129. A systematic classification of agrobots to inform farmers' choice and clarify market development

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Abstract

The agricultural robots (agrobots) market is rapidly expanding yet remains fragmented with limited categorization to inform farmers' choices. This study analysed the commercial description of 71 robots currently available on the market through a cluster analysis. K-means clustering allowed the identification of five clusters characterised by significant differences in turning radius and energy source ($p<0.05$), and in weight and battery life ($p<0.1$). Results also highlighted that energy source significantly impacts price, with endothermic agrobots generally being more expensive than electric ones, with hybrid models showing intermediate pricing. This categorisation illustrates current market trends while providing an updated reference framework for key stakeholders such as agri-tech companies, farmers, investors, and policymakers.

Keywords: agricultural robotics, K-means clustering, market segmentation, technical specifications

Introduction

The rapid development of agricultural robots (hereafter agrobots) represents a disruptive innovation in current farming systems, further advancing the capabilities of data-driven and precision agriculture (Oliveira *et al.*, 2021). While robotic systems have been operational in structured environments since the 1990s (e.g. milking robots), their development for use in unstructured and complex field environments is relatively recent. This evolution is generating a multitude of technical solutions, creating challenges for farmers and agricultural operators in making informed adoption decisions. The agrobots market reached a value of $17.5 billion in 2024, with a 22.7% average annual growth in 2023, a trend that is expected to persist in the coming years (TBRC, 2024). Despite this steady growth, systematic frameworks for comparing agricultural and technical features remain limited, particularly regarding operational costs and efficiency trade-offs (Redhead *et al.*, 2015). For instance, electric robots typically have lower operational costs, they may require expensive battery investments, whereas diesel-powered agrobots balance higher fuel expenses with longer operational hours.

Following Lowenberg-DeBoer *et al.* (2021), agrobots were defined in this study as "a mobile, autonomous, decision-making, and mechatronic device that performs crop production tasks under human supervision, but without direct human labour". Other researchers have described agricultural robots as programmable machines that conduct various agricultural activities (Bechar and Vigneault, 2016). These definitions highlight that agricultural robots comprise a diverse range of systems built with different technologies to serve various purposes at field level. For that, agrobots were described and classified using technical descriptions of commercial proposals.

This study aimed at providing a comparative framework to analyse the relationship between technical specifications and market positioning. This structured reference is meant to inform agrobot-related choice of both technology users (e.g. farmers) and developers.

Materials and methods

The methodology combined a series of statistical analyses to achieve a systematic classification of agrobots. First, a dataset of agrobots currently on the market was composed to describe the standard technical specifications available for the users. Second, a bivariate analysis explored the relationships between technical specifications and price levels. Next, a dataset segmentation was performed through an agglomerative cluster analysis based on binary variables only. Then, clusters were further evaluated with a pairwise ANOVA to analyse their distinctiveness based on quantitative variables. Finally, all these results were used to compose a summary description of the current agrobots market segments.

Data collection and preparation

Major agrobots manufacturers were retrieved from the Future Farming buyers' guide, being the most updated catalogue currently available for this sector of the market (https://www.futurefarming.com/dossier/field-robots/ accessed February 2025) with a focus on European and North American markets. The dataset was completed by identifying all the agrobots listed on the manufacturers' websites, also used to complete technical specifications along with grey literature and industry reports.

The screening of 153 potential candidates yielded a final dataset of 71 agrobots. The selection was based on three inclusion criteria:

1. commercially available agrobots, either for sale or as a service, as of September 2024; different models from the same manufacturer were considered as distinct agrobots.
2. complete availability of documentation on four technical specifications classes: sizes, power source, market availability, operations.
3. fully operational status, thus excluding prototypes under development and phased-out models.

This selection process ensured a dataset focused on market-ready solutions, which were described with the commercial and technical description available to the users. Data were then cleaned: (a) to harmonise measuring units, (b) to transform nominal entries into numerical or binary values (when possible, such that having this specification is a 1 and its absence is a 0) (Table 1).

Statistical analysis

Statistical analyses were performed using R version 4.4.1 (R Core Team, 2024), employing the factoextra package (Kassambara & Mundt, 2020) through RStudio interface version 2023.12.1-402 (Giorgi *et al*., 2022).

The dataset segmentation was preceded by a bivariate analysis which compared each technical specification against the agrobot market price using the non-parametric Wilcoxon–Mann–Whitney test. Prices were considered only for agrobots on sale, thus excluding agrobots available for renting as an outsourcing service. All prices were expressed in American dollars according to the manufacturers' declarations.

The dataset segmentation was performed on the operation capabilities of the agrobots (Table 1). K-means clustering was applied on the seven operational capabilities without any dimensional reduction while the optimal number of clusters was determined through Silhouette Score and WSS test. Next, the clustering algorithm aggregated items around representative centroids using the Lloyd–Forgy algorithm which efficiently minimizes the sum of squared distances between data points and cluster centroids through an iterative process of centroid reassignment and point reallocation. The Kruskal Wallis ANOVA evaluated multiple pairwise-comparisons between clusters and numeric technical specifications (i.e. sizes, operational autonomy, electric, endothermic, hybrid) to better define and describe each cluster.

Results and discussion

Dataset description

For the sake of clarity, the dataset variables were divided into four axes to better capture multi-dimensional relationships (Table 1). Each axis represents distinct features, enabling a clearer interpretation of how distinct characteristics contribute to the clustering. This approach also helps reduce redundancy and highlight key patterns, ensuring the analysis remains focused and interpretable while preserving the underlying variability of the data.

Market price trend

About market price, while the large part of robots falls in between US$50k and 300k, only seven items were found to have a price exceeding US$400k, which correspond to the outliers shown in Figure 1. Apart from not being based on an endothermic engine, these robots do not show any other difference in technical features compared to the others. Among the technical specifications analysed, only the energy source significantly influenced agrobot market price, yet with different significance levels (p-values): 0.081 for endothermic engines, 0.020 for hybrid power, and 0.001 for electric engines. The most significant association between electric-powered agrobots and price levels may be due to specific cost structures, market demand, or pricing strategies tied to the perceived value and sustainability benefits of electric models.

Table 1. Technical specifications retrieved for the 71 selected agrobots

Axis	Variable	Type (unit)	Frequency
Physical characteristics	Height	Numeric (m)	–
	Length	Numeric (m)	–
	Width	Numeric (m)	–
	Turning radius	Numeric (m)	–
	Weight	Numeric (kg)	–
Power source	Electric	Binary	63%
	Endothermic	Binary	21%
	Hybrid	Binary	16%
	Operational autonomy	Numeric (h)	–
Commercial attributes	Product	Binary	90.14%
	Product price	Numeric ($)	–
	Service	Binary	18.30%
	Service price	Numeric ($)	–
Operational capabilities	Seeding	Binary	24%
	Weeding (mechanical)	Binary	51%
	Harvesting	Binary	27%
	Soil preparation	Binary	39%
	Spraying (chemical weeding and liquid dispatch)	Binary	56%
	Fertilizing	Binary	13%
	Monitoring	Binary	31%

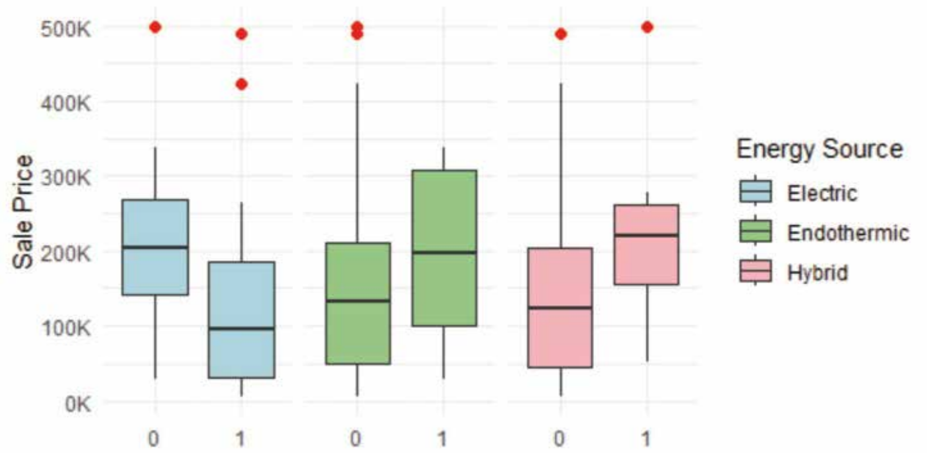

Figure 1. Detail of market price by type of energy sources.

Agrobot clusters

The K-means clustering based on the seven operational capabilities led to identify five clusters. Table 2 represents the contribution of each operation to the identified clusters, while Figure 2 shows clusters plotted along a pair of dimensions representing the transformed space used to display clusters.

Table 2. Variable means (centroids) across cluster.

Cluster	Seeding	Weeding	Harvesting	Soil preparation	Spraying	Fertilising	Monitoring
1	0.666	0.933*	0.066	0.800	0.533	0.133	0
2	0	0	0.100	1*	0.900*	0.100	0
3	0.411	0.705	0.294	0.294	0.764	0.352*	1*
4	0	0.600	0	0	0.533	0	0
5	0	0.071	0.857*	0.071	0.142	0	0.357

Asterisks identify the highest value per operational capability.

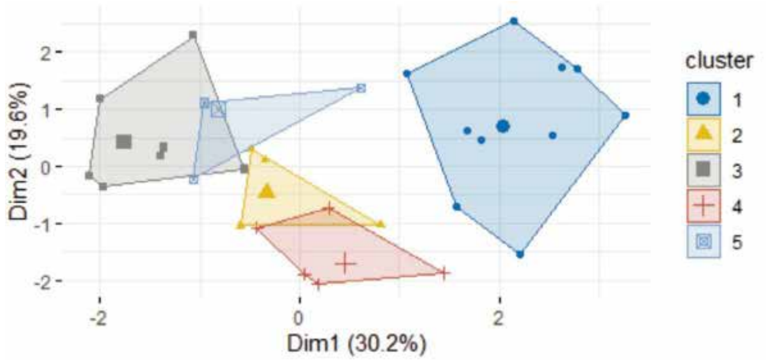

Figure 2. Cluster plot based on the agrobot operation capabilities.

Table 3. Kruskal–Wallis ANOVA test results.

Cluster	Height (m)	Length (m)	Width (m)	Weight (kg)	Turning radius (m)	Autonomy (h)	Electric	Endothermic	Hybrid
1	1.69	2.88	1.73	1958.66	1.53	19.08	0.53	0.33	0.13
2	1.52	3.27	1.84	2328.96	2.62	19.33	0.30	0.40	0.30
3	1.27	2.73	1.72	1112.88	0.59	10.80	0.76	0.05	0.17
4	1.66	3.69	2.27	1912.06	2.29	14.03	0.60	0.26	0.13
5	4.76	4.23	3.90	1180.61	0.86	24.20	0.85	0.07	0.07
ANOVA	0.207	0.645	0.887	0.063*	0.047**	0.058*	0.047**	0.104	0.647

ANOVA revealed significant differences among clusters (Table 3) for electric power usage and turning radius (both at p=0.047) and, at a lower level for autonomy (p=0.058) and weight (p=0.063). For example, cluster 2 exhibits the largest turning radius (2.63 m) and the highest weight (2323 kg), whereas cluster 3 includes the agrobots with the narrowest turning radius (0.60 m) and the lowest weight (1113 kg). Cluster 3 was also associated to the shortest autonomy (10.8 h) contrasting with cluster 5 with the longest (24.2 h).

In summary, the five clusters can be described as follows (Figure 3):

1. Multifunctional (n=17). Mechanical weeding and soil preparation are the most distinctive operations, along with a moderate role of spraying capabilities. These agrobots are compact, averaging 1.70 m in height, 2.88 m in length, and 1.74 m in width, with a weight of 1958.67 kg and a moderate turning radius of 1.53 m. Shared actuators and adaptable components, enabling seamless switching between tasks such as seeding, weeding, and soil preparation, support the multifunctionality of these agrobots. Energy sources include for the most electric engines (53%), providing eco-friendly and cost-effective solutions, particularly for extended weeding operations.
2. Heavy-duty tillers (n=17). Soil preparation and spraying are the most distinctive operation capabilities. They are the heaviest, averaging 2328.97 kg, and have moderate dimensions (1.53 m height, 3.28 m length, 1.85 m width) and a turning radius of 2.63 m, optimised for stability during high-intensity operations. These robots are predominantly powered by endothermic engines (40%), with the remaining models relying on electric (30%) and hybrid (30%) systems. This energy configuration underscores their focus on durability and resilience for demanding soil management tasks even in large fields.
3. Weeding and monitoring (n=15). These two operational capabilities are the most distinctive of this cluster that includes the most compact (1.28 m height, 2.73 m length, 1.72 m width), and lightweight (1112.88 kg) agrobots, with the narrowest turning radius (0.60 m), enabling high manoeuvrability in confined spaces. Mostly powered by electric engines (76%), these agrobots support low-emission, eco-friendly operations. Their versatility in monitoring and weeding is supported by shared sensor systems and actuators optimized for precision tasks.
4. Field weeders (n=12). Mechanical weeding and spraying are the most distinctive operational capabilities for this cluster of agrobots adapted for large-area coverage. They exhibit moderate height (1.67 m), length (3.69 m), and width (2.27 m), with a turning radius of 2.29 m and a weight of 1912.07 kg, balancing stability and manoeuvrability. Energy sources include mostly electric engines (60%), endothermic engines (27%), and hybrid systems (13%), making them suitable for consistent spraying over expansive fields.
5. Large-scale harvesters (n=10). Harvesting is the most distinctive operational capability, with a lower contribution of monitoring and a minimal role of weeding. This cluster features the largest

robots (4.77 m in height, 4.23 m in length, and 3.90 m in width), yet with a moderate weight and a narrow turning radius of 0.86 m. The majority are electric powered (86%). These robots appear to prioritise sustainability for large-scale harvesting operations.

In the cluster analysis, it is evident that some families of robots share common capabilities or even exhibit multiple capabilities simultaneously. This overlap may arise from the presence of advanced actuators designed to perform more than one agricultural practice. For example, a robot equipped with a multi-functional actuator might handle both seeding and fertilizing tasks efficiently, reducing the need for separate equipment.
A significant limitation of the clustering study on robots lies in the impact of certain robots with extreme attributes, particularly in terms of size, on the numerical values used for analysis. These outliers can disproportionately influence cluster centroids or medoids, leading to distortions in the grouping of robots and misrepresenting the true functional or operational similarities within clusters. For instance, exceptionally large robots might skew the average dimensions of a cluster, causing smaller yet functionally similar robots to be misclassified. Consequently, such robots should not be considered in isolation but rather contextualized within their specific operational niche to ensure the study's conclusions are robust and representative of the broader dataset.

Conclusion

This study has provided valuable insights for grouping robots into homogeneous clusters within a population of 71 robots. These findings could support the development of targeted regulatory policies and market strategies by identifying recurring characteristics across agrobot families. Additionally, stakeholders like investors and policymakers can use these clusters to better target support, subsidies, ultimately fostering the adoption of technology that best addresses agricultural challenges and user requirements. However, the research has certain limitations. Information gathered from company websites is often incomplete, as many businesses are reluctant to disclose details unless required for commercial purposes.

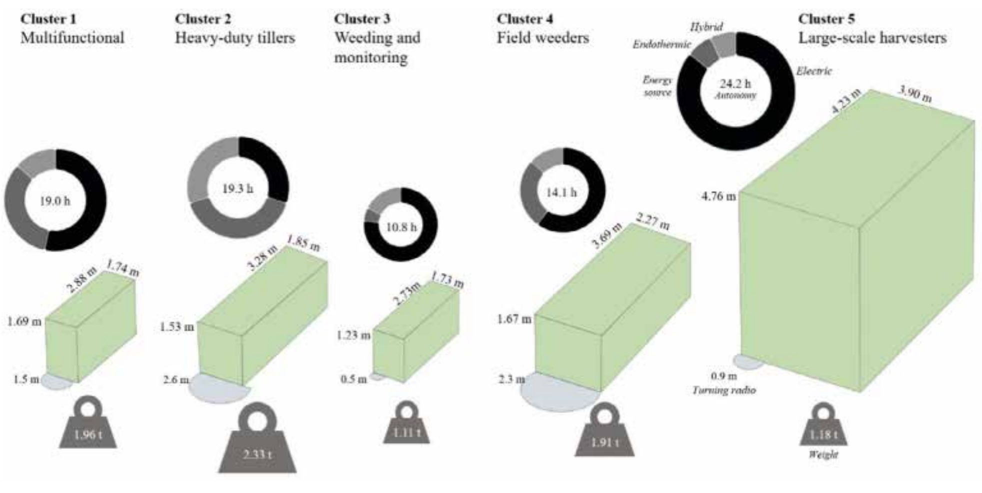

Figure 3. Schematic representation (out of scale) of the agrobot average technical specifications per cluster, as resulting from the statistical analyses.

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References

Bechar, A., & Vigneault, C. (2016). Agricultural robots for field operations: Concepts and components. Biosystems Engineering, 149, 94–111. https://doi.org/10.1016/j.biosystemseng.2016.06.014

Giorgi, F.M., Ceraolo, C., & Mercatelli, D. (2022). The R language: an engine for bioinformatics and data science. Life, 12(5), 648. https://doi.org/10.3390/life12050648

Kassambara, A., & Mundt, F. (2020). factoextra: extract and visualize the results of multivariate data analyses (Version 1.0.7). Available online at https://cran.r-project.org/web/packages/factoextra/index.html (accessed February 2025).

Lowenberg-DeBoer, J., Behrendt, K., Canavari, M., Ehlers, M.-H., Gabriel, A., Huang, I., *et al*. (2021). The impact of regulation on autonomous crop equipment in Europe. In J.V. Stafford (Ed.) Precision Agriculture '21, Proceedings of the 13th European Conference on Precision Agriculture. Wageningen Academic Publishers, Wageningen, pp. 711–717. https://doi.org/10.3920/978-90-8686-916-9_85

Oliveira, L.F.P., Moreira, A.P., & Silva, M.F. (2021). Advances in agriculture robotics: a state-of-the-art review and challenges ahead. Robotics, 10(2), 52. https://doi.org/10.3390/robotics10020052

R Core Team. (2024). R: A language and environment for statistical computing (Version 4.4.1: Race for Your Life). R Foundation for Statistical Computing, Vienna. Available online at https://www.R-project.org

Redhead, F., Bawden, O., Russell, R., & Perez, T. (2015). Bringing the farmer perspective to agricultural robots. Non-peer reviewed preprint at http://dx.doi.org/10.1145/2702613.2732894

TBRC. (2024). Agricultural robot market report 2024. The Business Research Private Company, Hyderabad. Available online at https://www.thebusinessresearchcompany.com/report/agricultural-robot-global-market-report (accessed February 2025).