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Research Paper

Assessment of readiness for conservation agriculture in Morocco: implications for targeting smallholder support

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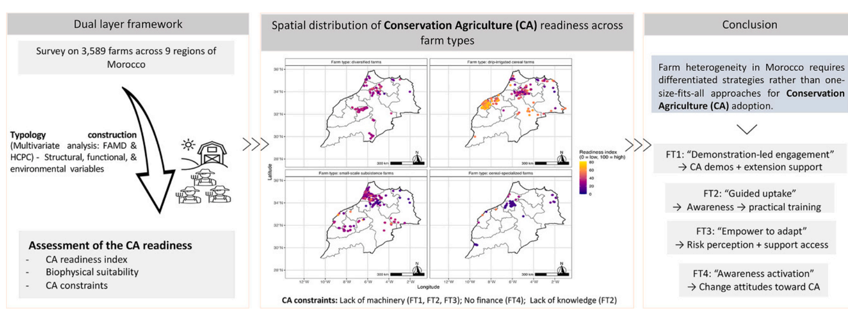
HIGHLIGHTS

- A dual-layer framework links farm types to conservation agriculture readiness.
- Farm survey of 3589 households reveals four distinct smallholder systems.
- Readiness emphasize CA knowledge, education, and digital engagement limits.
- Structural constraints and behavioral barriers act jointly in limiting adoption.
- One-size-fits-all policies are ineffective; farm type strategies are required.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Morocco has prioritized conservation agriculture (CA) as an important pillar of its Green Generation 2020–2030 strategy, aiming to convert one million hectares of cereal farmland to CA by 2030 in response to land degradation, water scarcity, and climate stress.
OBJECTIVE: This study assesses the readiness of Moroccan smallholder farms to adopt CA practices by developing a farm typology with behavioral, attitudinal, and informational variables of CA readiness.
METHODS: Using data from a 2024 survey of 3589 farm households across nine regions of Morocco, we applied a multivariate approach to identify distinct farm types. We then overlaid these typologies with CA readiness variables, such as perception of CA utility, climate vulnerability, digital tool use, extension access, and CA knowledge, to quantify a CA readiness index for each group.
RESULTS & CONCLUSIONS: Four farm types were identified: diversified farms, drip-irrigated cereal farms, small-scale subsistence farms, and cereal-specialized farms. Drip-irrigated cereal farms showed the highest CA readiness (49.8%), whereas cereal-specialized farms showed the lowest (10.6%), driven by informational and

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perceptual deficits. The comparison between farm-type readiness and biophysical suitability, using soil and rainfall data, indicates that lower readiness groups operate in environments well-suited for CA. Structural constraints, including limited mechanization, lack of CA-specific equipment, and lack of financial support, were the most reported barriers to adoption.

SIGNIFICANCE: These findings highlight the limitations of a one-size-fits-all approach to CA scaling in heterogeneous farming systems. By linking farm structure with behavioral readiness, the study identifies farm-type-specific entry points for intervention to overcome binding constraints to CA adoption. Tailored policies, such as bridging awareness-knowledge gaps in drip-irrigated systems, improving climate risk communication among subsistence farmers, and expanding mechanization services, are essential to accelerate overall readiness for CA adoption in Morocco.

1. Introduction

With its benefits for soil health, water-use efficiency, carbon sequestration, and climate change adaptation (Hobbs et al., 2008; Devkota et al., 2022), conservation agriculture (CA) has drawn global interest as one approach to improving the sustainability of farming systems. CA is defined by three core principles: minimal soil disturbance (no-till or reduced tillage), permanent soil cover (through crop residues or cover crops), and crop diversification (typically via rotations or intercropping) (Hobbs, 2007). Although CA can contribute to improvements in soil properties, its effects on yields are variable. Meta-analyses show that yield benefits are more likely under semi-arid conditions and on well-drained soils, particularly when all three CA principles are fully applied (Rusinamhodzi et al., 2011; Corbeels et al., 2020; Pittelkow et al., 2015). CA has also been associated with improved socioeconomic outcomes, including income stability, community engagement, improved nutritional security, and increased labor-use efficiency (Devkota and Yigezu, 2020; Yigezu et al., 2021). While CA can reduce specific input costs, particularly fuel and labor for tillage, it may also increase expenditures on herbicides and mineral fertilizers, especially during the early stages of adoption (Thierfelder et al., 2018), which highlights trade-offs related to CA.

In North Africa, Morocco has prioritized CA within its national strategy, introducing a dedicated initiative under the Green Generation Plan 2020–2030 that sets an ambitious target of converting one million hectares of current cereal farmland to CA practices by 2030 (ICARDA, 2021). CA adoption in Morocco has primarily focused on reduced or no-tillage practices and the introduction of legume crops through rotations or intercropping, i.e., partial adoption of CA.

Despite policy commitment, the scaling out of CA in Morocco remains constrained by limited access to machinery, high equipment costs, crop residue competition, insufficient farmer training, climate and environmental challenges, land tenure, and limited research (Moussadek et al., 2021; Bonzanigo et al., 2016; ICARDA, 2021; UN-Habitat, 2024; Brache et al., 2025; Kertolli et al., 2024). Moreover, over 70% of Morocco's 1.5 million farms are less than five hectares, with an average size of just 1.6 ha, meaning the success of CA expansion largely depends on the capacity and willingness of smallholders (UN-Habitat, 2024). Yet, the lack of recent data on CA coverage makes it difficult to assess Morocco's progress toward national targets. While these studies identify key structural and institutional constraints to CA adoption in Morocco, they provide limited insight into how these constraints vary across different farm types or how they relate to farmers' behavior in adopting CA practices.

Beyond the issues mentioned above, an underexplored challenge to CA scaling out lies in the heterogeneity of smallholder farming systems. Moroccan smallholders vary in terms of their resource endowments, market integration, production goals, and exposure to innovation, all factors influencing their capacity to adopt CA. These differences can be better understood through farm typologies, which are useful in developing interventions aligned with farmer characteristics (Eshetae et al., 2024; Rivera et al., 2020). Developing farm typologies can help identify which farm types face specific binding constraints that limit CA adoption. Moreover, typologies can help to close gaps between understanding farm systems and informing policy design (Prosperi et al., 2023).

While national policy has set ambitious targets for CA expansion, there is limited empirical insight into how different types of farms are positioned, not only structurally but also functionally and behaviorally, for the adoption of CA practices. Work in Morocco has begun to develop typologies to classify smallholder systems and analyze their diversity using multivariate or participatory methods (El Ansari et al., 2020; Alary et al., 2021; Hossard et al., 2021; Er-rayhany et al., 2022; Tidjani and Adamou, 2023; Baccar et al., 2017; Sraïri and Lyoubi, 2003) but not explicitly integrating variables that capture farmers' readiness toward CA practices. In this study, readiness refers to the degree to which a farm demonstrates the cognitive, attitudinal, behavioral, and institutional conditions necessary to consider and implement conservation agriculture practices.

The objective of this study is to understand the readiness of Moroccan smallholder farms to adopt CA across diverse types of farms, with the goal of informing more effective targeting strategies in support of national policy ambitions for CA expansion.

First, we construct farm typologies based on structural and functional variables that capture resource endowments, production, and environmental contexts using multivariate statistical techniques on data collected in a 2024 cross-sectional survey of 3589 farm households across nine regions of Morocco to identify distinct farm types.

Second, after identifying these structurally distinct farm types, we assess their readiness to adopt CA by examining behavioral, attitudinal, informational, and institutional variables within each group. By linking farm typology with CA readiness, this study contributes an evidence-based framework for identifying farm-type-specific binding constraints for CA scaling in Morocco, with direct implications for targeting policy and institutional support.

2. Materials and methods

2.1. Description of the study area

Morocco is in the northwest of Africa. Its climate ranges from a Mediterranean climate in the northern and coastal parts to arid and semi-arid conditions in the interior and south (World Bank, 2021a; World Bank, 2021b). Agro-climatic risks have increased in Morocco: since 1961 average temperatures have increased by 0.2 °C every decade, and recent years have shown an increased frequency of droughts (World Bank, 2021a; FAOSTAT, 2025). Climate risks have contributed to declines in cereal production, which dropped by 68%, from 10.4 million tonnes of cereals produced in 2021 to 3.3 million tonnes in 2022 (FAO, 2022).

2.2. Data collection

The primary data used in this study were from 3589 farming households in Morocco, collected through a survey conducted in 2024 by the International Center for Agricultural Research in the Dry Areas (ICARDA). The survey covered nine of Morocco's twelve administrative regions: Béni Mellal-Khenifra, Casablanca-Settat, Drâa-Tafilalet, Fès-Meknès, Marrakesh-Safi, Oriental, Rabat-Salé-Kenitra, Souss-Massa, and

Tanger-Tétouan-Al Hoceima (Fig. 1). These regions were purposively selected to cover Morocco's major agro-ecological zones and agricultural production systems, with a particular emphasis on cereal crops. This includes the country's main cereal-producing regions: Fès-Meknès, Rabat-Salé-Kenitra, and Tanger-Tétouan-Al Hoceima, which together account for approximately 84% of national cereal production (Ed-dahmany et al., 2026). Tree crops were not included, and this scope shaped both the sampling design and the distribution of surveyed households.

Although results are presented at the regional level, data collection was conducted at the village level (lower administrative unit), with farm households serving as the primary unit of observation. Within each region, farmer lists were obtained from local extension offices and agricultural cooperatives to identify eligible farms engaged in cereal-based systems.

Sampling intensity varied geographically; for instance, in the eastern and southeastern provinces, such as Errachidia, Tinghir, and Zagora (part of the Drâa-Tafilalet region), only a small number of surveys could be conducted. This reflects the agricultural reality of these areas, where annual rainfall often falls below 100 mm, limiting cereal production. In addition to agro-ecological constraints, fieldwork safety considerations, particularly in high-risk or remote zones, also influenced the final distribution of sampled households. The final sample included 3589 households, slightly exceeding the initial target of 3500 surveys.

Data were collected through face-to-face interviews conducted by enumerators using a structured questionnaire. The survey collected both quantitative and qualitative data, and it included 114 variables ranging from socio-economic indicators (e.g., family size, education), crop types (Appendix A) to detailed agronomic practices (e.g., irrigation timing, pest types) and environmental factors (e.g., perceptions of soil moisture) (see Supplementary material S1).

2.3. Typology construction

Scaling out is one of the main reasons for developing a farm typology (Alvarez et al., 2014), and in our study, we aimed to inform the scaling out of CA by identifying groups of farms with similar conditions that influence their readiness to adopt CA practices. By linking the farm types to readiness indicators, our analysis provides insights into which farming systems face distinct binding constraints that influence CA adoption. This approach aligns with the perspective of Woltering et al. (2019), who argue that sustainable scaling requires going beyond short-term adoption numbers and understanding the broader system

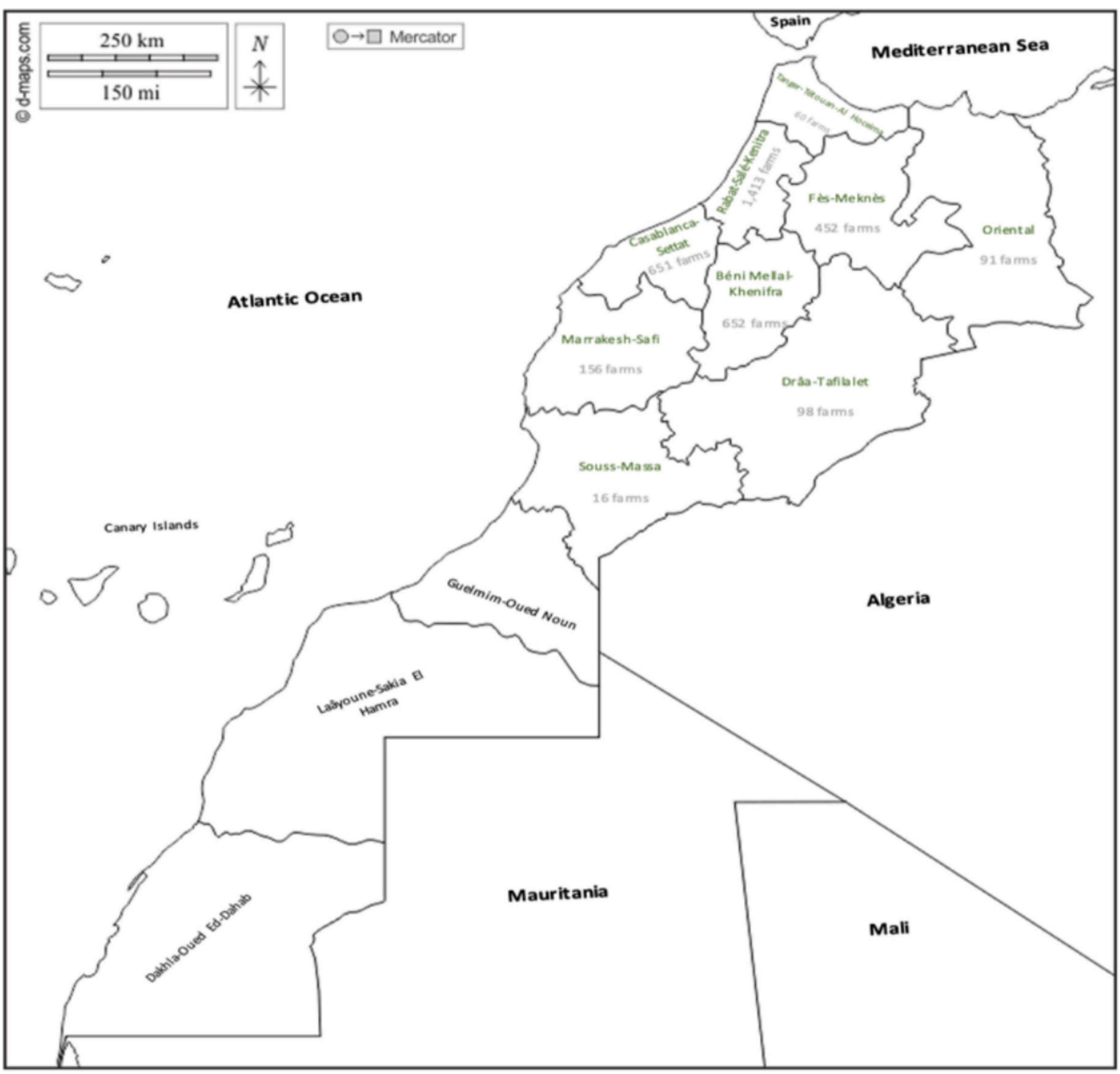

Fig. 1. Regional distribution of surveyed household heads in Morocco.
Note: Surveyed farm regions are highlighted in green; numbers represent the number of farms surveyed in each region.

conditions that enable long-term, context-appropriate uptake. The typology, therefore, contributes to identifying entry points for scaling CA in ways that account for local diversity and system-specific constraints.

Farm typology approaches are widely used to analyze heterogeneity in smallholder farming systems because they capture differences in resource endowments, production strategies, and management practices at the farm level (Alvarez et al., 2018; Komarek et al., 2019). While geospatial approaches (Muthoni et al., 2017), do combine biophysical and socio-economic data to identify the suitability of agricultural practices for specific contexts, they do not directly capture behavioral, institutional, and management characteristics that influence farmers' decisions to adopt practices such as conservation agriculture. A farm typology approach is therefore more bottom-up, in the sense that it draws on household-level data to classify farms according to their structural and functional characteristics (Komarek et al., 2019).

To develop the farm typology, we followed a multivariate statistical approach combining Factor Analysis of Mixed Data (FAMD) and Hierarchical Clustering on Principal Components (HCPC) (Bousbia et al., 2024). FAMD was used to reduce the dimensionality of the dataset, which included both continuous and categorical variables. HCPC was then applied to identify clusters of farms based on the FAMD dimensions. HCPC was selected because it is particularly well-suited for exploratory typology development in heterogeneous farm populations and provides transparent, interpretable farm groups for subsequent analysis.

The first step involved selecting variables to classify farm households by capturing the main structural, functional, and environmental characteristics influencing production decisions, drawing on previous typology studies (Eshetae et al., 2025). In total, 12 variables were used in the FAMD (Table 1). Cultivated land area reflects the physical size of the farm and production capacity. Household size provides context for consumption needs and labor availability, while the age of the household head captures farming experience, management styles, and risk behavior, which may influence production strategies and adoption patterns. These two have been widely used as variables in farm typologies (Komarek et al., 2019; Bousbia et al., 2024). Water resource availability and management were captured through two complementary variables: supplemental irrigation frequency (measured as irrigation events per growing season), which reflects access to water resources, and irrigation system type (drip, sprinkler, flooding, or none), which reflects the technological level and efficiency of water use intensity and water management strategies across farms. Soil problems such as erosion, salinity, or sodicity are environmental constraints that influence land productivity, input decisions, and management options, thereby contributing to structural differentiation across farm types. Total costs per hectare of production inputs (irrigation, fertilizers, pesticides, and supplemental organic inputs such as manure and compost) were used as a proxy for input use intensity. Production patterns are captured by the share of cereals in total crop output, providing insight into the extent to which households prioritize cereals for market orientation and home consumption. Straw use was included as a functional variable reflecting crop-livestock integration and residue management practices. In cereal-based systems such as Morocco's, straw represents a high-value commodity used either as livestock feed or for sale, creating a structural trade-off between maintaining soil cover under CA and meeting livestock or income needs. Differentiating farms based on straw use therefore allows us to identify systems where residue retention may constitute a binding constraint to adopting CA's second pillar (permanent soil cover). Fallow land was included as fallowing is widely used in semi-arid systems to manage soil fertility, conserve moisture, and reduce production risk, thereby reflecting differences in land-use intensity and management strategies.

Finally, climate-related variables were used, including perceived climate risks and the tools farmers use to access climate information. This allows us to distinguish between farms based on a range of sources of climate information.

Table 1
Variables used for identifying farm types.

Variables	Use of variable	Unit	Data type	Description
Cultivated crop land area	Typology	ha	Continuous	Total area under crop cultivation by the farmer.
Age	Typology	years	Continuous	Age of the household head.
Supplemental irrigation	Typology	number	Continuous	Times of applying supplemental irrigation in winter season.
Fallow land	Typology	–	Categorical	If the farmer keeps their land fallow or not.
Family size	Typology	number	Continuous	The number of members in a farming household.
Straw use	Typology	–	Categorical	Livestock feed, livestock feed and selling, selling.
Irrigation system	Typology	–	Categorical	Type of irrigation system used on the farm, categorized as drip, sprinkler, flooding, or none.
Cereals share of total production	Typology	%	Continuous	(Cereal production ÷ total farm crop production) × 100
Total costs	Typology	MAD/ha/year	Continuous	Sum of irrigation, N, P, K fertilizers, pesticides, and supplemental organic inputs costs.
Soil problems	Typology	–	Categorical	Type of soil problems (e.g., erosion, salinity, arsenic, sodicity, hardpan).
Climate services	Typology	–	Categorical	Source of climate information: apps, mosque, TV, newspaper, radio, or extension agents.
Climate risks	Typology	–	Categorical	Type of climate risks faced: drought, heatwaves, pests and diseases, strong winds.

Note: MAD is Moroccan dirhams. All variables were collected through the 2024 national farm household survey conducted across nine regions in Morocco.

Following variable selection, we conducted data preprocessing, during which highly correlated variables ($r > 0.5$) were removed (Appendix B). FAMD was performed on the cleaned dataset to generate dimensions summarizing variation across farms. The dimensions that explained at least 60% of the total variance (Hair et al., 2019) were retained for clustering. Using these retained dimensions, HCPC was applied to identify farm types. To validate the clusters identified by HCPC, candidate numbers of clusters (k = 2 to 10) were visualized on the retained FAMD dimensions by using factor maps (Appendix C). Candidate clusters were evaluated based on the degree of separation observed on the factor map; solutions that showed substantial overlap, indicating poor differentiation between groups, were discarded. We retained the number of clusters that showed clear and interpretable separation, acknowledging that minor overlap is expected in complex farm-level data. In addition to this visual assessment, we applied the silhouette method to assess the compactness within clusters and the separation between them (Shi et al., 2021) (Appendix D).

2.4. Assessment of the CA readiness

After identifying farm types, we assessed their readiness to adopt CA practices by introducing a set of CA-specific readiness variables. The concept of readiness used in this study draws on behavioral adoption frameworks such as the Theory of Planned Behavior (Ajzen, 1991) and Diffusion of Innovations (Rogers, 2003), which emphasize that adoption decisions are influenced not only by structural conditions but also by farmers' perceptions, knowledge, and access to institutional support. Accordingly, the readiness variables included in this study capture multiple dimensions influencing adoption behavior, including attitudes toward conservation agriculture, awareness and knowledge, access to extension and information, and existing adaptive practices.

This framework recognizes that CA adoption depends not only on structural, functional, and environmental characteristics captured in the typology, such as cultivated area, input intensity, irrigation practices, and perceived climate risks, but also on behavioral and informational factors reflected in the readiness variables (Table 2).

The CA readiness index was first computed for each individual farm, and these farm-level scores were then aggregated at the farm-type level to quantify how prepared different farming systems in Morocco are to adopt CA practices. The index ranges from 0 to 100, where higher values indicate greater readiness across selected variables, reflecting more favorable conditions for CA adoption, while lower values indicate constraints that may limit readiness. For each readiness variable, the percentage of CA-positive responses (P_i) was calculated as the proportion of farmers within each farm type showing supportive behaviors or perceptions toward CA adoption. Here, the subscript i refers to each readiness variable listed in Table 2.

$$\mathrm{Pi} = \left(\frac{\mathrm{N\_positive}}{N\_total}\right) \times 100 \tag{1}$$

where N_positive is the number of farmers in a farm type supporting, having a positive perception, or behavior toward CA, and N_total is the total number of farms in that farm type.

For clarity and consistency:

- For binary variables (e.g., belief in CA's usefulness), only responses supporting CA, e.g., “yes” were considered; responses such as “no” were excluded, as they indicate low commitment toward CA (Table 2).
- For ordinal variables (e.g., vulnerability to climate change), only the CA-compatible option (e.g., highly vulnerable) was counted as CA positive.
- For categorical variables (e.g., type of irrigation system), only the CA-compatible option (e.g., drip irrigation) was counted as CA positive.

Finally, an overall readiness index (R_t) for each farm type was calculated as the average of all P_i values:

$$\mathrm{Rt} = \frac{\sum_{i=1}^{n} P_i}{n} \tag{2}$$

where n is the total number of readiness variables.

This unweighted average was used so that each indicator contributes equally to the overall readiness score.

2.5. Biophysical data extraction for comparison with farm-type readiness

To compare the readiness levels of each farm type with the agro-ecological conditions under which conservation agriculture is likely to perform well, we extracted additional soil and rainfall data from global geospatial datasets and linked it to each surveyed household using their GPS coordinates.

Soil characteristics were obtained from the SoilGrids global soil information system at 250-m resolution (Poggio et al., 2021). For each farm, values were extracted for the 0–5 cm depth layer for the following variables: clay, sand, and silt fractions (%), soil organic carbon (SOC, g kg^{-1}), and bulk density (BD, g cm^{-3}). Raster layers for each soil property

Table 2
Variables used for CA readiness assessment.

Variables	Use of variable	Note
Farmer perception toward usefulness of CA	Readiness	If a farmer believes CA improves yield, reduces labor, or helps soil health, they are more likely to adopt it. However, scepticism could slow down adoption, especially if they don't see immediate benefits (Ogieriakhi and Woodward, 2022). As a CA-positive response will be counted: “Yes” farmer reports CA as useful
Extension services support	Readiness	Without support, farmers may lack the knowledge or confidence to adopt CA (Nkonki-Mandleni et al., 2022). As a CA-positive response will be counted: “yes” farmer receives extension support.
Awareness toward climate smart agriculture	Readiness	Awareness is a key stage in the process by which farmers adopt new practices (Pannell et al., 2006; Kuehne et al., 2017). Farms that are aware of CSA are more inclined to adopt CA as a long-term strategy. As a CA-positive response will be counted: “yes” farmer is aware of CSA principles.
Vulnerability toward climate change	Readiness	Conservation agriculture helps farmers cope with climate change by improving soil health, increasing water retention, and reducing erosion, which makes crops more resilient to droughts and heavy rains (Pisante et al., 2015; Li et al., 2023; Lee and Gambiza, 2022). Based on this, farms that perceive themselves as highly vulnerable to climate change may have a greater motivation to consider CA as a potential coping strategy. We acknowledge, however, that vulnerability may also drive alternative responses such as reduced investment, short-term coping behavior, or dis-adoption. Therefore, in our framework, perceived vulnerability reflects *potential motivation* rather than guaranteed readiness to adopt CA. As a CA-positive response will be counted: “highly vulnerable” farmer reports high exposure to climate risks.
Follow practices to increase water-use efficiency	Readiness	Farmers who already follow water use efficiency techniques are more likely to adopt CA, as these practices align with CA's focus on resource conservation (Narayanamoorthy, 2010; Assefa et al., 2018). As a CA-positive response will be counted: “yes” farmer applies one or more water-efficiency practices.
Use of digital tools	Readiness	Farmers using digital tools (e.g., apps for weather or soil monitoring, or market updates to support farm decisions) are more likely to adopt CA, as they can access data to optimize practices. Those without digital access may rely on traditional methods, slowing CA adoption. Brown et al., 2017; Asante et al., 2024 As a CA-positive response will be counted: “often” frequent use of digital tools for farming decisions.
Alternative adaptation strategies adopted	Readiness	Adoption of other adaptive practices signals a farmer's openness to innovation (Masi et al., 2022). As a CA-positive response will be counted: any form of adaptation practice

(*continued on next page*)

Table 2 (*continued*)

Variables	Use of variable	Note
		already adopted by the farm (e.g., adjusting sowing dates, drought-resistant varieties, improving irrigation).
CA knowledge	Readiness	A good understanding of CA- principles, practices, benefits, etc., plays an important role in increasing farmers' willingness to adopt CA (Chatterjee et al., 2022). As a CA-positive response will be counted: "yes" farmer reports knowing CA practices.
Education	Readiness	Human capital (Komarek et al., 2019). Farmers with higher education levels are more likely to understand the scientific basis of CA. As a CA-positive response will be counted: bachelor and postgraduate studies.
Number of legume crops per year	Readiness	Legume integration contributes to crop diversification, one of the core CA principles (Islam et al., 2023; Thierfelder et al., 2018). In this study, legume cultivation is used as a readiness indicator because farms that are already growing legumes are structurally closer to implementing CA rotations. As a CA-positive response will be counted: farmers cultivating at least one legume crop per year.

were downloaded and point extraction was performed by overlaying household GPS coordinates recorded in the survey onto the SoilGrids rasters. After extraction, all soil indicators were averaged within each farm type, producing one representative soil profile per typology.

Rainfall was derived from the CHIRPS v2.0 monthly precipitation dataset (Funk et al., 2015), which provides 0.05° (∼5 km) resolution rainfall estimates by combining satellite imagery with ground station observations. All monthly rainfall files for the Africa domain were downloaded, uncompressed, and aggregated to annual totals by summing all monthly layers for each calendar year. A long-term rainfall climatology was then computed by averaging annual totals from 1991 to 2025. Using the geographic coordinates of surveyed households, long-term mean rainfall values were extracted from the climatology raster and assigned to each farm, then averaged to generate a single representative rainfall value for each typology.

2.6. Identification of constraints to conservation agriculture adoption

To complement the readiness analysis, we examined reported constraints to CA adoption across farm types. Understanding these constraints at the farm type level is important, as farm types differ in their resource endowments, labor availability, crop choices, and management capacities, all of which shape their capacity to adopt CA. Moreover, it allows for a better understanding of the adoption challenges faced by farmers in their specific farm systems, rather than applying a one-size-fits-all approach (Knowler and Bradshaw, 2007). Based on previous studies in Morocco and other Mediterranean contexts, commonly reported barriers included: lack of CA-specific mechanization (no-till planters being scarce and expensive) (Mrabet et al., 2012); knowledge gaps (Guerrieri et al., 2026); limited access to capital and increased upfront costs (Guerrieri et al., 2026); land tenure insecurity, as fragmented landholdings and unclear tenure arrangements discourage long-term investments (Verner et al., 2018; Caulfield et al., 2020; Bahrami et al., 2025); cultural factors, with tillage practices deeply rooted (Topp et al., 2023; Mrabet et al., 2012), and the complexity of CA itself, which requires careful management and involves additional learning costs (Moussadek et al., 2021). For each farm type, responses were first summarized as the absolute number of farmers reporting each constraint. To ensure comparability across typologies of different sizes, these absolute values were converted into proportions, representing the share of farmers within each typology experiencing a given constraint.

The proportion of farmers within a given farm type reporting a particular constraint was calculated as:

$$p_{ij} = \frac{C_{ij}}{N_i} \tag{4}$$

where p_{ij} is the proportion of farmers in farm type *i* reporting constraint *j*, C_{ij} is the number of farmers in farm type *i* reporting constraint *j*, and N_i is the total number of farmers in farm type *i*. This was repeated for each constraint across all farm types to provide results on the percentage of farmers per farm type reporting each constraint.

3. Results

3.1. Characterizing farm households in Morocco

Descriptive statistics of the surveyed 3589 farming households for key variables, including demographics, income, crop type, and input costs, highlight heterogeneity across the households (Table 3). The age of household heads ranges from 25 to 85 years (mean = 49.5; median = 50.0; SD = 10.0). Nearly half (48%) are between 45 and 56 years, indicating that Morocco's farming population is predominantly middle-aged, reflecting a mature farming population.

Family size varies from 1 to 15 members (mean = 4.5; median = 4.0). Most households are moderately sized (IQR: 3–6), typical of rural agricultural settings, though larger families may indicate extended households with greater labor availability.

The cultivated area per household ranges from 1 to 28 ha (mean = 6.0; median = 3.0;

SD = 7.1). In total, 82.89% of surveyed households cultivate less than 5 ha, reflecting that smallholder farming remains predominant, typical of Moroccan agriculture.

Average total net income from cropping activities was 38,821.7 MAD/ha/year, with a wide range (4550–171,700 MAD/ha/year).

Most of the land is dedicated to cereal production, which makes up about 80% of the total cultivated area, with many households entirely dependent on cereal, emphasizing its role as a staple crop for food security and market sales. In contrast, crops such as vegetables, grain legumes, forage legumes (alfalfa), oilseeds, cotton, and fruit are cultivated on smaller areas.

Lastly, input costs are a significant component of cropping expenses but also a determinant of household performance. Fertilizer costs were the largest cost category (mean = 4535.8 MAD/ha/year), reflecting reliance on chemical inputs, followed by irrigation costs that varied across seasons (mean = 883.5 MAD in the winter season; mean = 1080.1 MAD in the summer season). Seasonal variations in irrigation costs highlight water scarcity challenges during warmer months, with some farms reporting very high irrigation costs in both seasons.

3.2. Construction of farm typologies in Morocco

3.2.1. Factors identified by FAMD

The FAMD analysis retained nine dimensions based on the Kaiser criterion (eigenvalue >1) (Appendix F), explaining 63.5% of the total variance (Fig. 2a; Appendix E). The correlation circle illustrates the relationships among variables, their representation quality, and how strongly they are correlated with the principal dimensions (Fig. 2b and c). Variables positioned close together are positively correlated, while those located on opposite sides of the origin are negatively correlated. Each arrow represents a variable, with the length and direction indicating its correlation with the dimensions and other variables. The color gradient (from blue to red) shows the contribution of each variable to the dimensions, with red indicating higher contributions.

Table 3
Descriptive statistics of farm household characteristics (n = 3589).

Variable	Min	First quartile	Median	Mean	Third quartile	Max	SD
Age	25	40	50	49.5	56	85	10.0
Family-size	1.0	3.0	4.0	4.5	6.0	15.0	2.1
Total cultivated area (ha)	1.0	2.0	3.0	6.0	5.0	28.00	7.1
Total net income (MAD/ha/year)	4550.0	18,600.0	33,000.0	38,821.7	45,200.0	171,700.0	28,821.2
Cereals share of total production (%)	0.0	62.5	100.0	82.6	100.0	100.0	27.7
Vegetables share of total production (%)	0.0	0.0	0.0	2.3	0.0	89.3	11.0
Grain legumes share of total production (%)	0.0	0.0	0.0	10.3	16.7	100.0	18.6
Forage legumes share of total production (%)	0.0	0.0	0.0	4.4	0.0	96.0	16.9
Oilseeds share of total production (%)	0.0	0.0	0.0	0.0	0.0	62.5	1.0
Fruit share of total production (%)	0.0	0.0	0.0	0.4	0.0	59.6	4.3
Cotton share of total production (%)	0.0	0.0	0.0	0.0	0.0	97.5	1.6
Other costs (pesticides and supplemental nutrients) (MAD/ha/year)	570.0	1789.0	2127.0	2152.2	2400.0	8650.0	560.4
Total fertilizer costs (MAD/ha/year)	1529.0	3850.0	4679.0	4536.8	5150.0	17,510.0	1136.6
Total irrigation costs in winter (MAD/ha/season)	0.0	720.0	840.0	883.5	1000.0	4000.0	234.6
Total irrigation costs in summer (MAD/ha/season)	1.0	800.0	950.0	1080.1	1300.0	8200.0	463.3
Number of supplemental irrigations (per season)	1.0	3.0	3.0	3.6	5.0	8.00	1.2

3.2.2. Clustering of farm types

Hierarchical Clustering on Principal Components applied to the FAMD results identified four farm types. The dendrogram illustrates the hierarchical structure of similarities among farm households (Fig. 3a). The height of each branch reflects the dissimilarity between groups, and the color-coded divisions represent the four clusters retained based on the largest inertia gain. This indicates that partitioning the sample into four clusters best balances within-group homogeneity and between-group separation. The factor map displays the spatial distribution of the identified clusters along the first two dimensions (23.4% of total variance) (Fig. 3b). Each color corresponds to a distinct farm type: cluster 1 (black), cluster 2 (red), cluster 3 (green), and cluster 4 (blue). The clusters are well separated, confirming that the classification effectively distinguishes different farm profiles.

3.3. Identification of farm household types

The results of the farm typology classification using FAMD and HCPC revealed four distinct farm types based on variations in structural and functional variables. Accordingly, the farm household types identified were given names based on their dominant characteristics: diversified farms (FT1), drip-irrigated cereal farms (FT2), small-scale subsistence farms (FT3), and cereal-specialized farms (FT4). Among the identified types, FT2 was the most dominant type, representing 30.4% of the sample (n = 1091), followed closely by FT3 at 30.2%, FT1 accounted for 21.6%, and FT4 represented the smallest group at 17.7% (n = 636) (Table 4).

Diversified farms (FT1) represented households cultivating the largest areas (8.2 ha above the dataset mean of 6 ha), managed by middle-aged farmers with small households (around 3 members), suggesting reliance on hired labor. These farms used sprinkler irrigation and applied supplemental irrigation more frequently than any other group (4.7 times per winter season). Cereals account for 68% of total production, reflecting a diversification strategy that balances staple crops with other crops. The relatively low input costs compared with other farm types suggest efficient input use despite their large operational scale. The main soil problem was hardpan formation, while drought was their dominant climatic stressor. Farmers in this group use television to access climate information, indicating moderate engagement with digital services.

Drip-irrigated cereal farms (FT2) were managed by older farmers with an average family size of 4–5 members, cultivating plots averaging 5.4 ha. Production was strongly specialized in cereals (82%), complemented by a small proportion of other crops. These farms were drip-irrigated and applied approximately 4.3 supplemental irrigations per winter season, demonstrating significant investment in water-saving infrastructure. Input costs are relatively high (9048 MAD/ha), suggesting an intensive farming approach. These farms were in erosion-prone areas, suggesting sloping terrain or degraded soils, and reported drought as the dominant climate risk. Despite the older age of farmers, they frequently access climate services through mobile applications, reflecting some level of digital adoption and openness to technological innovation.

Small-scale subsistence farms (FT3) represented the smallest farms, with an average cultivated area of 3.7 ha, managed by the youngest household heads with family sizes of approximately 4 members. These systems used sprinkler irrigation and applied fewer supplemental irrigations than other types, indicating limited access to water or financial constraints. Cereal production was highly dominant (89%), emphasizing a subsistence-oriented strategy with minimal diversification. Despite their small scale, input costs remained relatively high (9095 MAD/ha), which points to potential inefficiencies or high per-hectare input prices. These households primarily obtain climate information from television, suggesting lower engagement with digital services. Soils were often saline, and drought remained the most reported climate risk.

Cereal-specialized farms (FT4) corresponded to large farms (7.9 ha) with the largest family sizes (around 7 members). Despite their large scale, these farms irrigated least frequently (2.5 times), possibly due to water scarcity, high irrigation costs, or both. Cereal crops dominated the production (91% of total output), representing the highest degree of specialization among all farm types. This orientation aligns with Morocco's national emphasis on cereal production for food security. The main soil constraint was salinity, compounded by exposure to heatwaves as the dominant climatic risk. Most farmers in this group relied primarily on radio as their primary source of climate information, reflecting a dependence on traditional information networks.

3.4. Readiness analysis

Fig. 4 presents the readiness results across farm types, quantifying the current readiness of smallholder farming systems to adopt CA practices. Among the four identified farm types, drip-irrigated cereal farms (FT2) show the highest overall readiness (49.8%), positioning these farmers as the most likely to adopt CA if the right interventions take place. In contrast, cereal-specialized farms (FT4) show the lowest total readiness (10.6%), while small-scale subsistence farms (FT3) (28.8%) and diversified farms (FT1) (32.4%) also record comparatively low levels, indicating that multiple constraints must be addressed before CA adoption becomes feasible in these systems (Appendix G).

Across all farm types, three variables consistently showed low scores (below 18%): education, CA knowledge, and use of digital tools. Education levels remain limited (2.6% in FT1; 15.9% in FT2; 1.3% in FT3; 0% in FT4) while reported CA knowledge is uniformly low, ranging from 0.3% to 1.9%. Use of digital tools varies between 0% and 18.7%, with

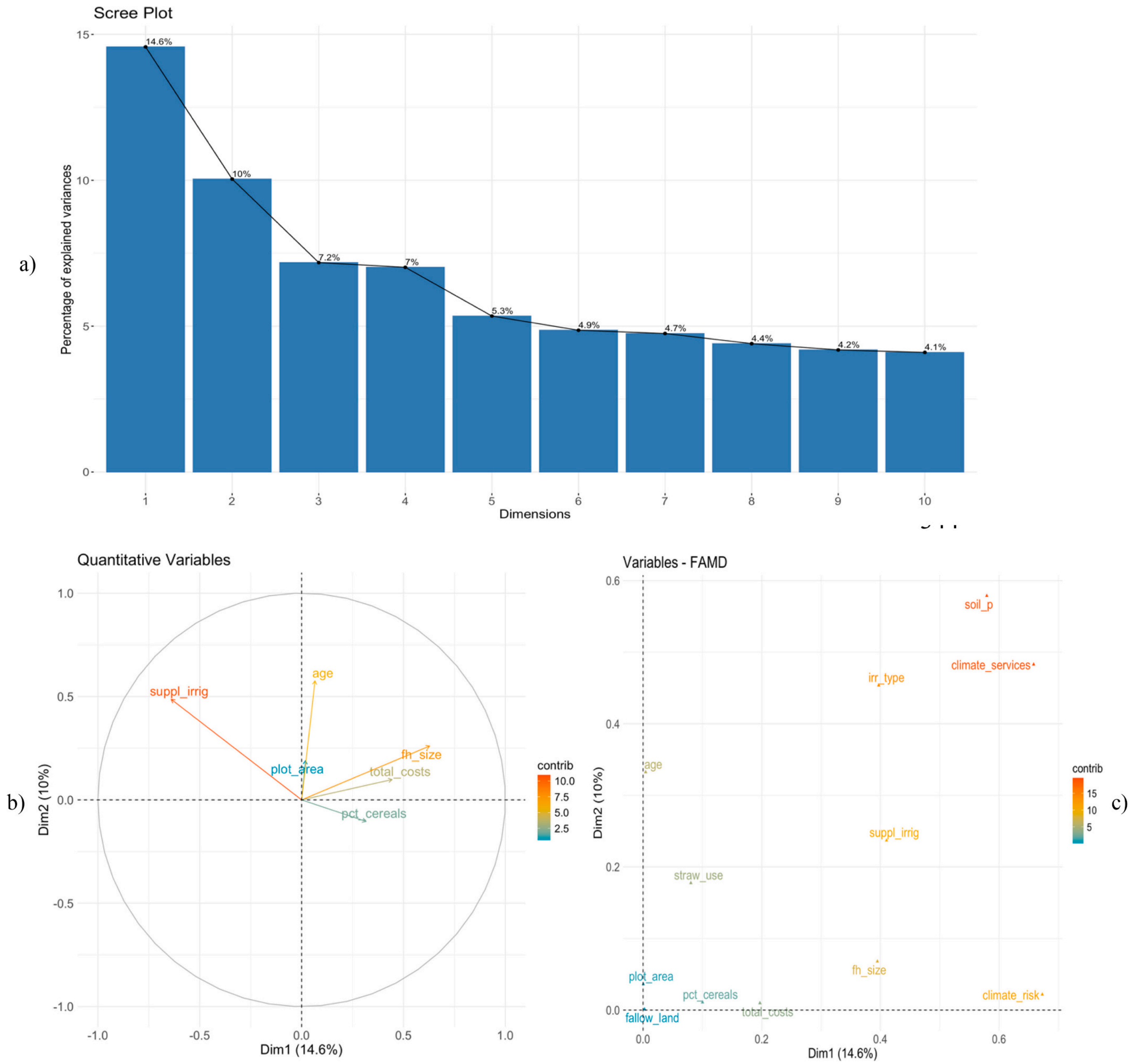

Fig. 2. (a) Scree plot displaying the percentage of total variance explained by each retained dimension; (b) Correlation circle of continuous variables showing their loading and contributions to the first two FAMD dimensions; (c) Projection of categorical and continuous variables on the first two FAMD dimensions.
Note: Dim1 and Dim2 represent the first two dimensions extracted from the FAMD. Variables positioned farther from the origin contribute more strongly to the corresponding dimension. Colors indicate the relative contributions of variables to the dimensions.

most farmers relying on traditional sources of information, such as television and radio.

Beyond these common deficiencies, farm-type-specific readiness levels reveal additional constraints unique to certain groups that contribute to their overall low readiness levels. Among all farm types, FT4 farms, which stand out with the lowest overall readiness, are mainly located in Rabat-Salé-Kenitra, with an additional presence in Oriental and Drâa-Tafilalet. Although this group has implemented some adaptation strategies that contribute to CA readiness and reflect a degree of adaptive capacity, all other readiness variables remain deficient. Legume incorporation is very low (7.5%), extension support is absent (2.0%), CSA awareness is 0.47%, and CA knowledge is 0.31%. Perceived climate vulnerability is also low within this group.

In contrast, FT2 farms demonstrate a stronger readiness profile, with high awareness of CSA (77.5%) and strong positive perceptions of CA's usefulness (76.6%), while reported CA knowledge remains low (1.9%). Legume cultivation reaches 39.0%, and perceived climate vulnerability is at 35.1%. This farm type is primarily located in Casablanca-Settat and Fès-Meknès.

FT1 and FT3 show relatively moderate readiness compared with FT4, yet remain substantially below FT2, indicating that both groups still face significant barriers to CA adoption.

FT1 dominates in Béni Mellal-Khenifra and consists of large, sprinkler-irrigated farms that lack access to extension support (6.0%), show limited CSA awareness (3.6%), scepticism toward CA's usefulness (4.2%), and report low CA knowledge (0.6%). Perceived climate vulnerability is high (92.3%), and legume integration is the highest among farm types (55.6%).

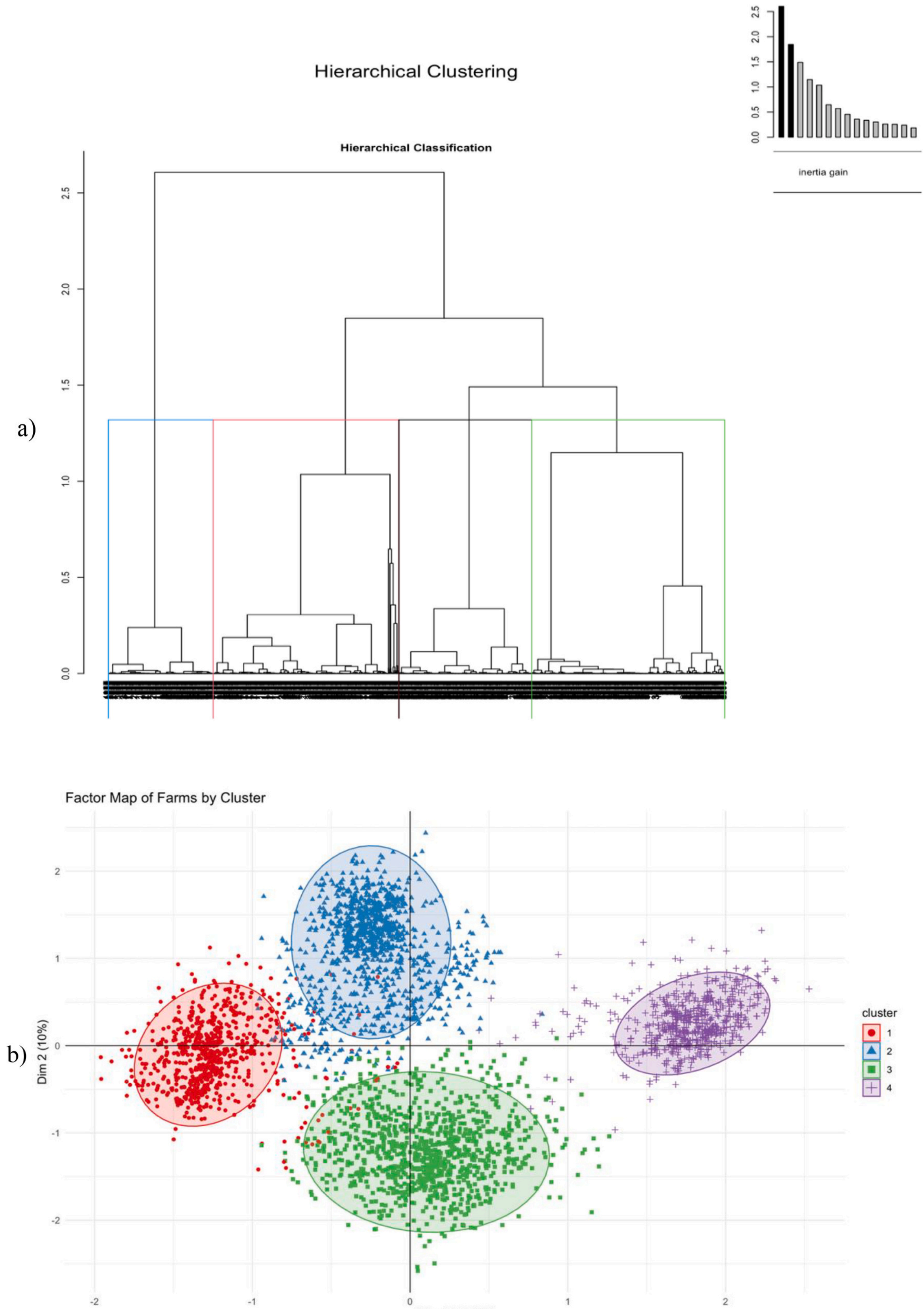

Fig. 3. a) Dendrogram illustrating the hierarchical structure of similarities among farms; (b) Factor map displaying the spatial distribution of the four identified farm types along the first two FAMD dimensions.

Note: The dendrogram shows the hierarchical clustering of farm households based on the retained FAMD dimensions. The factor map presents the distribution of farms across the first two FAMD axes (Dim1 and Dim2), with colors representing the four identified farm types.

Table 4
Average characteristics of the four farm types.

Farm types	Diversified farms (FT1)	Drip-irrigated cereal farms (FT2)	Small-scale subsistence farms (FT3)	Cereal-specialized farms (FT4)
Number of households per farm type	777	1091	1085	636
Variables				
Cultivated crop land area (ha)	8.16	5.65	3.74	7.96
Age	49.56	54.50	42.71	52.25
Supplemental irrigation (per winter season)	4.68	4.25	2.76	2.52
Fallow land	yes	yes	yes	yes
Family size	3.21	4.60	3.76	7.34
Straw use	selling	selling	selling	selling
Irrigation system	sprinkler	drip	sprinkler	drip
Cereals share of total production (%)	68.00	82.00	89.00	91.00
Total costs (MAD/ha/per year)	6860.90	9048.00	9094.76	9408.60
Soil problems	hardpan	erosion	salinity	salinity
Main source of information for climate services	tv	through apps	tv	radio
Climate risks	drought	drought	drought	heatwaves

Note: Values represent averages for each farm type. "Straw use" indicates the dominant residue management strategy reported by farmers.

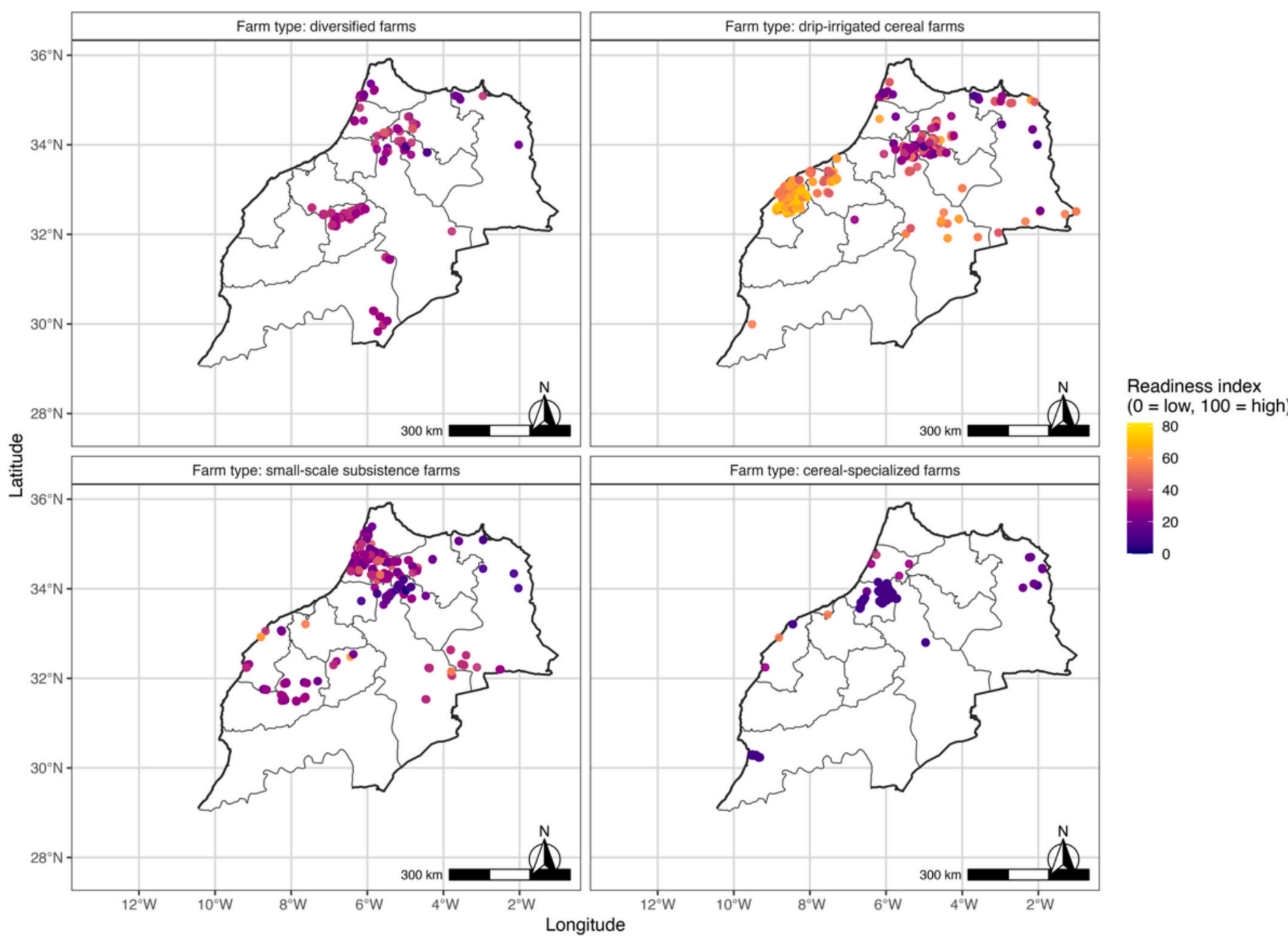

Fig. 4. Spatial distribution of CA readiness across farm types.

FT3 presents an intermediate readiness level, with a spatial distribution concentrated in Rabat-Salé-Kenitra, and additional presence in Marrakesh-Safi and Oriental. This farm type is characterized by limited extension support (23.5%), very low perceived climate vulnerability (2.2%), and legume cultivation (18.3%).

3.5. Comparison of farm-type readiness with soil and rainfall conditions

To assess whether differences in readiness are driven by biophysical limitations or by non-biophysical binding constraints, we conducted an analysis using average soil characteristics and rainfall associated with each farm type (Table 5). The readiness index, ranging from 10.6% to 49.8%, was analyzed in relation to soil texture, soil organic carbon, bulk

Table 5
Cross-tabulation of farm types by soil characteristics and rainfall conditions.

Farm type	Clay (%)	Sand (%)	Silt (%)	Bulk density (g cm^{-3})	SOC (g kg^{-1})	Rainfall (mm)	Readiness (%)
Diversified farms (FT1)	28.04	34.27	34.39	1.46	22.16	403.64	32.44
Drip-irrigated cereal farms (FT2)	27.21	34.40	34.62	1.44	30.35	357.48	49.80
Small-scale subsistence farms (FT3)	30.55	30.34	35.46	1.45	28.97	505.50	28.78
Cereal-specialized farms (FT4)	28.34	35.24	33.27	1.45	26.20	424.08	10.65

density, and average annual rainfall (Table 5).

All farm types operate within broadly semi-arid conditions and share loam-based textures; however, variations in SOC, sand proportion, and rainfall differentiate the farm types in their biophysical suitability (Appendix H). When these factors are considered jointly, no farm type scores highest on all biophysical characteristics simultaneously; however, FT3 and FT2 show relatively stronger conditions depending on whether moisture availability (FT3) or soil structure and SOC (FT2) are given priority. FT3 receives the highest rainfall (506 mm) and has relatively high SOC (28.97 g kg^{-1}). Its soil texture is heavier (30.5% clay; 35.5% silt) compared to the other farm types, and it records relatively high rainfall and SOC.

FT2, despite having the highest readiness score, operates in the driest environments, receiving only 357 mm of rainfall. Nonetheless, it has the highest SOC (30.4 g kg^{-1}), and the lowest bulk density (1.44 g cm^{-3}). FT1 has a balanced loam texture and moderate rainfall (404 mm), a slightly higher bulk density, and lower SOC (22.2 g kg^{-1}). Lastly, FT4 has the highest sand content (35.24%), and receives 424 mm of rainfall, higher than in FT1 and FT2, providing comparatively greater moisture availability. Yet its SOC (26.20 g kg^{-1}) is lower than that of FT2 and FT3, providing less organic matter for soil-building processes under CA.

3.6. Constraints to adopting conservation agriculture

The heatmap highlights that the main constraints to adopting CA across farm types, as reported by farmers, are a lack of machinery, finance, and knowledge, reflecting structural challenges in the country's agricultural sector (Fig. 5). Lack of machinery was the most commonly reported barrier to CA adoption, with an average share of 0.65 and a maximum of 0.99, where all farm types except FT4 reported a lack of machinery as the main constraint to adopting CA.

The finance constraint shows an average share of 0.23 and a maximum of 0.87, primarily affecting FT4 farms and, to a smaller degree, FT3 farms. Lack of knowledge is a moderate constraint, with an average share of 0.11 and a maximum of 0.31.

Profitability concerns are minimal, with an average share of 0.02 and a maximum of 0.07.

Pests and diseases and crop varieties, based on the farmers' responses across all farm types, are negligible constraints, with an average share of 0.0005 and 0.001, and a maximum of 0.0016 and 0.005, respectively.

4. Discussion

This study developed a dual-layer framework to identify farm types in Morocco and assess their readiness to adopt conservation agriculture practices. Morocco's goal of scaling CA to one million hectares by 2030 represents a significant step toward agricultural transformation, particularly given the country's climate variability and reliance on rainfed cereal production. However, both the national statistical data and farm-level evidence suggest that achieving this target is unlikely under current conditions. As of 2022–2023, only 85,000 ha were under direct seeding (AgriMaroc.ma, 2023), well below the interim target of converting 200,000 ha by 2025, which was intended to serve as a stepping stone toward the 2030 goal. While the increase is promising, maintaining such a high growth rate remains a major challenge.

This pattern mirrors broader evidence showing that conservation

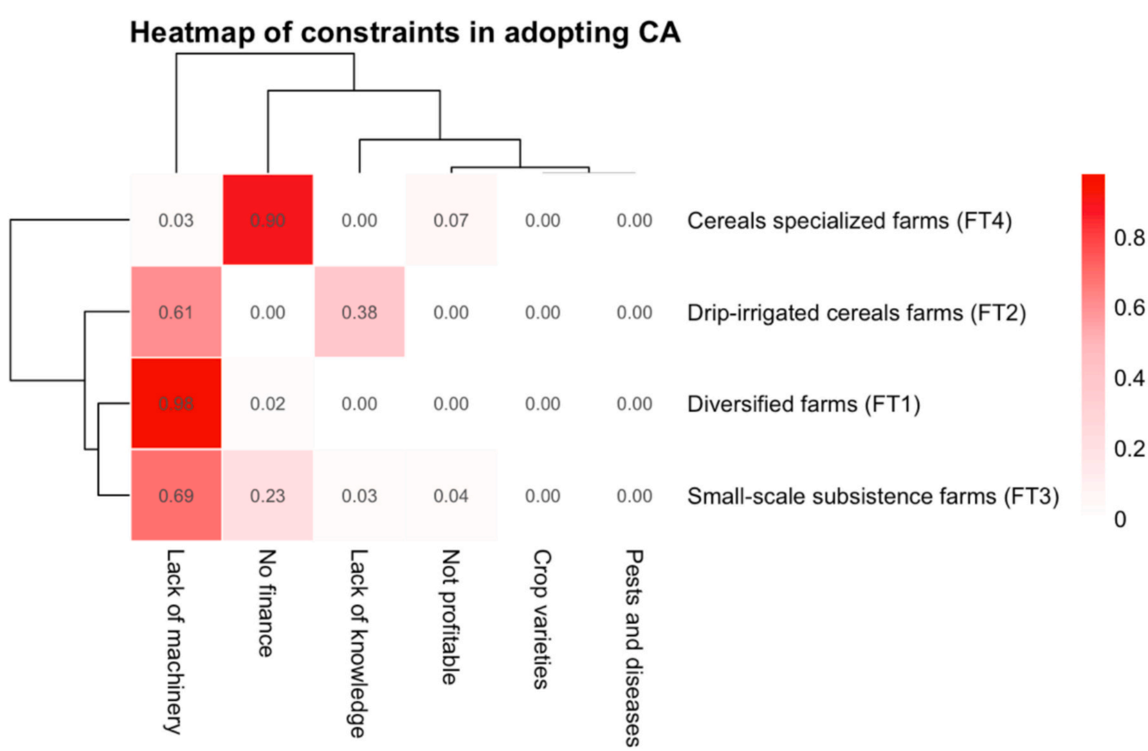

Fig. 5. Heatmap of constraints in adopting CA based on farmer perception per farm type.

agriculture has often scaled more slowly than expected across Africa and other regions despite more than two decades of promotion efforts, largely due to structural, institutional, and system-level constraints (Giller et al., 2021). The Moroccan case appears consistent with this wide scaling debate. Understanding why this growth remains limited requires looking beyond national figures to the realities at the farm level.

In this study, the typology is not presented as an output in itself but is used as the basis for a broader systems analysis, specifically to examine how structural, behavioral, and informational factors shape readiness for CA adoption. The typology captures relatively stable structural characteristics of farms, while the readiness variables reflect more dynamic behavioral and institutional dimensions. Together, they help identify farm-type-specific binding constraints that influence conservation agriculture adoption.

The typology identified four farm types: diversified farms (FT1), primarily concentrated in Béni Mellal-Khenifra; drip-irrigated cereal farms (FT2) mainly located in the fertile plains of Casablanca-Settat and Fès-Meknès; small-scale subsistence farms (FT3) largely distributed in Rabat-Salé-Kenitra with an additional presence in Marrakesh-Safi and Oriental; and cereal-specialized farms (FT4) concentrated in Rabat-Salé-Kenitra with some presence in Oriental and Drâa-Tafilalet.

Although, FT1 farms are large and well-diversified compared to other farm types, equipped with irrigation infrastructure and managed by experienced farmers, by conventional metrics, they should be ideal candidates for CA adoption. Yet, their limited awareness of CSA and the lack of extension support demonstrate that resource abundance alone does not guarantee readiness. The near absence of extension support in FT1 (6%), despite their large landholdings and irrigation infrastructure, may reflect a form of "resource-rich isolation," where these experienced farmers likely rely on private input providers or self-taught knowledge rather than interacting with public advisory services. By contrast, FT2 farms, which are smaller and more cereal-specialized, show a higher perceived usefulness of CA and greater awareness of CSA. Moreover, results indicate a mismatch between farmers' awareness and their procedural knowledge of CA practices in FT2. Although many farmers are aware of CSA, only 1.9% possess actual knowledge of CA techniques. This likely reflects a failure in extension services, where farmers know CA exists and may be beneficial but lack the practical understanding to implement it. This disconnection likely shows an extension system that prioritizes broad reach over depth (FAO, 2023), delivering general messages about CA's benefits without providing farm-specific training. As a result, farmers have received the message but not the tools or training to act on it. In this case, if awareness is high but knowledge remains negligible, the progression is broken (Rogers, 2003).

It is important to note, however, that the low levels of formal education observed do not necessarily imply limited farming knowledge. Many farmers are middle-aged and have long-term farming experience. This suggests that knowledge gaps should not necessarily be interpreted as a lack of capability but rather suggests that effective interventions may rely more on peer-to-peer learning and farmer-to-farmer knowledge exchange rather than formal academic training.

Another variable contributing to the low readiness is farmers' perceived vulnerability to climate change. The assumption of analyzing this variable to capture the CA readiness was that farmers, facing threats to their activities, would seek CA practices as an adaptive solution. If they perceive no threat, they have no motivation to adapt. However, results show the opposite: farmers most exposed to climate stress, particularly in FT3 and FT4, perceive themselves as the least vulnerable. FT3 farms operating in saline soils with limited irrigation capacity, and FT4 farms facing recurrent heatwaves, both show an absence of perceived vulnerability. First, this may be because chronic exposure to stressors leads farmers to perceive these conditions as part of routine farming, normalizing the risk rather than recognizing it as a crisis requiring adoption (Ricart et al., 2024). Second, this may reflect an information deficit, as both groups rely primarily on one-way communication sources such as television and radio, which provide general warnings rather than localized risk assessments. While perceived vulnerability can increase motivation to adopt adaptive practices, it does not necessarily translate into readiness or adoption intent; farmers might instead reduce investment, delay decisions, or even consider exiting agriculture (Tingey-Holyoak et al., 2024; Yaseen et al., 2025). Therefore, treating perceived vulnerability as a readiness indicator should be interpreted as capturing potential motivation rather than a direct predictor of CA adoption, which is a conceptual limitation of the index.

The main aim of this comparison between farm-type readiness and biophysical conditions was to assess whether differences in readiness are associated with underlying biophysical constraints. The results show that higher CA readiness does not necessarily match with the most favorable environmental conditions. Although all farm types operate under broadly similar semi-arid and loamy conditions, each presents a slightly different combination of supportive and limiting soil and rainfall characteristics. FT3 benefits from higher rainfall and relatively high SOC, yet its readiness remains low, indicating that behavioral factors, not biophysical ones, are the primary bottlenecks. If its informational, perceptual, and institutional binding constraints were addressed, this group could substantially increase its adoption potential. FT2, conversely, operates in the driest environments, but it is the group with the highest readiness, suggesting that favorable perceptions, stronger exposure to CSA concepts, and better access to information may play a role in shaping adoption potential. FT1 cultivates in areas where biophysical factors are unlikely to constitute binding constraints to CA performance. Their low readiness, therefore, reflects social and informational limitations rather than binding biophysical constraints. Meanwhile, FT4, the group with the lowest readiness, operates in areas with higher sand content, which is generally more favorable for CA because it drains well, but the low SOC level may slow soil-building benefits under CA.

More broadly, the spatial distribution of readiness across farm types indicates that several regions expected to contribute to Morocco's national target of one million hectares under conservation agriculture currently show relatively low readiness levels. This suggests that achieving the national target may require substantial institutional support, extension efforts, and targeted interventions across multiple farming systems.

Moreover, analyzing the constraints that farmers face in adopting CA practices revealed that structural issues such as a lack of mechanization, poor access to credit, and limited extension support are widespread among farmers, supporting findings from earlier studies (Mrabet et al., 2012). While the readiness index provides a useful summary of behavioral and informational conditions for CA adoption, it assumes equal importance across indicators. In practice, however, certain structural constraints, such as access to specialized machinery, may exert a stronger influence on adoption outcomes than attitudinal variables such as awareness or perceptions.

The extremely high proportion of farmers reporting lack of machinery (up to 98% in FT1) indicates that even farmers who show relatively high readiness for CA adoption may remain effectively excluded from implementation if specialized equipment such as no-till seeders is not accessible. At the national level, Morocco's mechanization rate is low, with only 15% of farmers using modern equipment, and CA-specific tools like no-till planters are scarce and expensive, particularly for smallholders. Most farmers rely on traditional tools or rented machinery, which are often unsuitable for CA practices like direct seeding (a form of no-tillage) or the retention of crop residues in the field (Mrabet et al., 2012).

These constraints are particularly critical in the early stages of the CA transition, which often involves yield penalties and increased management complexity. Interestingly, profitability concerns were relatively minor, suggesting that farmers recognize the long-term economic potential of CA but lack the knowledge to implement it.

Another structural constraint relates to crop residue management. Across all farm types, farmers report selling straw rather than retaining it in the field (Table 4). In cereal-based systems, straw represents an important economic resource, often used as livestock feed or sold in local markets. This creates a direct trade-off with the second principle of conservation agriculture, which requires permanent soil cover through crop residues. Similar crop-livestock competition for residues has been widely documented as a major constraint to CA adoption in Mediterranean and dryland farming systems (El-Shater and Yigezu, 2021). As a result, interventions aimed at scaling CA in Morocco may need to consider alternative forage sources or strategies that reduce farmers' reliance on crop residues for livestock feeding. This finding also reflects the pattern of partial CA adoption observed in Morocco, where farmers may be more aligned with certain pillars, such as reduced tillage, while structural factors, such as competing uses of crop residues limit the implementation of others. In this sense, readiness for one component of CA does not necessarily translate into readiness for all three principles simultaneously, highlighting the multidimensional nature of readiness.

An unexpected result was that farmers consider pests and diseases to be negligible constraints. While farmers ranked them as negligible, scientific evidence and practical considerations suggest that pests and diseases can pose real challenges to CA adoption (Jasrotia et al., 2023). According to FAO (2019), pests are responsible for the loss of between 20% and 40% of global crop production each year, while plant diseases cost the global economy around $220 billion annually. One explanation may be that farmers prioritize more immediate structural barriers, such as limited mechanization and financial constraints, over biological ones. Another explanation is related to the very limited scale of CA implementation in Morocco. Most farmers have not progressed far enough into the transition phase to experience ecological adjustments commonly reported under sustained no-till systems. Evidence from long-term CA studies shows that shifts in weed pressure, pest dynamics, and disease prevalence often emerge after 3–5 years of continuous residue retention and reduced soil disturbance (Hossain et al., 2021; Nichols et al., 2015). Therefore, the current low perception of biological constraints may reflect limited experiential exposure rather than the absence of potential challenges under long-term CA adoption.

Overall, strengthening agricultural education, participatory training, and digital literacy is essential to improve farmers' readiness for CA adoption. However, real progress depends on replacing the current one-size-fits-all model with a segmented, typology-based approach that tailors messages, practices, and support to different farmer groups. While the simplicity of uniform programs is understandable given limited resources, it remains ineffective in a heterogeneous farming landscape. Differentiated interventions, for example, targeted training for FT2 farmers to strengthen their practical understanding of CA, participatory demonstrations for FT1, and improved climate communication for FT3 and FT4, offer a more realistic pathway. Only through such typology-informed strategies can Morocco advance from isolated CA successes to a broader transformation of its smallholder systems.

5. Conclusion

This study provides insights into the heterogeneity of Moroccan farming systems and their readiness to adopt CA practices by integrating multivariate statistical analysis with a readiness assessment across nine diverse regions.

Our findings reveal four distinct farm types: diversified farms (FT1), drip-irrigated cereal farms (FT2), small-scale subsistence farms (FT3), and cereal-specialized farms (FT4), with significant variations in the identified variables for CA adoption. Drip-irrigated cereal farms (FT2) show the greatest potential and the highest readiness (49.8%) due to their alignment with government-supported cereal production. In contrast, cereal-specialized farms (FT4) face the lowest readiness (10.6%), driven by limited awareness of CA's benefits. The comparison between farm-type readiness and biophysical suitability indicates that overall differences across farm types remain modest, as all operate within similar semi-arid climates and loam-based soil textures. Within these small variations, FT3 benefits from higher rainfall and relatively high SOC, FT2 combines high SOC with the lowest bulk density, FT1 has balanced soils but the lowest SOC levels, and FT4 offers better drainage due to higher sand content.

Common barriers across all farm types include a lack of machinery, limited access to finance, and inadequate knowledge of CA practices, reinforcing structural and informational challenges in Morocco's agricultural sector.

Although Morocco's Green Generation 2020–2030 strategy is ambitious, the current situation suggests that the 2030 target is unlikely to be met without more urgent efforts.

From a policy and institutional perspective, the findings suggest that conservation agriculture promotion strategies should be more carefully targeted across farm types. Farm types such as drip-irrigated cereal farms (FT2), which already show relatively higher readiness, represent promising entry points for scaling CA through targeted training and access to appropriate machinery. At the same time, broader adoption will require addressing structural constraints affecting all farm types, particularly improving access to no-till equipment, strengthening extension systems to provide practical CA training, and promoting alternative forage options to reduce competition for crop residues. Such targeted and coordinated interventions will be essential for translating Morocco's national CA ambitions into effective farm-level adoption.

Future research should integrate variables such as livestock, land tenure, gender dynamics, and climate variability to better understand the multifactorial drivers of CA adoption.

Availability of data and materials

The datasets generated and analyzed during the current study are not publicly available as they were obtained from CGIAR initiative on Climate Resilience (ClimBer), and we cannot share without their permission but are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Emirjona Kertolli: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Adam Komarek:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis. **Paolo Prosperi:** Writing – review & editing, Validation, Supervision, Formal analysis. **Seyed-Ali Hosseini-Yekani:** Writing – review & editing, Methodology. **Xiaoli Fan:** Writing – review & editing, Validation, Methodology. **Ajit Govind:** Writing – review & editing, Validation, Resources. **Rachid Harbouze:** Writing – review & editing, Visualization. **Hatem Belhouchette:** Writing – review & editing, Validation, Supervision, Funding acquisition, Formal analysis, Conceptualization.

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Declaration of competing interest

Co-author Adam Komarek currently serves as an editor of the journal. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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Appendix A. Crop types

Table A1
Classification of crop types.

Type of crops	Winter Season	Summer season
Cereals	Wheat, barley, rye	Corn, sorghum
Grain legume	Chickpea, fababean, lentil	Green beans, chickpea, peanut, small pea
Forage legumes		Alfalfa
Oilseeds		Rapeseed
Fruit		Melon, watermelon
Vegetable		Cucumber, pepper, potatoes, onion, tomato, zucchini
Cotton		Cotton

Appendix B. Correlation matrix

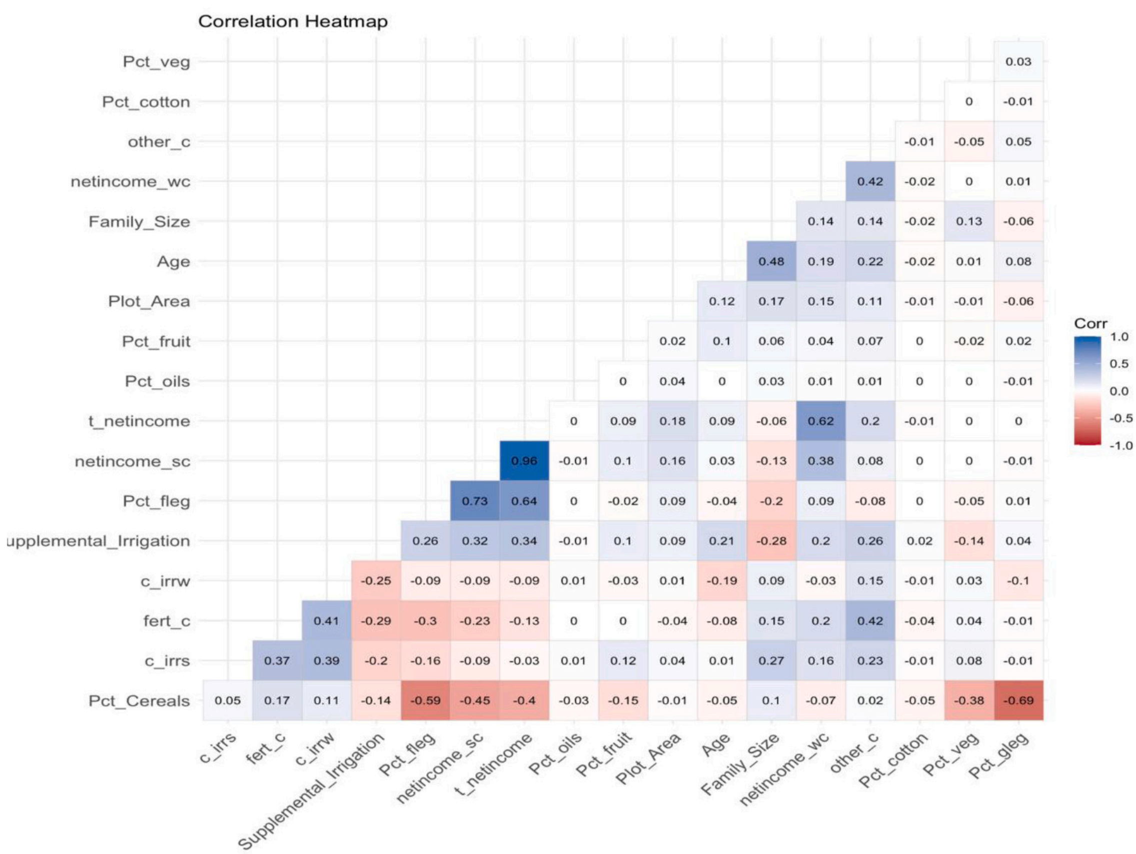

Fig. B1. Correlation matrix - before removing or merging variables with correlations greater than 0.5.
Note: The intensity of the color indicates the strength of the correlation, with darker color representing stronger correlations. Red represents a negative correlation, blue represents a positive correlation, and white indicates no correlation. The following codes correspond to the variables in the correlation matrix: Pct_veg = % of vegetable production; other_c = other costs; netincome_wc = net income from winter crops; Pct_oil = % of oilseed production; t_netincome = total net income; netincome_sc = net income from summer crops; Pct_fleg = % of forage legume production; c_irrw = cost of winter irrigation; cirrs = cost of summer irrigation; fert_c = cost of fertilizers.

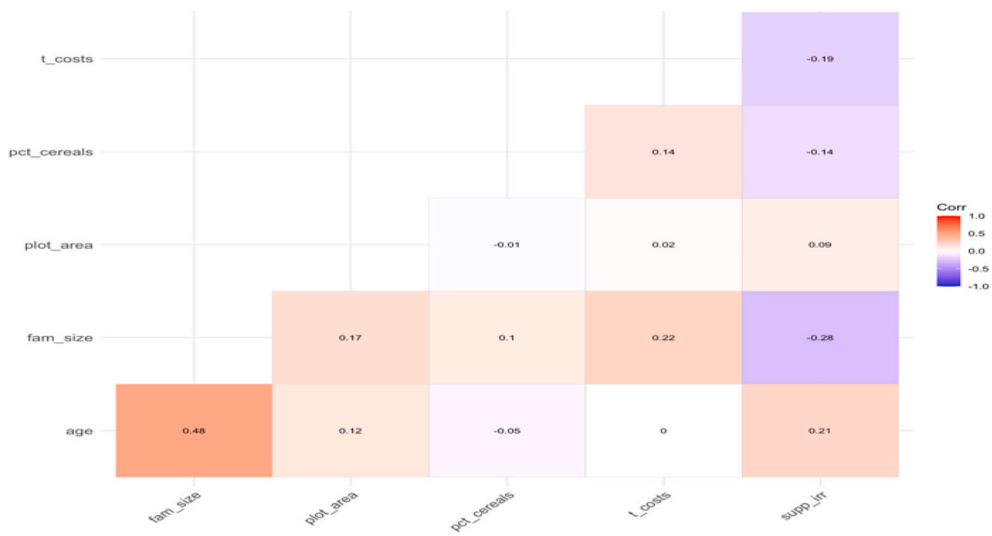

Fig. B2. Correlation matrix-after removing or merging variables with correlations greater than 0.5, and excluding variables considered non-relevant.

Appendix C. Factor maps showing candidate clusters (k = 2–10) for farm types

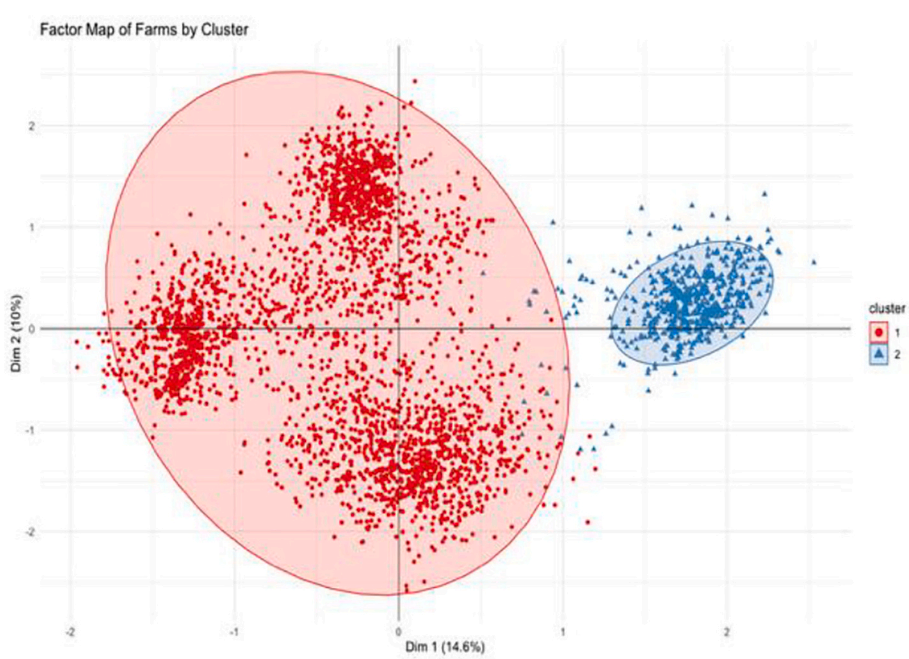

Fig. C1. Cluster validation: k = 2.

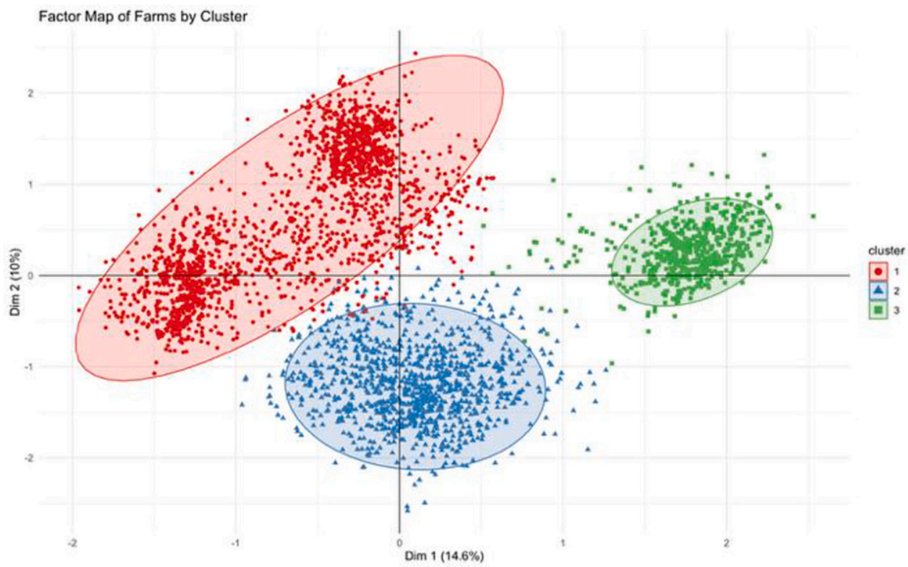

Fig. C2. Cluster validation: k = 3.

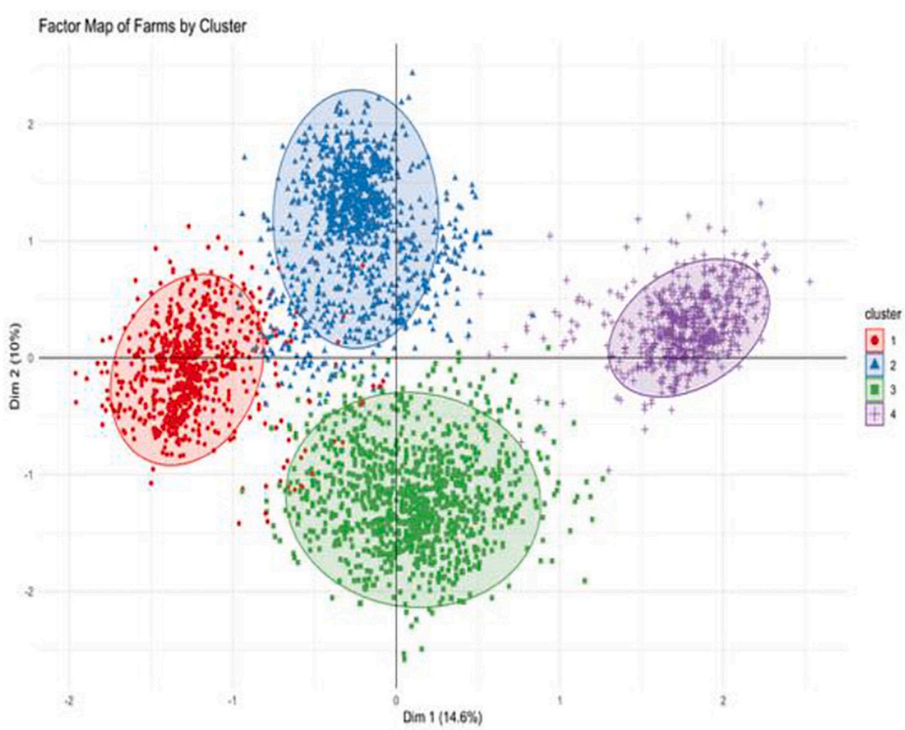

Fig. C3. Cluster validation: k = 4.

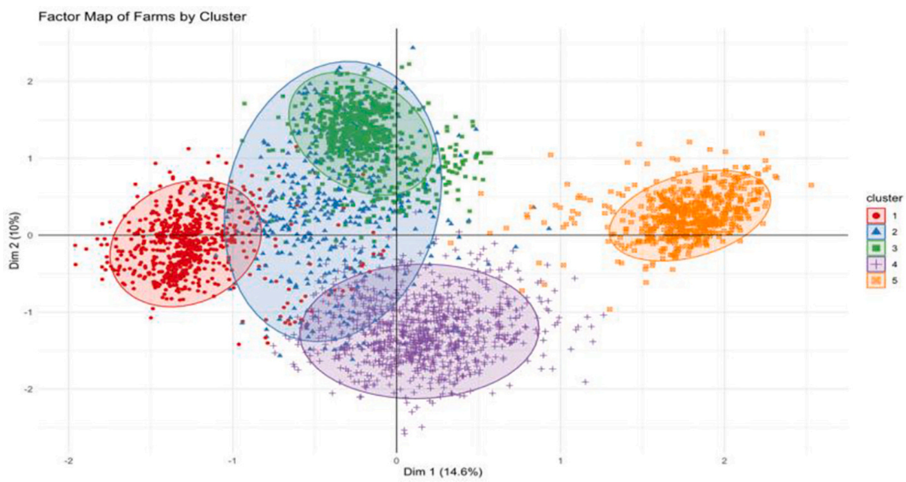

Fig. C4. Cluster validation: k = 5.

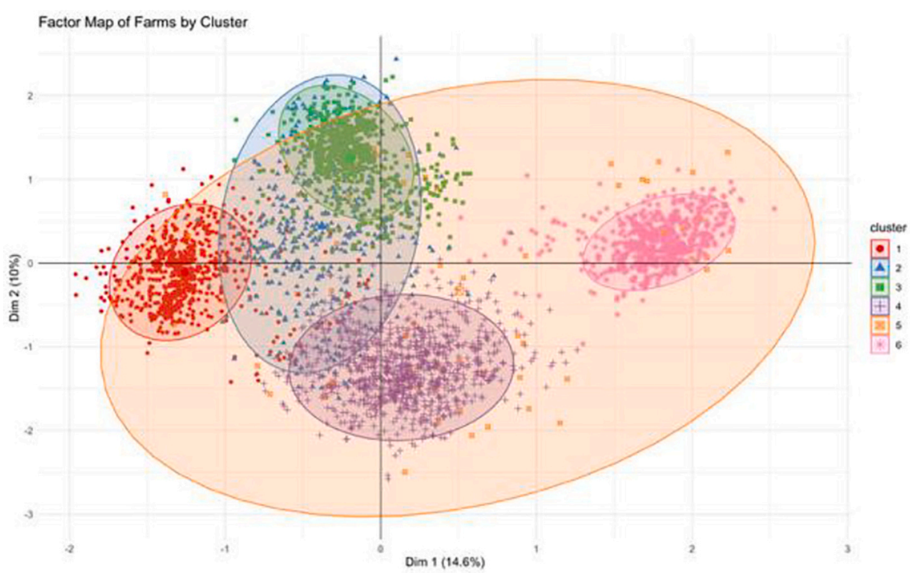

Fig. C5. Cluster validation: k = 6.

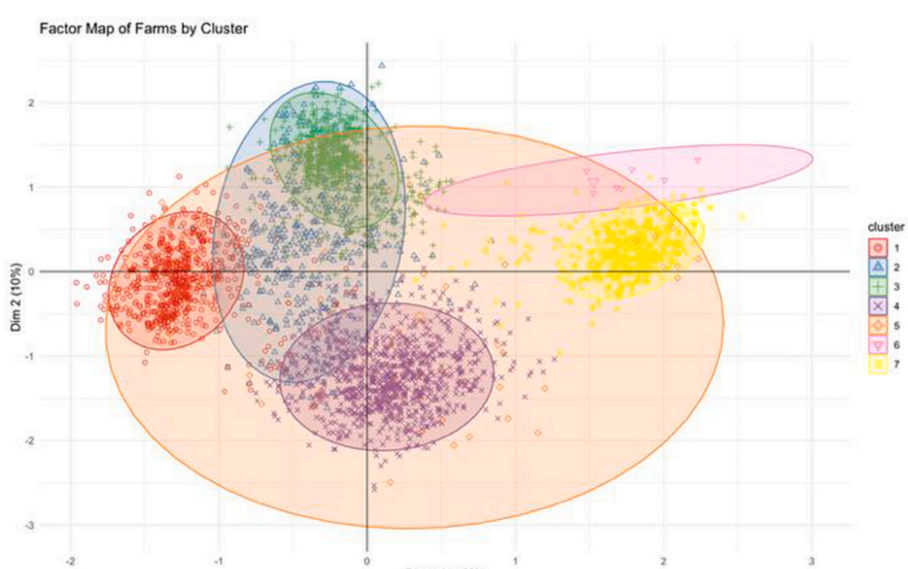

Fig. C6. Cluster validation: k = 7.

Fig. C7. Cluster validation: k = 8.

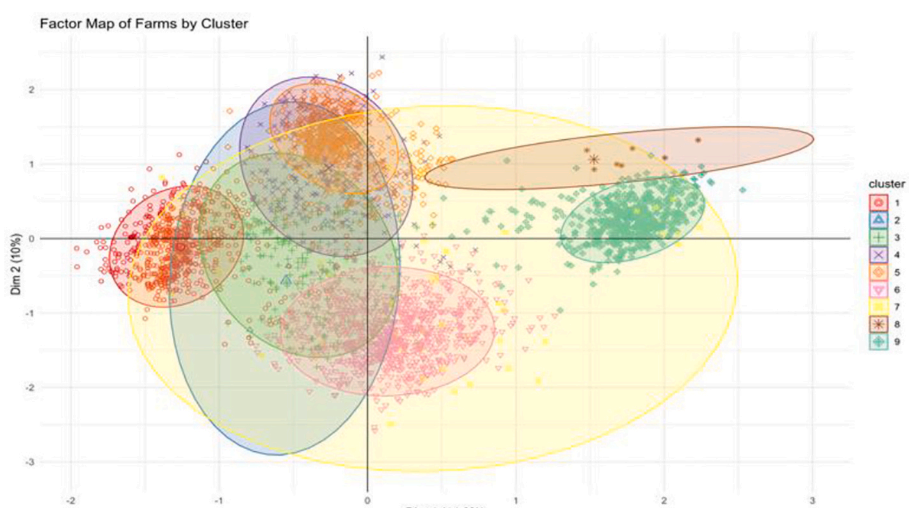

Fig. C8. Cluster validation: k = 9.

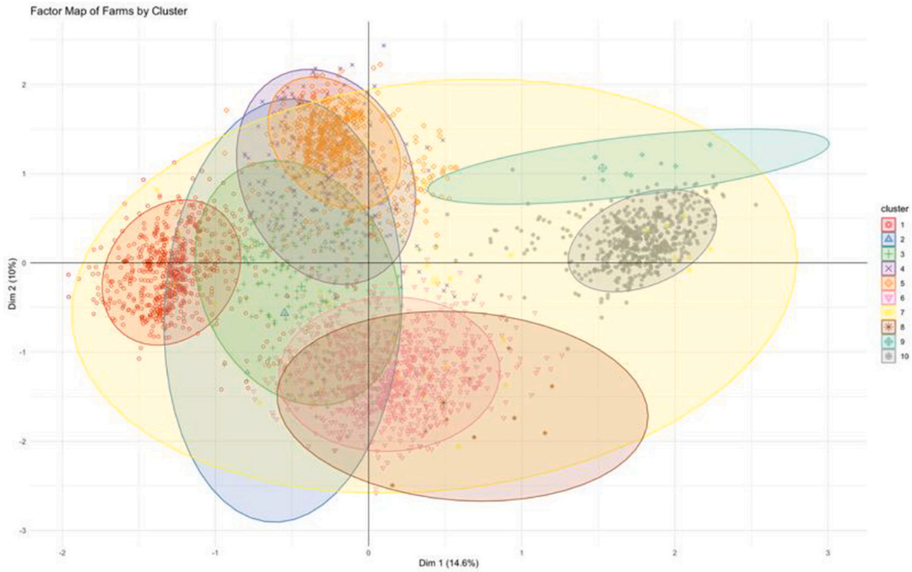

Fig. C9. Cluster validation: k = 10.

Appendix D. Silhouette method

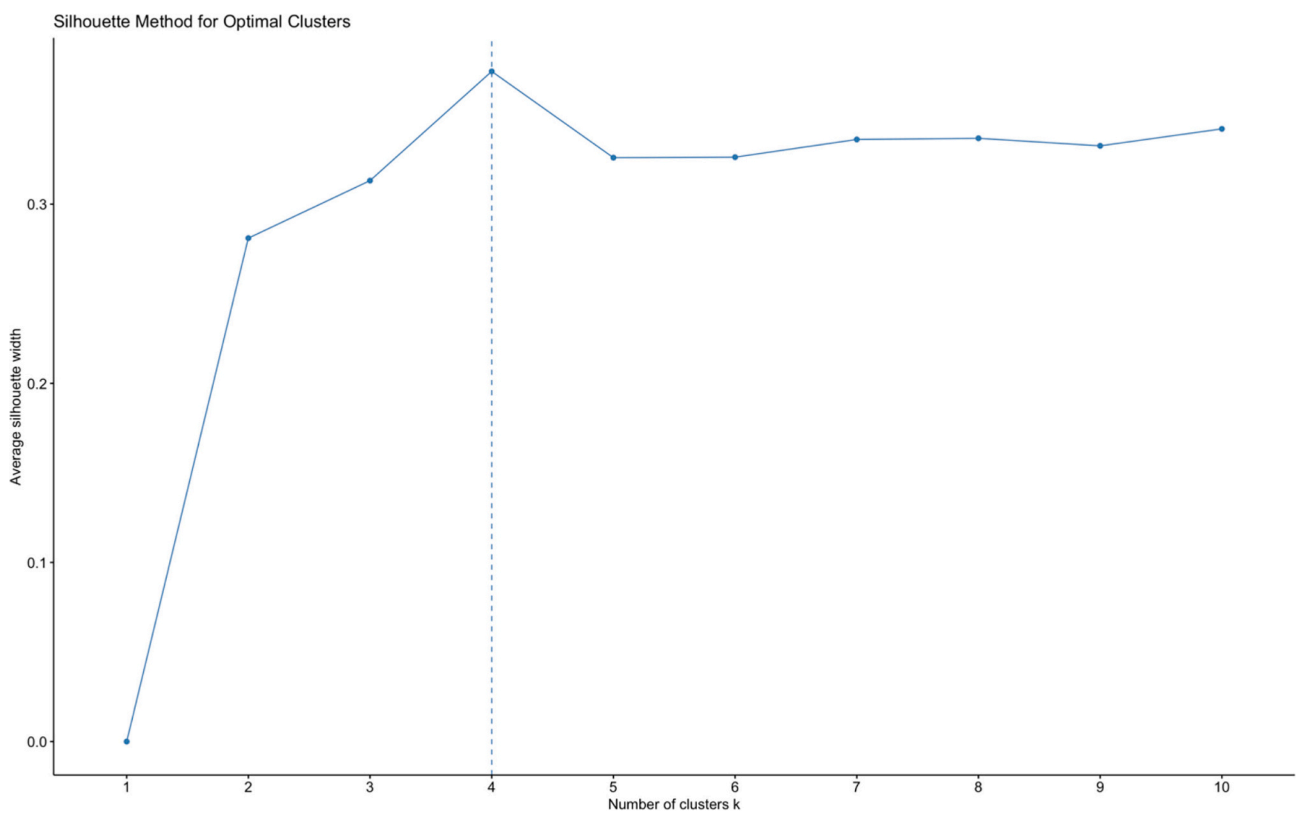

Fig. D1. Silhouette method.

Appendix E. Contributions of variables to dimensions

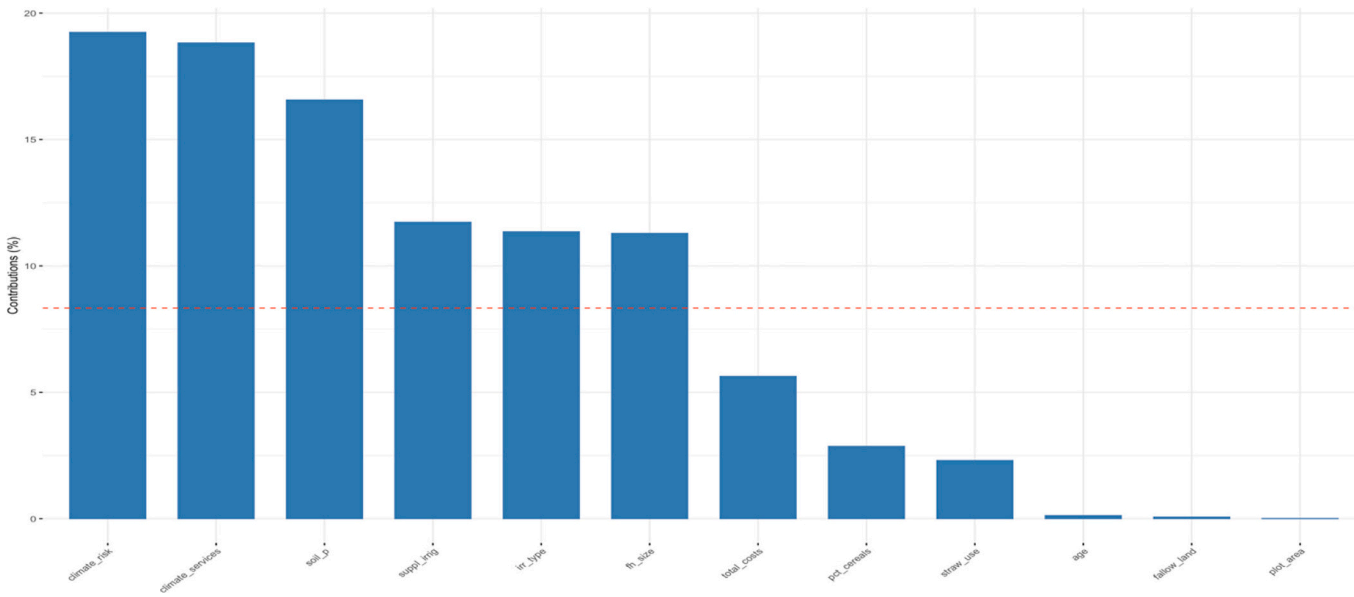

Fig. E1. Contributions of variables to Dim.

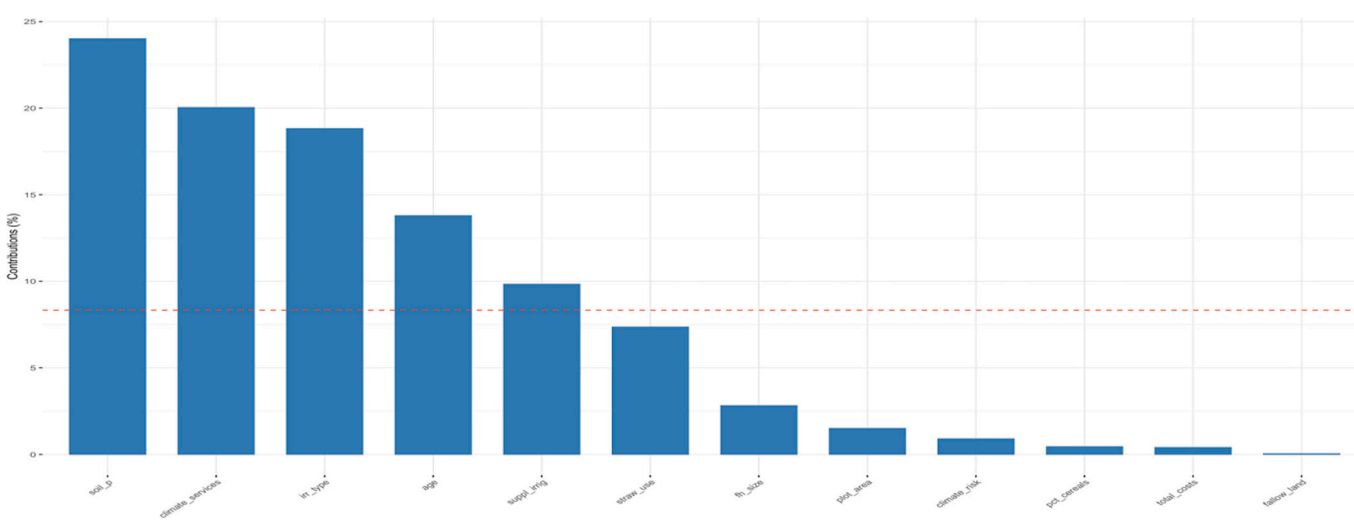

Fig. E2. Contributions of variables to Dim 2.

Table. E1
Contribution of variables to each dimension in FAMD.

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5	Dim.6	Dim.7	Dim.8	Dim.9	Dim.10
soil_p	16.57	24.01	15.52	25.56	13.65	20.12	16.09	59.61	35.12	26.45
climate services	18.82	20.04	12.17	25.55	27.41	13.42	8.79	2.97	21.80	56.54
irr_type	11.35	18.82	5.61	5.14	17.13	6.57	2.46	2.18	2.53	0.91
age	0.12	13.79	12.20	2.09	0.01	8.69	1.18	1.46	0.09	4.78
suppl_irrig	11.73	9.84	1.46	0.31	0.89	1.15	1.59	1.27	0.03	0.19
straw_use	2.30	7.37	34.61	5.97	5.17	1.77	3.30	6.45	1.73	0.19
fh_size	11.29	2.82	15.71	2.68	0.22	1.20	0.29	0.00	0.29	0.70
plot_area	0.01	1.51	1.33	7.11	8.34	4.52	2.76	0.99	16.85	2.60
climate_risk	19.24	0.90	0.26	10.25	9.38	19.83	27.10	20.13	15.24	7.10
pct_cereals	2.86	0.45	0.36	2.09	5.36	5.20	2.56	2.33	5.37	0.18
total_costs	5.63	0.40	0.48	13.19	12.09	2.42	0.01	2.27	0.88	0.35
fallow_land	0.07	0.05	0.30	0.05	0.35	15.12	33.87	0.34	0.07	0.01

Note: Contributions above 10% are highlighted in green.

Appendix F. Eigenvalues, variance, and cumulative variance of each dimension in FAMD

Table F1
Eigenvalues, variance, and cumulative variance of each dimension in FAMD.

	Eigenvalue	Variance (%)	Cumulative variance (%)
Dim.1	3.50	14.57	14.57
Dim.2	2.41	10.04	24.61
Dim.3	1.72	7.18	31.79
Dim.4	1.68	7.02	38.81
Dim.5	1.28	5.35	44.16
Dim.6	1.17	4.86	49.02
Dim.7	1.14	4.75	53.77
Dim.8	1.06	4.40	58.16
Dim.9	1.00	4.18	62.35
Dim.10	0.98	4.10	66.45

Appendix G. Readiness level

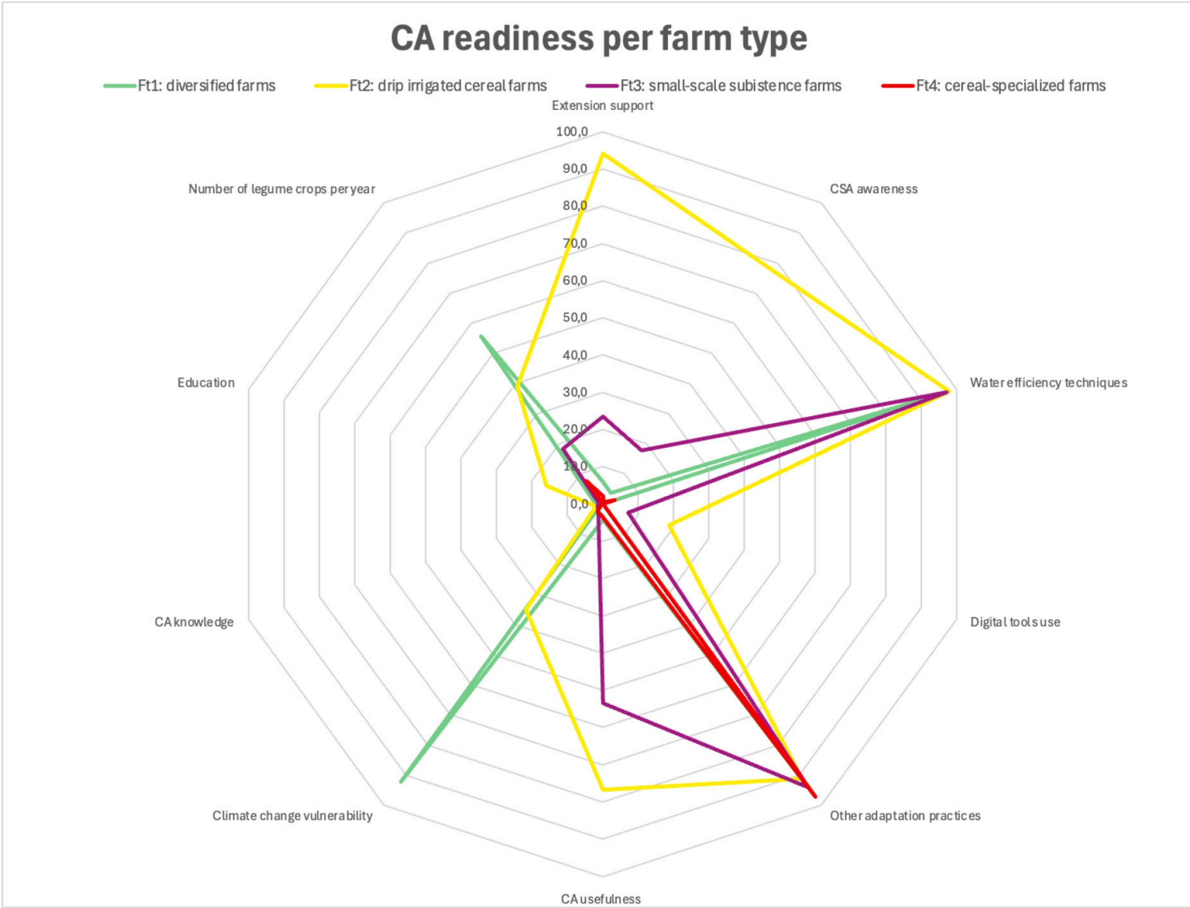

Fig. G1. Readiness level per farm type.

Appendix H. Soil characteristics influencing suitability for CA

To contextualize the comparison between farm-type readiness and biophysical conditions, we synthesized evidence from soil science and CA literature to describe indicative ranges of soil and rainfall characteristics associated with favorable CA performance. Because no standardized threshold values for CA suitability exist, these descriptions were not treated as strict classification boundaries but rather as interpretive guides that helped us assess how well each farm type aligned with conditions where CA tends to perform effectively. The literature consistently notes that medium-textured soils (not extremely sandy or hardsetting), adequate moisture availability, moderate bulk density, and sufficient soil organic carbon (SOC) favor positive CA outcomes.

For example, evidence from soil physics and CA research suggests that medium proportions of clay and silt support good aggregation, water-holding capacity, and reduced compaction risk under minimal tillage (Dexter, 2004). In contrast, hardsetting or structurally unstable soils are considered less suitable because minimum tillage can intensify surface sealing and limit root penetration-challenges (FAO, 2005).

In broad agronomic terms, maintaining bulk density below 1.5 g cm^{-3} is desirable to allow adequate movement of air and water through the soil (Hunt and Gilkes, 1992). Higher bulk density tends to restrict root growth, reducing the potential benefits of CA (Tracy et al., 2013; Shah et al., 2017; Menary and Kruger, 1966). Panagos et al. (2024) present evidence from European croplands that adopting conservation tillage practices can help lower bulk density and improve soil structure, which is fundamental for the effective functioning of CA systems.

Soil organic carbon was included due to its central role in moisture retention, nutrient cycling, and aggregate stability. While precise thresholds do not exist, Musinguzi et al. (2013) indicate that SOC above ~20 g kg^{-1} supports key soil functions, suggesting such soils may respond more positively to CA because residue retention and reduced disturbance help maintain or increase SOC stocks.

For rainfall, suitability was based on the findings of Rusinamhodzi et al. (2011), who showed that maize yields under CA were generally higher than under conventional tillage when annual precipitation was below 600 mm. This aligns with broader evidence showing that CA tends to offer stronger yield benefits in semi-arid and drier environments, on well-drained soils, and when multiple CA principles are applied together (Rusinamhodzi et al., 2011; Pittelkow et al., 2015; Thierfelder and Wall, 2010).

Appendix I. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2026.104797.

Data availability

Data will be made available on request.

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