is defined broadly without reference to spatial or temporal data. It states "Precision farming as an approach uses inputs in precise amounts to get increased average yields compared to conventional farming techniques. It is a comprehensive system designed to optimize production by using a key element of information, technology, and management." (Chaudhary et al. 2025). The northern India data collection includes some familiar PA technologies, such as variable rate applicators for fertilizer, but also chisel ploughs and non-robotic milking machines which predate the PA era in other parts of the world. Any attempt to compare PA adoption among countries needs to pay careful attention to definition of PA as well as to the sampling and analysis methods. This study uses the ISPA PA definition.

This study builds on decades of quantitative research on crop PA patterns. For example, Lowenberg-DeBoer (1998) reviewed data since the early 1990s and hypothesized that the PA adoption path would be highly irregular, with many stops and starts because of technological barriers and economic uncertainties. The 2018 review of global PA adoption data (Lowenberg-DeBoer and Erickson, 2018) reviewed national representative survey data from several countries, as well as information from some less statistically robust studies. It showed that some PA technologies were becoming standard practice for mechanized agriculture worldwide, while others were lagging. The most prominent example of widespread PA adoption in 2018 was GNSS guidance and related technologies such as sprayer boom control and seeder row shut offs. Technologies that were used in some farming regions, but lagging worldwide included VRT fertilizer and satellite remote sensing. An update to the 2018 study (McFadden et al. 2024) included national data from the USA, United Kingdom, Australia, Denmark, Hungary, Estonia, Portugal and Mexico. The 2024 update showed continuing widespread adoption of GNSS related technologies, and on-going modest global adoption of VRT fertilizer and remote imagery. The 2024 report included commercial use crop robotics and UAV input application at statistically detectable levels. The 2024 update acknowledged the commercial introduction of artificial intelligence (AI) machine vision weed detection technology but did not find this technology reflected in national statistics.

The objective of this study is to update global PA adoption information using national census estimates and adoption surveys with statistically reliable random sampling. Specific objectives include to: 1) update estimates on GNSS guidance technology adoption, 2) track the VRT adoption estimates for all crop inputs, 3) review new information on UAV usages with attention to UAV input application, 4) gather estimates on crop robotics, and 5) add a focus on precision livestock technology. This introduction is followed by a methodology section which outlines key differences in sampling and analysis methods among the PA adoption sources. The results section summarizes the information for each of the five specific objectives and the discussion provides a brief overview of what those adoption trends suggest for the future of PA.

Methods:

Among the organizations that collect statistically robust data on PA adoption there are still important differences in sampling and how adoption is measured. The most important difference in adoption measurement is between a focus on farms using the technology versus estimating the farm area managed with that technology. This difference is important because in most of the countries where PA data is available the farm number distribution is skewed toward small farms with only a few larger farms, but farm area is skewed toward larger farms which manage a much larger portion of farm land. In many countries PA technologies are adopted first on larger farms and consequently the percentage of area managed with a technology is often much larger than the percentage of farms using that technology.

The USDA Agricultural Resource Management Survey (ARMS) production practices (Phase II) survey is one that focuses on crop area. The ARMS Phase II survey is a stratified random sample of a set of rotating target crops with each crop surveyed every 4-10 years. In the screening phase, ARMS selects among farmers producing over US$1000 of farm products in a year (USDA's definition of a farm). In Phase II, it randomly selects among fields managed by the selected farms among those that were planted to the target crop in the most recent crop season and asks the farmer about production practices for that field in the crop season (USDA, 2025). Typically, adoption is reported as a percentage of planted area of that crop. This approach provides a benchmark national measure of the intensity of technology usage for the target crop in the specific year. Intensity of technology use can be important in understanding impact on overall crop production and food security.

But for many policy purposes, the number of farmers using a technology matters more than the area managed with the technology. Farmers vote; hectares and acres do not. Farmers are the end users and a bedrock of the agricultural and rural economies in which they live and work. Consequently, many organizations count the number of farms (or farmers assuming one farmer per farm) using a specific technology and report results in terms of percentage of farms benefiting from the technology. This provides a measure of the public support for a given technology, or conversely the pushback if use of that technology is regulated.

Farm level data collection often results in more ambiguous estimates than a per field approach. For example, in some countries farmers are given a list of technologies and effectively asked: "Do you use any of the listed technologies on your farm?" (e.g. UK DEFRA 2020; Eurostat 2023a). One farmer might have used VRT fertilizer on every field for the last few years, but another farmer just on one field in the most recent crop season, and both would answer "yes." They might even have used VRT fertilizer once several years ago and still answer "yes". With farm level data, a high farm level adoption percentage might not be linked to a substantial impact on productivity, because intensity of use on many farms might be low. This ambiguity persists even if the adoption percentage is reported as a percent of farm area because the technology might be used with varying intensity but is attributed to the whole farm area. An example of this is the Denmark precision agriculture surveys which show that only a modest percentage of farms use most PA technologies, and while those farms manage the majority of farm area (Denmark Statistics, 2025), those surveys do not measure the intensity of use on those larger farms.

Another set of methodological differences is in how samples are selected. Many surveys use stratified random samples but vary widely on which variables are used to determine strata. Many surveys stratify by geographical area (e.g. state, province, region) and farm type with varying levels of specificity by crop and livestock species. Some stratify by economic size of the farm business (e.g. farm value of sales), while others use the physical size of the business (e.g. utilized agricultural area, number of livestock). For example, the USDA ARMS uses a multiphase, stratified probability sample. Farms are first identified in Phase I and a subsample of farms producing the target commodity in the reference year are randomly selected stratified by state and farm business size. For the ARMS Phase II production practices data, on each selected farm one field that produced the target commodity in the reference year is randomly selected with selection probability proportional to that operation's production of the target commodity (USDA, 2026a). For the 2023 IFS the sample is drawn from national farm registers based on the 2020 agricultural census and administrative sources with strata by region, farm business size and farming type (Eurostat, 2026c). Only holdings above legally specified production thresholds are eligible.

For the Tur Cardona et al. (2025) survey of selected EU countries, the sampling method involved identification of farm interest groups based on specialization and physical size. The countries included were France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Poland, and Spain. The 2020 EU farm specialization statistics were used to create a list of potential respondents for each specialization. Physical farm size was determined by utilized agricultural area for crop farms and livestock units for livestock farms. A simple random sample was done within each specialization group.

In the USA the CropLife survey is in some ways more like a census of agricultural input retailers than a sample survey. This is relevant for PA adoption because in the US many farmers initially access PA as services provided by agricultural retailers. The survey is sent to a list of all US agricultural retailers maintained by the CropLife publisher, Meister Media (Erickson and Lowenberg-DeBoer, 2025). Not all ag retailers respond, but in the three decades of surveying a history of consistent responses that correspond with on-the-ground reality has given the survey a reputation as a reliable source.

Results:

Because the definition of "precision agriculture" differs widely from place-to-place and even from person-to-person, the most reliable PA adoption estimates come from surveys which ask about specific technologies. But some studies try to answer the general question of how many farmers use precision agriculture in any form. The USDA National Agricultural Statistics Service (2023) included both crop and livestock technology in its definition of "precision agriculture" and reported that 27% of US farms used some type of PA, with adoption much higher on larger farms. The EU IFS (Eurostat 2026c) limits PA to crops but covers a different set of technologies than the US data. The IFS (Eurostat 2026d) shows that for all EU countries, except Slovenia, the average is 17% of all farms using PA (Table 1, Appendix). EU country level estimates ranged from 0% in Cyprus to 66% of farms in Luxembourg. The percentage of utilized agricultural area on farms managed with PA in the EU, except Slovenia, was 45% in 2023. The country level range of farm area managed with PA ranged from 1% in Cyprus to 86% in Luxembourg. The Tur Cardona et al. (2025) study of selected EU countries covered a broader range of digital technologies, including digital field records and farm management software, and estimated that 79% of farmers had adopted at least one digital agriculture technology. The adoption of precision agriculture (smart agriculture) in Japan has seen progress in recent years. A survey by the Japan Finance Corporation (JFC) in 2025 defined "smart agriculture" to include both crop and livestock technologies that are elsewhere labelled "precision agriculture". Like Tur Cardona et al. (2025), the JFC survey includes software and management systems. The JFC (2025) survey shows that 45% of Japanese farmers across all agricultural sectors have already adopted smart agriculture. By sector, adoption is particularly advanced in field crops at 69% with rice farming in the Hokkaido region at 55%, and in other prefectures at 49%, indicating significant adoption in crop cultivation. Overall, data indicate a strong interest by farmers in the general idea of precision agriculture, but because of differences in definitions of PA, understanding adoption requires a look at data on specific technologies.

GNSS Technologies – Global navigation satellite systems (GNSS)-based guidance and GNSS-dependent systems, such as sprayer boom section control and seeder row shut offs, continue to be an adoption success story.

- USDA ARMS data show that most US row crop area is managed with autosteer and guidance systems. The most recent USDA ARMS data show adoption on 78% of cotton area in 2025 (USDA, 2026b), 72% of soybean area in 2023, 60% of winter wheat area in 2022, and 67% of corn area in 2021 (McFadden et al. 2024). Recent farm level data from the USDA Economic Research Service (ERS) estimates that 70% of large-scale family farms, 52% of midsize family farms and 9% of small family farms used GNSS guidance in 2023 (Lim et al. 2024).

- The 2025 CropLife agricultural retailer survey in the USA estimated that 82% of agricultural retailers working with field crops used GNSS guidance (manual or autoguidance) in their custom fertilizer and pesticide application services in 2025 (Erickson and Lowenberg-DeBoer, 2025). Autosteer was used by 74% of the retailers in 2025. Manual lightbar guidance was used by 24% in 2025, with some retailers using both autosteer and lightbars on different machines in their fleets. Lightbar guidance is a good example of rapid adoption and disadoption. Lightbars were introduced into the US market in the late 1990s. When the question was first asked on the CropLife survey in 2000, 24% of retailers were using the technology. Lightbar use peaked in 2009 at 79% and dropped off as retailers switched to autosteer. GNSS boom section and nozzle controllers were used by 67% of retailers in 2025. Sprayer turn compensation was used by 32% of retailers. Turn compensation equalizes rates along the sprayer boom accounting for the fact that during a turn the outer end of the boom is moving much faster than the inner side of the turn.
- US agricultural retailers reported that in 2025 in their market areas, an average of 74% of farmland was managed with GNSS guidance technology (Erickson and Lowenberg-DeBoer, 2025).
- The Tur Cardona et al. (2025) survey of selected EU countries reports that 15% of farmers have tractors equipped with GNSS. Nine percent of farmers in those countries use automated steering systems (i.e. autosteer). Five percent of farmers in those countries report using lightbar guidance systems. The autosteer and lightbar percentages can not be added to produce an overall GNSS guidance adoption estimate because a farm might use both. Usage of both autosteer and lightbars is higher in the southern EU countries (i.e. Spain, Italy and Greece) with 11% using autosteer and 8% lightbars (JRC, 2026). Twelve percent of farmers report using sprayer or seeder GNSS section control with adoption highest in the southern EU countries at 15% of farms. The Eurostat IFS does not separate out use of GNSS guidance, but includes machines with very high accuracy (RTK 1 cm accuracy) GNSS guidance in the robotics category (Eurostat, 2026c).
- The Denmark Statistics data in 2025 show 33% of farms covering 74% of farmland used GNSS guidance (denoted in their survey as RTK guidance), and 31% of farms managing 66% of farmland used sprayer boom section control.
- In Japan, 32% of farmers used GNSS guidance in 2024 (Government of Japan, Cabinet Secretariat, 2025).

Yield monitoring is not a GNSS guidance technology, but it depends on GNSS to spatially locate yield measurements. Availability of yield monitoring technology is quite high because it is commonly standard equipment on large combine harvesters. Data on use of yield monitor information is quite mixed because whereas many farmers in high income and middle income countries have access to the data, they may not convert it into a map or use that map for decisions.

- USDA data shows 68% of midsized family farms used yield monitors in 2023 and 55% of both large-scale family farms and non-family farms (Lim et al. 2024). Thirteen percent of small family farms used yield monitors. Yield monitors were used on 28% of planted cotton area in 2025 (USDA, 2026b) and 79% of planted soybean area in 2023 (McFadden et al. 2024).
- US agricultural retailers reported that in 2025 in their market areas 66% of farmland had yield monitors in use (Erickson and Lowenberg-DeBoer, 2025). Fifty-three percent of those agricultural retailers reported that they offer yield monitor data analysis services to their clients.
- The IFS 2023 included yield monitoring in the “precision monitoring of crops” cluster with weather stations, digital soil mapping, remote sensing for crop health and crop scouting

(Eurostat, 2026c). For all EU countries, except Slovenia, the average is only 3% of farms use any of the technologies in the precision monitoring of crops category with several countries in eastern and southern Europe reporting 0% of farms adopting (Table 1, Appendix). The highest adoption percentage is in Germany with 21%. In terms of utilized agricultural area, the overall average using precision monitoring of crops technologies for all EU countries, except Slovenia, is 15%. The highest percentage of area is 47% in Germany. The lowest percentage is 1% in Greece.

- In Australia in 2025, data from the Grains Research and Development Corporation (GRDC) indicates that 74% of crop area was harvested with yield mapping technology (Watson and Umbers, 2025). Yield monitoring use is highest in the Western Australia Mallee/Sandplain region at 87% of crop area and lowest in Tasmania with 28%.

Variable Rate Technologies – Variable rate fertilizer adoption has increased only modestly since the technology was introduced in the 1990s, but is always higher than variable rate seeding, variable hybrid or variety placement, or variable rate pesticide applications.

- The USDA estimates that 12% of crop farms used VRT application (for fertilizer, seeds, or pesticides), although adoption rates were higher for large (45%) and midsize (32%) family farms (Lim et al. 2024). The most recent USDA ARMS data indicates that VRT was used for any purpose on 17% of planted cotton area in 2025 (USDA, 2026b), 34% of soybean area in 2023, 21% of winter wheat area in 2022, and 37% of planted corn area in 2021. Adoption for other crops was generally lower (McFadden et al. 2024).
- In the USA in 2025, 84% of agricultural retailers who do custom application offered VRT fertilizer application. Forty eight percent offered VRT lime and 52% helped farmers with VRT seeding prescriptions. Those US agricultural retailers estimated that in 2025 in their market areas 43% of farmland was managed with VRT fertilizer, 40% VRT lime and 20% VRT seeding (Erickson and Lowenberg-DeBoer, 2025).
- In Australia, 30% of cropland used VRT fertilizer in 2025 (Watson and Umber, 2025). Adoption of VRT fertilizer was highest in Western Australia Northern Region at 53% and lowest in Tasmania with 7%.
- The EU IFS survey in 2023 showed that for all EU countries except Slovenia, 5% of farms used VRT for any input (Table 1, Appendix). The country with the highest percentage of farms using VRT is Germany with 18%. Several countries in southern Europe report zero percent of farms using VRT. In terms of utilized agricultural area for all EU countries, except Slovenia, 16% is reported to be managed on farms using VRT. The highest percentage of area is in Germany with 43%. Cyprus reports that a negligible area is managed with VRT.
- The JRC study of selected EU countries reports that VRT for any input was used by 11% of farmers. Adoption is highest in southern European countries with 14% of farms using VRT (JRC, 2025).
- In Japan, roughly 20% of farms use any VRT (Smart Agri Consortium, 2020). JFC (2025) estimated 14% adoption of VRT fertilization and 18% VRT or targeted pesticide spraying among those who have adopted some form of smart agriculture, which as previously noted was 45% of Japanese farmers. This translates to about 6% of farmers using VRT fertilization and 8% using VRT or targeted pesticides.

Machine vision targeted herbicide technologies are a form of variable rate pesticide application. In particular in recent years, major farm machine manufacturers and several start-up companies have commercialized AI driven machine vision weed detection systems. Those systems are starting to show up in national statistics:

- Forty percent of US agricultural retailers who do custom application report offering VRT pesticides. Because of technical challenges in mapping pests, this percentage languished in the 10%-20% range in the early 2000s. In the second decade of the 21st Century it was in the 20%-30% range. Much of the recent increase is linked to improved targeted herbicide technology. Those retailers report that in their market areas about 5% of farmland was using machine vision weed detection (Erickson and Lowenberg-DeBoer, 2025)

- The EU IFS 2023 has a question about robotics for plant protection (Eurostat, 2026c) which includes systems that target pests but also a wider range of technologies. In addition to targeted pesticides, it includes ground-based robots which apply pesticides, pesticide spraying UAVs, and spraying robots in greenhouses. For all EU countries, except Slovenia, the IFS 2023 (Eurostat, 2026d) estimated that 2% of farms used pesticide application robotics (Table 1, Appendix). The country reporting the highest percentage is Denmark with 19%. Many countries reported zero percent use. For all EU countries, except Slovenia, the IFS 2023 reports 11% of utilized agricultural area is on farms which use robotics for plant protection.

Uncrewed aerial vehicles (UAVs) - In crop production UAVs can be used for both data collection and input application. While overall use for both is relatively low, UAV use for input applications is growing.

- USDA (2026b) data for 2025 show UAV use on 3% of planted cotton area. The 2023 ARMS data indicate that UAVs for any purpose are most often used by non-family farms (13%), large family farms (12%) and mid-size family farms (9%) (Lim et al. 2024). Only 2% of small family farms reported any use of UAVs.
- US agricultural retailers indicate that in 2025 37% of their businesses offered UAV imagery services to farmers. Forty-five percent offered satellite or crewed aircraft aerial image services. Those retailers estimate that in their market areas, UAV imagery is collected on 8% of farmland and satellite or aerial imagery on 22% of farmland (Erickson and Lowenberg-DeBoer, 2025).
- US agricultural retailers report that 27% of their businesses offer input application with UAVs. Those retailers estimated that in their market area 8% of farmland was managed with UAV input application.
- The JRC study of selected EU countries showed that 3% of farmers used UAV for imagery and also 3% for input application. The UAV use average in the JRC study is pulled up by slightly greater use in the southern European countries in this study (i.e. Greece, Spain, Italy) where use for both imagery and input application is estimated at 4% of farms. In the 2023 IFS study UAV imagery is included in the "precision monitoring of crops" cluster.
- Industry sources suggest that one third of agricultural land in China is managed with UAV spraying (Barnard, 2025).
- In 2024 about 20% of crops in Japan were managed with UAV pesticide applications (Japan MAFF, 2024)

Crop robots - Crop robots are also starting to be used in countries with mechanized agriculture and high labor costs. By the end of 2024 there were almost 350 companies worldwide developing autonomous crop machines (Taylor et al. 2024) and at least 70 crop robots were commercially available for farmers to buy and use (Future Farming, 2025). Data shows:

- In 2025, the CropLife survey showed 8% of agricultural retailers used robots for crop scouting or soil sampling (Erickson and Lowenberg-DeBoer, 2025). Robotic weeding services were offered by 4% of US agricultural retailers. The agricultural retailers estimated that in their market areas, 4% of farmland used robotics for harvest, 3% for scouting and 2% for weeding.
- In France, 834 farms used crop robots in 2023 (French Republic, 2025). This is less than 1% of the roughly 350,000 farms in France. Of those robots, 319 (38% of crop robots) were weeding machines. Another 280 (34%) robots were for pesticide application. Most of the remaining robots were for tillage. Only 15 harvest robots were reported in France in 2023.
- For selected EU countries, Tur Cardona et al. (2025) report that 6% of farms used fully automatic crop robots, mostly for mechanical weeding. In that study robot use was highest in the southern EU countries (i.e. Spain, Italy, Greece).

- The EU IFS 2023 used a broader definition of crop robots than the French Ministry of Agriculture. In addition to weeding robots, autonomous mowing machines for permanent crops and harvesting robots, it includes UAVs, farm machines equipped with highly accurate GNSS guidance (1 cm accuracy), and greenhouse robots (Eurostat, 2026c). Data from the crop robotics question are not reported on the IFS Dashboard but are reported by government agencies in some countries. The country level robotics data show substantially higher robotics estimates than other sources. For example for Spain, 120,372 robots are reported for 2023 (National Institute of Statistics, 2026) which is about 15% of the total of 784,141 farms in Spain.

Precision livestock - Precision livestock is often defined by the ability to manage individual animals, instead of managing on a group basis (Eckelkamp, 2019). Because precision livestock does not necessarily require location finding (i.e. GNSS), it has been commercially available longer than crop precision agriculture technology. Electronic methods to identify and manage individual animals in large herds were developed in the 1970s (Hanton and Leach, 1974). Electronic animal identification technology led to individualized feeding of animals (particularly dairy cows) according to age, production, lactation stage and other factors. Milking robots were commercially introduced in 1992 (Lely, 2022; Sharipov et al. 2021). However, national statistical data for precision livestock technology use has been less widely available than for crop precision agriculture, perhaps because livestock technology has attracted less public policy attention than crop technology. A few recent reference points:

- McFadden and Raff (2026) provide an overview of precision dairy farming in the USA. They indicate that in 2021, 4% of US dairy farms used some form of robotic milking and 6% of milk was produced on farms with robotic milking. Lim et al. (2024) indicate that in the USA robotic milking was most common for large-scale family farms (19% of milk producing farms in that category) compared to 6% of midsized family farms, 10% of non-family farms and less than 1% of small family farms.
- Lim et al. (2024) showed that 12% of US large scale family livestock farms used wearable technologies (e.g. sensors), compared to 3% of midsized family farms, 1% of nonfamily farms and 1% of small family farms.
- The EU IFS 2023 data show that for all EU countries, except Slovenia, 7% of livestock farms use some welfare and health monitoring of animals (Table 2, Appendix). Precision livestock welfare and health monitoring technologies include: biometric and biological sensors, cameras, activity sensors, animal location tracking, and feeding and drinking registration (Eurostat, 2026b). That welfare and health monitoring percentage ranges from 0% in Romania to 41% in France.
- For northern EU countries (i.e. Sweden, Finland, Denmark, Germany, Netherlands, Luxembourg and Belgium), the IFS 2023 data (Table 2, Appendix) shows that about 23% of dairy farms use robotic milking (Eurostat, 2026b). Milking robot adoption is lower in southern and Eastern Europe. This calculation used the number of dairy holdings in the EU in 2023 from Eurostat (2023b).
- Japan had 9605 farms with dairy cows in 2025 (e-Stat, 2025) and 720 robotic milking machines (Morita et al. 2025). This indicates that about 8% of farms with dairy cows had a robotic milker in 2025.

Discussion:

Among the initial wave of PA technologies introduced in the 1990s, GNSS guidance has been most successful. Data indicates that in the USA it has become standard practice for many agribusinesses and for larger-scale farmers. Disaggregated data from the USA suggests that guidance is also being adopted on medium and smaller US farms, probably as machines with GNSS guidance enter the used equipment markets. GNSS guidance is less widely adopted in the EU, probably because of the predominance of smaller and mixed crop and livestock farms where guidance provides less competitive advantage.

When politicians, policymakers and environmentalists complain that slow adoption of PA technologies is constraining public policy goals, they most often focus on VRT. After over three decades of commercialization, national adoption percentages for VRT are often still in the low double digits. The technical and economic challenges for VRT technology have frequently been analyzed (e.g. Sawyer, 1994; Colaço and Bramley, 2018; Lowenberg-DeBoer, 2019; Griffin and Traywick, 2020). One of the bright spots in the VRT adoption estimates has long been the VRT fertilizer services offered by US agricultural retailers; if US crop farmers wanted to apply variable fertilizer they had easy access to VRT services. However, in recent years the percentage of dealers offering VRT fertilizer has declined. Some analyses suggest that this may be because larger US farmers are acquiring the machines and expertise to implement this themselves instead of outsourcing, so there is less demand for custom VRT application services and some retailers cease offering them (Malone et al. 2026).

In recent years the growth in UAV use seems to be in input applications, especially spraying. Imagery is useful for diagnosing crop challenges and making crop management plans, but imagery does not have the same urgency for most farmers as accomplishing field operations in a timely way. Imagery from satellites and crewed aircraft has been available to US farmers for decades, but according to retailers only 22% of the land in their market areas use these services (Erickson and Lowenberg-DeBoer, 2025). Currently they estimate use of UAV imagery at 8% of farmland. While UAV imagery has advantages over satellite and crewed aircraft imagery in resolution and reliable availability, adoption is unlikely to exceed the overall current use of crop imagery.

While variable rate pesticide application (i.e. spot spraying) is often mentioned in the UAV research literature, in practice much of the UAV spraying is whole-field. UAV spot spraying faces the same pest mapping challenges that limited the development of variable rate pest management since the 1990s.

One of the most surprising statistics related to UAVs is the 4% of farms in the southern EU using UAV spraying. The EU sharply limits all aerial pesticide application, including UAV application. The main use for which waivers for aerial application are granted is for applications on steep hillside vineyards or orchards where the main alternative is backpack sprayers (Maritan et al. 2025). These waivers are motivated by the desire to limit pesticide exposure to the workers using backpack sprayers and to keep those steep hillsides in production. Steep hillside vineyards and orchards are important in some areas of Spain, Italy and Greece, but it is doubtful if they are as much as 4% of all farms.

The most important adoption fact about crop robotics in this study is that they are showing up in official government statistics. As with UAVs, the adoption of crop robots for scouting and other data collection is probably limited because for most farmers accomplishing timely field operations is more urgent. In the longer run, data collection will probably be a side benefit done while the robots are preparing the seedbed, seeding, implementing plant protection strategies and harvesting. Because of the farmer priority on timely field work, the economics of crop robotics is often driven primarily by labor availability and secondarily by labor cost.

Analysis of the economics of crop robotics is a challenge. It is not yet clear which robot designs are most practical and profitable. Long run crop robot manufacturing and maintenance costs are difficult to estimate. Adaptation of crop production practices to take advantage of the capabilities of crop robots remains to be worked out. Some ex-ante modelling studies with conventional machines retrofitted for autonomy (Lowenberg-DeBoer et al. 2021; Shockley et al. 2021) have shown modest benefits compared to conventional machines. But those early studies can also be criticized for optimistic assumptions about human supervision requirements, retrofit costs and reliability. Some other ex-ante studies have shown that with current technology human operators have the economic advantage at current wage rates, but the solution switches to robotics if adequate labor is not available during key periods (Strine et al, 2025; Al-Amin et al. 2025).

Some early studies using observed work time data for crop robots suggest that field-to-field and field-to-farmstead logistics play a large role in the economic viability of crop robotics (Spykman et al. 2025, Jorissen et al. 2025). This is especially true of machines made by the original equipment manufacturer (OEM) to be used only autonomously (i.e. they cannot be operated manually because they do not have a seat and steering wheel). Because regulatory approval for autonomous farm machines on public roads is probably many years in the future, OEM autonomous machines need to be loaded on a trailer and moved by a human driver to the next work site. This takes time and requires investment in logistics equipment. Logistics costs create a specific type of farm and field economies of size that favors use of crop robots on farms with large fields, or those with contiguous fields that do not require field-to-field travel on public roads.

Precision livestock technology has a longer track record than crop PA, but that history is less comprehensively documented. Milking robots are one of the most visible precision livestock technologies and the one that has attracted the most attention from economists and social scientists (e.g. Bach and Cabrera, 2017; Vik et al. 2019; Martin et al. 2022; McFadden and Raff, 2026; Lage et al. 2024; Lee et al. 2024). In spite of well documented work life benefits (i.e. more flexible work schedule for dairy farmers) and economic advantages on some farms, the adoption path has been quite slow. One key adoption challenge has been in using milking robots in grazing based systems (Jacobs and Siegford, 2012). Because the investment to move a farm from conventional milking to robotic milking often does not occur until facilities are updated, the milking robot adoption time path may be longer than crop PA technologies.

This study has many limitations. High quality national PA adoption data is available in only a few countries and even those few countries include different technologies under the PA definition, so comparability is not always obvious. This study has not delved into the few cases in which the national statistics provide disaggregated data (by state, province, county, or other geographical area) which may provide insights on adoption in specific farming systems and for specific technologies. Some local PA adoption studies have collected potentially representative farm data (e.g. Blasch et al. 2022; Damasceno et al. 2026; Silvi et al. 2021), but they have not been included here because of the challenge of understanding the local agricultural system well enough to interpret those results clearly. This study focuses on documenting PA adoption. The next step is to better understand the forces that drive adoption.

Conclusions:

PA adoption is a hot topic for agricultural journalism and on social media, but only a few countries collect robust statistics (e.g. US, EU, UK, Australia, Japan). Unfortunately, the media is replete with PA adoption stories based on badly designed studies that do not provide generalizable results. Sometimes it is a challenge to distinguish PA adoption fact from fiction. This study summarizes national crop and livestock PA adoption statistics from those countries that collect representative data and make results public.

Overall, PA adoption continues everywhere that data is available, but in most cases it is highest where farms are large, labor costs are relatively high and farmers are better educated. This adoption pattern was shaped by commercial decisions by companies who design and market technologies for farms with high levels of financial and human capital. It leaves unanswered the question of what could adoption be globally if PA technologies were designed and marketed for medium and small-scale farmers.

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Appendix:

Table 1. Technology adoption in European Union crops in 2023 from the EU Integrated Farm Survey (IFS) (Eurostat, 2026d).

Country	Precision Farming		Robotics for Plant Protection		Band Spraying for Plant Protection		VRT		Precision Monitoring of Crops		Soil Analysis	
	% Farms	% Area	% Farms	% Area	% Farms	% Area	% Farms	% Area	% Farms	% Area	% Farms	% Area
Austria	16%	26%	0%	0%	2%	3%	6%	12%	2%	4%	9%	17%
Belgium	51%	61%	6%	10%	8%	9%	9%	12%	6%	12%	46%	56%
Bulgaria	2%	18%	0%	5%	0%	4%	1%	10%	0%	5%	2%	11%
Croatia	15%	39%	0%	3%	5%	11%	2%	6%	1%	7%	10%	31%
Cyprus	0%	1%	0%	0%	0%	NA	0%	0%	0%	0%	0%	0%
Czechia	5%	35%	1%	5%	1%	6%	3%	28%	2%	16%	1%	11%
Denmark	35%	75%	19%	52%	3%	7%	11%	36%	5%	17%	25%	59%
Estonia	31%	76%	5%	24%	5%	15%	9%	39%	5%	24%	29%	73%
Finland	65%	78%	12%	25%	3%	4%	9%	20%	9%	17%	58%	68%
France	47%	68%	13%	28%	5%	5%	4%	9%	13%	23%	41%	62%
Germany	47%	74%	3%	8%	8%	12%	18%	43%	21%	47%	37%	62%
Greece	6%	10%	0%	1%	3%	5%	2%	3%	0%	1%	2%	5%
Hungary	10%	40%	1%	4%	3%	14%	6%	26%	5%	25%	5%	26%
Ireland	42%	76%	7%	21%	3%	7%	2%	7%	2%	5%	40%	73%
Italy	9%	17%	0%	1%	0%	0%	4%	8%	2%	4%	6%	12%
Latvia	8%	49%	3%	27%	1%	11%	4%	36%	1%	13%	5%	34%
Lithuania	3%	21%	0%	NA	0%	4%	1%	10%	1%	8%	2%	17%
Luxembourg	66%	86%	3%	7%	9%	17%	15%	27%	4%	8%	62%	82%
Malta	27%	38%	NA	NA	0%	1%	3%	3%	3%	2%	25%	37%
Netherlands	15%	27%	7%	13%	3%	7%	11%	20%	3%	6%	2%	4%
Poland	31%	50%	0%	2%	13%	19%	14%	20%	3%	9%	12%	28%
Portugal	11%	38%	0%	3%	1%	4%	0%	4%	1%	9%	10%	36%
Romania	1%	13%	0%	2%	0%	5%	1%	9%	0%	6%	0%	7%
Slovakia	1%	15%	1%	6%	0%	2%	1%	8%	0%	4%	1%	6%
Spain	17%	27%	2%	4%	7%	10%	4%	6%	2%	6%	10%	17%
Sweden	16%	50%	5%	17%	1%	3%	5%	22%	1%	7%	12%	39%
EU except Slovenia	**17%**	**45%**	**2%**	**11%**	**4%**	**8%**	**5%**	**16%**	**3%**	**15%**	**11%**	**35%**

Table 2. Technology adoption in European livestock holdings.

Percentage of EU holdings with livestock* using selected technologies

Country	Machinery for Livestock	Welfare & Health Monitoring	Grinder Mixer	Automatic Feeding System	Automatic Regulation of Barn	No Machinery for Livestock
Austria	53%	23%	39%	15%	13%	50%
Belgium	49%	29%	19%	19%	19%	55%
Bulgaria	15%	5%	14%	1%	1%	45%
Croatia	19%	6%	15%	1%	0%	61%
Cyprus	7%	3%	5%	3%	2%	71%
Czechia	16%	5%	13%	3%	4%	89%
Denmark	44%	28%	26%	21%	21%	56%
Estonia	34%	28%	14%	6%	6%	72%
Finland	65%	27%	24%	28%	43%	36%
France	52%	41%	21%	12%	18%	54%
Germany	53%	19%	38%	21%	21%	58%
Greece	4%	1%	3%	1%	1%	91%
Hungary	28%	6%	26%	3%	2%	45%
Italy	39%	22%	15%	8%	9%	53%
Latvia	15%	4%	12%	1%	1%	74%
Lithuania	4%	2%	3%	0%	0%	78%
Luxembourg	65%	38%	43%	21%	17%	39%
Malta	20%	9%	6%	8%	13%	43%
Netherlands	60%	35%	34%	25%	26%	39%
Poland	29%	6%	26%	4%	4%	53%
Portugal	3%	1%	2%	1%	1%	79%
Romania	2%	0%	1%	0%	0%	33%
Slovakia	6%	1%	5%	1%	1%	97%
Spain	46%	32%	8%	15%	10%	55%
Sweden	59%	30%	34%	15%	22%	77%
EU except Ireland & Slovenia	**16%**	**7%**	**10%**	**4%**	**4%**	**48%**

Milking Robot Adoption in Northern Europe

Country	Holding with Milking Robots 2023**	Total Dairy Holdings 2023***	Rough Estimate % with Milking Robots
Belgium	940	7,850	12%
Denmark	690	2,230	31%
Finland	1,390	4,640	30%
Germany	8,820	46,610	19%
Luxembourg	220	570	39%
Netherlands	4,710	14,260	33%
Sweden	1,250	2,680	47%
N Europe	**18,020**	**78,840**	**23%**

Sources:
* Eurostat, 2023b. Ireland and Slovenia omitted for lack of data.
** Eurostat, 2026a. Data Browser: Machinery for livestock management by age and training of manager, size classes of livestock and NUTS 2 region. https://ec.europa.eu/eurostat/databrowser/view/ef_mp_digilsk__custom_20778353/default/table
*** Eurostat Data Browser, Bovine by NUTS 2 Region. https://ec.europa.eu/eurostat/databrowser/view/ef_lsk_bovine__custom_21055901/bookmark/table?lang=en&bookmarkId=d23b0b17-5e2d-4a20-8cc7-1447e0de840d&c=1776452937000