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Efficiency of agricultural systems in Morocco: A meta-frontier analysis of resource use and water management

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ABSTRACT

Context: To improve agricultural productivity and water sustainability in water-scarce regions, it is essential to understand the efficiency and diversity of farming practices

Objective: This study aims to assess the diversity and efficiency of farming systems in Morocco's Chtouka-Massa plain. It focuses on resource management, agricultural intensification, and water use, identifying inefficiencies and proposing sustainable solutions.

Methods: Using Principal Component Analysis and Hierarchical Clustering, we classify 40 farm households into three distinct typologies: (i) extensive cereal-arboriculture systems, (ii) semi-intensive mixed cereal-vegetable systems, and (iii) intensive vegetable farming systems. A meta-frontier approach combined with Data Envelopment Analysis (DEA) is then applied to assess disparities in resource efficiency, technological performance, and environmental sustainability among these typologies.

Results and conclusions: Our results show that extensive cereal-arboriculture systems exhibit the highest resource efficiency—particularly in water, nitrogen, and labor—but achieve the lowest gross margins due to limited agricultural intensification. Semi-intensive mixed systems demonstrate moderate efficiency but consume the largest amounts of water, largely sourced from subsidized private wells. Intensive vegetable farming systems, while generating the highest gross margins, are the least efficient due to high input costs, reliance on desalinated water, and labor-intensive practices. Targeted policy interventions are needed to optimize resource use and promote sustainable practices adapted to each farming typology.

Significance: This study provides actionable insights for policymakers aiming to enhance the sustainability of agricultural systems and groundwater resources in arid and semi-arid regions. The findings support the need for targeted policies to enhance groundwater management.

1. Introduction

Groundwater resources are essential for agricultural irrigation in arid and semi-arid regions (Vecchio and Kuper, 2022). However, the increasing reliance on groundwater for agriculture has significantly contributed to aquifer depletion, jeopardizing the sustainability of agricultural systems and the groundwater resources (Scanlon et al., 2012). Morocco is a typical example of this phenomenon. Indeed, Moroccan agricultural intensification policies and the expansion of irrigated perimeters have exacerbated this issue (Molle and Tanouti, 2017; Vecchio and Kuper, 2022). Actually, a significant shift occurred in the 1980s when persistent droughts pushed agriculture, previously dominated by rain-fed systems, toward irrigated farming (Stour and Agoumi, 2008). This transition was facilitated by farmers gaining access to groundwater resources through private boreholes, as traditional wells were increasingly converted into deeper boreholes (Vecchio and Kuper, 2022). Consequently, more and more aquifers are showing alarming signs of overexploitation. Since the 1990s, groundwater pumping has intensified, causing water table drawdowns of 5–65 m between 1990 and 2019 across various Moroccan regions (Bahir et al., 2021;

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Hssaisoune et al., 2020; Ouassanouan et al., 2022). This persistent imbalance between groundwater extraction and recharge has further led to cumulative declines of 20–65 m over the last three decades (Hssaisoune et al., 2020). In addition, significant groundwater deficits were already reported in 2007, amounting to −58 Mm^3 in the Chtouka aquifer and −283 Mm^3 in the Souss aquifer (Bouchaou et al., 2017). Recognizing the importance of the agricultural sector, Morocco has implemented several targeted strategies. One of the most notable initiatives is the Green Morocco Plan (GMP), an agricultural strategy launched in 2008 and implemented until 2020. Developed by the Ministry of Agriculture and Maritime Fisheries under the supervision of the Moroccan government, the GMP aimed to boost agricultural productivity and attract investment (ADA, 2025). The GMP encouraged and facilitated access to water and land by providing financial support for irrigation systems, such as drip irrigation, and crop cultivation (Kuper et al., 2012). In practice, this policy promoted the intensification and conversion of cereal lands into arboriculture and market gardening (Saidi et al., 2023), more profitable and export-oriented crops, but also significantly more water-intensive. This plan reports a negative aquifer balance for 15–20 out of Morocco's 40–50 major aquifers (Molle and Tanouti., 2017).

These challenges underline the urgent need to analyze existing agricultural systems and assess their overall efficiency, encompassing technological, economic, and environmental dimension, in order to propose adaptation strategies for water scarcity and climate change (Scanlon et al., 2012). Ensuring the long-term sustainability of agricultural practices and food security requires solutions that are not only effective but also adapted to the specific characteristics and constraints of each farming system (El Ansari et al., 2020; Reidsma et al., 2018).

To design context-specific adaptation strategies, it is essential to first understand the diversity of farming systems and their varying levels of resource efficiency. In Morocco, the combined effects of agricultural policies promoting intensification (Molle and Tanouti., 2017) and recurrent droughts linked to climate change have created a highly heterogeneous farming landscape. Some farms have successfully adopted profitable but water-intensive systems, while others struggle to maintain productivity under resource scarcity (Stour and Agoumi., 2008). In this context, identifying farm typologies is a necessary step to capture this diversity and to understand how different categories of farms respond to policy incentives and climatic pressures. Linking these typologies with an efficiency analysis allows us to determine not only which farm types make better use of scarce water resources, but also to highlight the constraints that limit others (Reidsma et al., 2018). This integrated perspective is essential for designing adaptation strategies that reconcile agricultural development with groundwater sustainability.

Farm typologies are widely used in agriculture and rural development to identify and understand the diversity of farming systems and farmer profiles within a given region (Kumar et al., 2019). They serve as an effective tool to capture the heterogeneity of agricultural practices, considering the complex interplay of ecological, economic, and social factors that shape different farming systems (Poussin et al., 2008). According to the literature, farm typologies are generally based on three main characteristics: socio-environmental characteristics, farm structural characteristics, and farmers' individual characteristics (Huber et al., 2024). This multi-dimensional approach helps to categorize agricultural systems into distinct groups, facilitating a deeper understanding of their dynamics and enabling targeted interventions and policy formulations tailored to specific agricultural contexts.

There are two main approaches to developing farm typologies. The first relies on stakeholder inputs validated through surveys, which directly reflect local knowledge and expertise. For instance, stakeholder-based typologies have been employed in smallholder farming systems in Ethiopia to identify water use patterns and their impact on food security (Eshetae et al., 2024). The second approach uses statistical analyses of agricultural survey data, providing an empirical and data-driven classification of farms. For example, Maton et al. (2005) employed multivariate analysis techniques to develop typologies in irrigated agricultural systems in West Africa, identifying key drivers of variability such as farm size and access to markets. Both methods have their advantages, with stakeholder-based typologies offering practical insights and data-driven approaches providing robust classifications. In this study, we adopted the statistical-based approach: farm-level data were collected through field surveys with farmers and subsequently analyzed using Principal Component Analysis (PCA) and Ascendant Hierarchical Classification (AHC) to construct the typology. By enabling a deeper understanding of farm diversity, typologies contribute to more effective resource allocation, support mechanisms, and policy interventions, fostering sustainable agricultural development and addressing global food security challenges (Hammond et al., 2020).

Chtouka-Massa plain, situated in the southwestern part of Morocco, is a typical example of aquifer depletion, where surface water resources are almost nonexistent, making groundwater the primary source of water (Mouna et al., 2016). Given its high dependence on groundwater and its representativeness of the challenges faced in semi-arid Morocco, this study is based on data collected from 40 farm interviews in this region. In this context, the study integrates farm typologies with efficiency analysis to provide actionable insights for improving farm water management.

To ensure sustainability, agriculture must improve efficiency, either by maintaining production with fewer inputs or increasing output with existing resources, thereby ensuring future generations' access to energy and natural resources (Kyrgiakos et al., 2023). The two main approaches for estimating efficiency and inefficiency levels are the Stochastic Frontier Production Function (SFA), a parametric method, and Data Envelopment Analysis (DEA), a non-parametric method which was proposed by Charnes et al. (1978). DEA is a widely recognized non-parametric method that utilizes linear programming principles to assess the technical efficiency of various productive units (Charnes et al., 1978). DEA evaluates the relative performance of a group of producers or decision-making units (DMU), particularly in situations where multiple inputs and outputs complicate direct comparisons (Chen et al., 2009). The optimization method can be input-oriented, focusing on minimizing inputs used, or output-oriented, aiming to maximize the outputs produced (Moutinho et al., 2018; Bournaris et al., 2019), and both approaches can be used for the same dataset (Kyrgiakos et al., 2023). Classical DEA models include two types of scale: model with constant returns to scale (CRS) (Charnes et al., 1978) and model with variable returns to scale (VRS) (Banker et al., 1984).

DEA has been widely applied across various fields, including economics, ecology, and industry. In this context, Zheng et al. (2019) utilized a DEA evaluation approach to assess the agricultural production efficiency of seven provinces of the Yangtze River basin from 1996 to 2015.

However, previous studies have highlighted flaws in DEA, such as ignoring regional heterogeneity and integer constraints in key indicators, which can lead to biased evaluations and limited support for effective decision-making (Han et al., 2020; Yu et al., 2022; Chen et al., 2021). Traditional DEA models generally assume that all DMU are drawn from a homogeneous group and utilize the same underlying production technology (Yu and Chen, 2020). The Meta-frontier DEA model was introduced by O'Donnell et al. (2008) to account for technology heterogeneity. It has been applied in energy and environmental efficiency research. By constructing meta-group frontiers, the analysis captures technological heterogeneity arising from resource variability, production variations, and geographic differences, allowing for the identification of inefficiency sources (Ding et al., 2020). Agriculture is a typical example where DMU are highly heterogeneous. Farms use different combinations of inputs and outputs. These differences can be explained by differences in their organization, their farming practices, their differentiated access to natural resources (water, soil, etc.), finance resources, infrastructure, social and economic environment, etc. It is the case in the studied area where a diversity of farming systems coexist making comparisons between groups extremely hazardous. Lastly, it should be noted that DEA has been selected over SFA, due to the fact that it is a peer review technique that highlights the best performers that can act as lighthouses in local communities. Considering that farmers are highly influenced from neighbor's actions, DEA displays a higher potential for the implementation of the acquired results from farmers (Lampe and Hilgers, 2015).

This paper aims to identify and analyze the agricultural practices of farms to determine those who are efficient in terms of water management and those who are less efficient. To do so, this study developed a detailed typology of farms on the Chtouka-Massa plain in Morocco to assess the farming systems diversity. Then we conducted a DEA model based on the meta-frontier analysis framework to assess their efficiency in terms of input use and water management. This study employs the Technology Gap Ratio (TGR) index to assess both group-level and technological heterogeneity among the identified farm types. Additionally, it decomposes farm inefficiencies to identify the internal factors contributing to low performance, offering targeted strategies for improvement. The methodology is illustrated in the flowchart of Fig. 1.

After the introduction, Section 2 outlines the methodology used in this study, including the data collection process, the development of the farm typology, and the meta-frontier DEA model. Section 3 presents the results, detailing the identified farm types, their respective efficiency scores, and the analysis of technological heterogeneity using the Technology Gap Ratio (TGR). Section 4 discusses the findings, emphasizing their implications for water management and resource optimization, and explores potential strategies for improving efficiency. Finally, Section 5 concludes the paper by summarizing the key insights and providing recommendations for future research and policy development.

2. Methodology

2.1. Description of the study area

The Chtouka-Massa plain is located in the southern part of the Souss-Massa region in southwestern Morocco and covers approximately 1260 km^2 (Mouna et al., 2016) (Fig. 2).

The area experiences a semi-arid climate with abundant sunshine, influenced by its proximity to the Atlantic Ocean and the latitude of the Sahara Desert. This unique positioning results in hot, dry summers and relatively cold winters, contributing to highly variables precipitations levels. Annual rainfall ranges from as little as 200 mm in the plains to 600 mm in the mountainous areas (Ait Brahim et al., 2017), which significantly impacts agricultural activities and water availability.

The Massa River, situated 70 km south of Agadir, is the main surface water source in the Chtouka-Massa plain. Since the construction of the Youssef Ben Tachfine (YBT) dam in 1973, the river's flow has been regulated, playing a crucial role in the area's water management. The recharge of the Chtouka-Massa plain primarily comes from precipitations, groundwater from the formations of the Anti-Atlas Mountains (Krimissa, 2005), irrigation supplies, and regulated water releases from the YBT dam (Ait Brahim et al., 2017). Another irrigation water source implemented by the GMP to reduce pressure on the aquifer, is the desalination plant located in the Chtouka region. This facility supplies 13,600 ha with a capacity of 167,000 m^3 per day (Hirich et al., 2017). According to the Souss-Massa Hydraulic Basin Agency (ABHSM, 2015), the dominant irrigation methods are localized techniques such as drip irrigation (54 % of the irrigated area) and flood irrigation (26 %) (ABHSM, 2015). In the Chtouka-Massa perimeter, more than 3200 water points have been drilled, 70 % of which are boreholes and 30 % are irrigation wells (ABHSM, 2015). In the same zone, 94 % of extraction is used for agriculture, while only 6 % is used for drinking and industrial water supply (Bouchaou et al., 2011). This strong reliance on groundwater has contributed to overexploitation of the aquifer, raising concerns about the long-term sustainability of agricultural activities. Nevertheless, agriculture remains a dominant economic sector, accounting for more than 42 % of activities in the region, making it a key agricultural pole at both the regional and national levels (Haut-Commissariat au Plan (HCP), 2022).

The agricultural landscape of the Chtouka-Massa plain is highly productive, with approximately 2724 farms (ABHSM, 2015) covering 24,800 ha. This area contributes significantly to Morocco's agricultural exports, producing 50 % of the national exports in citrus and early fruits (Moha et al., 2016). The study area is characterized by a predominance of vegetable production, both in greenhouses and open fields, amounting to approximately 1600,295 tons in 2016 including 1.1 million tons of tomatoes, according to the Regional Office for Agricultural Development of Souss-Massa (ORMVASM, 2014).

2.2. Assessing diversity of farm household

2.2.1. Farm household data collection

The 30 farm households identified were surveyed in May and June 2023 with the collaboration of PhD students from the Ibn Zohr University. The selection process was initially guided by agricultural census data from the study area. However, these data were incomplete and contained gaps, limiting their direct use for a full classification of farming systems. To overcome this limitation, we relied on local agricultural experts (from research institutions and farmer organizations), who helped refine the identification of different farms based on their knowledge of the region. These experts played a crucial role in selecting the representative farms. This methodological approach is consistent with previous studies on farm typology in Morocco, such as the work of El Ansari et al. (2020).

To further validate the data and conduct an exploratory diagnosis of the area, 12 additional surveys were conducted in March 2024. These additional surveys were critical in corroborating the initial findings and providing a more comprehensive understanding of the agricultural practices and socio-economic conditions in the studied region. The surveys were conducted through face-to-face interviews with stakeholders, each lasting 2–3 h. We conducted a thorough verification of the

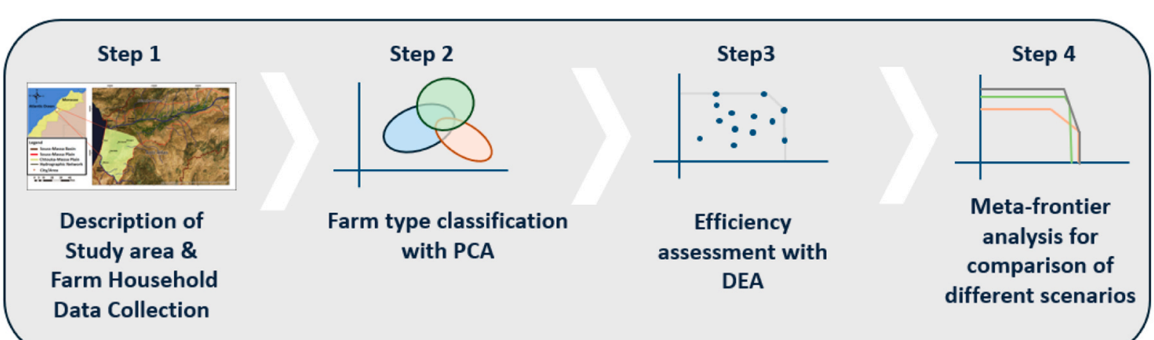

Fig. 1. Analytical Framework of the Study.

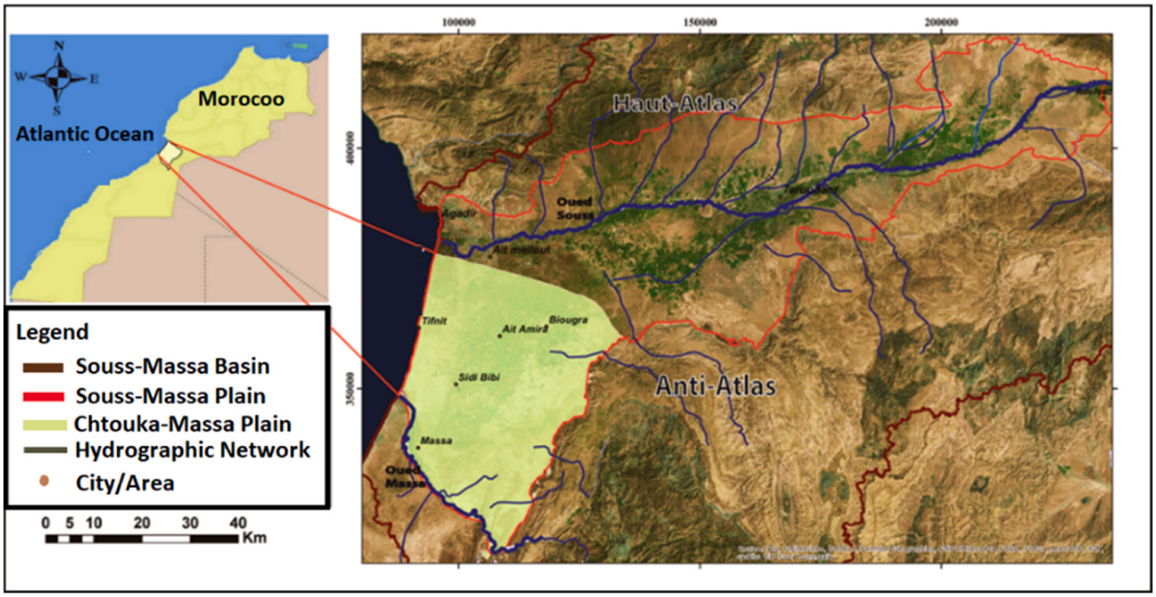

Fig. 2. Location of the Chtouka-Massa plain" study area.

survey data and excluded surveys containing too much missing or erroneous values. As a result, we obtained a dataset comprising 40 surveys, which served as the basis for constructing the typology.

Interviews with the heads of farm households were conducted using a structured interview guide divided into five main sections. This guide was inspired by the work of Chenoune et al. (2016) in Sierra Leone, which provided a robust framework for assessing farm household dynamics. The first section investigated the socio-economic characteristics of the farm household, the farm structure (number of household members, ages, labor, farmland, sources of income, etc.) The second section ("farming practices") deals with more detailed characteristics of each farm household's crop production. Questions about cultivated area, yield of each crop, soil preparation, planting, fertilizer application and irrigation (source, quantity, costs, etc.) were asked. The third part of the questionnaire was devoted to detailed questions on livestock production (herd structure, livestock expenses, production, etc.). The fourth section concerned questions regarding food security and access to financing. The fifth and last section of the questionnaire examined farm households' perceptions of agricultural development through a wide range of topics, including major constraints faced in farm management, exposure to shocks and crop losses, access to and use of crop insurance, reliance on advisory services and professional organizations, land dynamics (past and future changes, access, and transmission), labor availability and evolving needs, as well as changes in crop choices, farm management practices, and the use of plant protection products.

In order to better understand the study area, we conducted a focus group discussion with local experts and farmers, supplemented by an analysis of regional reports. This approach allowed us to distinguish four sub-zones based on water access and agricultural practices. The modern public perimeter consists of privately held plots that benefit from controlled irrigation supplied by the YBT dam, with farmers paying water fees to the ORMVASM based on metered consumption. The traditional public perimeter includes private plots that receive water from periodic dam releases, conveyed through traditional "séguias" (irrigation channels), where farmers pay only a nominal fee to the ORMVASM. In the private perimeter, farmers rely exclusively on groundwater accessed through private boreholes and can benefit from government subsidies to modernize their irrigation systems. Unlike in the public irrigated schemes, they do not pay water fees to the State but bear the costs of extraction (pumping, energy) and the maintenance of privately managed irrigation networks, either individually or collectively. Finally, the rainfed zone depends solely on precipitation, with farmers cultivating low water-demanding crops due to the absence of irrigation infrastructure. The insights gathered from the focus group were instrumental in refining our understanding of the agricultural landscape and guiding the subsequent data collection and analysis.

2.2.2. *Construction of farm household's typology*

To address the diversity of farm systems in the Chtouka-Massa plain and develop a comprehensive typology that considers both agricultural practices and water resource utilization, we took into account two main categories of classification criteria: water management and crop production (Table 1). This approach allowed us to capture the multiple dimensions and heterogeneity of agricultural practices within the region. The first category of criteria 'Irrigation management' includes variables related to the utilization and management of water resources, which are critical in this semi-arid region. Key variables include the source of irrigation (e.g., YBT dam, private well, or desalination), the quantity of water used per crop type, water costs, and the specific irrigation techniques employed (e.g., drip, sprinkler, or flood irrigation). In this study, the term "flood irrigation" refers to gravity-fed methods, mainly basin irrigation for arboriculture and furrow irrigation for cereals and vegetable crops. In practice, many farmers combine more than one of these methods depending on the crop.

The second category 'Crop production and labor' integrates variables such as the utilized agricultural area (UAA), soil types, crop yields, labor input, and associated costs. These factors are essential for understanding the broader agricultural practices of farms. Soil type, for instance, directly affects fertility, water retention, and crop growth conditions, which are critical determinants of yield potential. Other variables, including labor input and its cost, provide insights into the economic viability and intensity of farming operations. By analyzing these agro-economic characteristics, we can classify farms based on their productivity and overall agricultural performance.

A dataset comprising 40 farm households and 21 variables (Table 1) were selected based on their relevance to our research question and after a correlation test. These variables were used to characterize farm household heterogeneity and establish the typology. Table 1 was analyzed using two multivariate statistical methods: Principal Component Analysis (PCA) and Hierarchical Ascending Classification (HCA) (Madry et al., 2010).

The aim of PCA is to identify the principal axes, which summarize the maximum amount of information to be found in the variables (Bidogeza et al., 2009). In other words, PCA reduces the dimensions of a multivariate

Table 1
Variables used for farm household typology.

Criteria	Variable description	Code	Source
Irrigation management	1. Size of irrigated plot (ha)	SIP	Primary data from survey
	2. Total quantity of irrigation water (m3/ha)	TQW	
	3. Total water cost per farm (MAD[1]/ha)	TWC	Calculated from the survey as the quantity of water multiplied by the price (depend on the source of water and of energy)
	4. Quantity of water from private well (m3/ha)	Priv_well	Calculated from the survey, depending on the source of water
	5. Quantity of water from dam (m3/ha)	Dam	
	6. Quantity of water from desalination (m3/ha)	Desali	
	7. % Of irrigation water by drip irrigation	%_gag	Calculated from the survey as the percentage of the total irrigation water applied through drip, sprinkler, or flood irrigation methods.
	8. % Of irrigation water by sprinkler irrigation	%Asp	
	9. % Of irrigation water by flood irrigation	%Sur	
	10. Gross margin per water unit (MAD/m3)	GM-W	Calculated from the survey as the ratio of the gross margin obtained from crop production to the volume of irrigation water applied (MAD/m3).
Crop production and labor	11. Farming area (ha)	area	Primary data from survey
	12. Gross-margin per hectare (MAD/ha)	GM	Primary data from survey the total gross margin divided by the total volume of water used
	13. Surface of cereals (ha)	Cereals	The surface dedicated to cereal crops, vegetable and arboriculture
	14. Surface of Vegetable farming (ha)	Vegt	
	15. Surface of Arboriculture (ha)	Arbo	
	16. Total cost of seeds per ha (MAD)	See_co_ha	Calculated from the survey as the quantity of each input multiplied by the market price of each input as given by each farmer
	17. Total permanent labor (person/year/ha)	Perm_lab_	Calculated from the survey
	18. Total of seasonal labor (person/year/ha)	Seas_lab_	
	19. Total of family labor (person/year/ha)	Fam-lab	
	20. Total quantity of NPK (Kg/ha)	NPK	Primary data from the survey
	21. Total quantity of manure (Kg/ha)	Fumier	

[1] Moroccan dirham (MAD). 1MAD = 0.094 euros

data table to a few principal components, which can be visualized graphically, losing as less information as possible. From the eigenvalues, we obtain the inertia indicators, which present the sum of the variances carried by each axis. With these variables we will analyze farm household heterogeneity. PCA creates new variables as combinations of the original ones, using weights from the eigenvectors of the correlation matrix (Upadhaya and Dwivedi, 2019). Then the HCA was applied to group the farms into distinct clusters based on their shared characteristics. HCA is a method used to organize a complex dataset into homogeneous groups (clusters), ensuring that subjects within each group share similar characteristics (Kniggendorf et al., 2010). The process builds a dendrogram, a hierarchical tree structure, by progressively merging clusters based on similarity measures and grouping criteria (Leal et al., 2016). This classification tree effectively distinguishes the most homogeneous farm household groups while highlighting significant differences between them. To identify the optimal number of farm types (clusters), we identified the point where the largest increase in between-cluster inertia occurred. This method ensures that clusters are internally cohesive and externally distinct, minimizing within-cluster variance while maintaining balanced groupings (Kobrich et al., 2003). R software (version 2024.04.00) was used to conduct the PCA and the HCA.

2.3. Technical efficiency analysis

The methodology we followed consists of two main stages. In the first stage, we applied an output-oriented DEA model that constructs a single efficiency frontier using all observations, without distinguishing between types. This model identifies the most efficient farms, which define the frontier, while the remaining farms are assessed based on their distance from this benchmark. It assumes that all farms have access to the same technology.

In the second stage, we implemented the meta-frontier approach, which involves two key steps: (i) estimating a group-specific efficiency frontier for each type of farm (group frontier) and (ii) constructing the meta-frontier, which represents the most advanced technology available across all types and encompasses all existing technological frontiers. This allows for a comparison not only within each type but also across types, providing insight into technological gaps and relative efficiency differences among farm types.

2.3.1. Output-oriented DEA Model

In this study, DEA was preferred over the parametric Stochastic Frontier Analysis (SFA) because of the high heterogeneity of farms (Ding et al., 2020) in the Chtouka-Massa plain. Unlike SFA, DEA does not require the specification of a production function (Aigner et al., 1977), which is particularly advantageous in contexts where farms use diverse combinations of inputs and outputs. DEA is also more suitable for handling multi-input and multi-output production systems (Greene, 2008), which characterizes irrigated agriculture in Morocco. Furthermore, the adoption of the meta-frontier DEA framework allows us to explicitly account for technological heterogeneity between farm types, making it a robust and context-appropriate method for analyzing efficiency under conditions of climatic and policy-driven pressures. It should be noted, however, that unlike SFA, DEA does not separate inefficiency from "noise," where noise refers to random factors such as climatic variability, measurement errors, or other uncontrollable shocks (Lampe and Hilgers, 2015; Coelli et al., 2005) that may influence farm performance.

In the DEA framework, each farm household is treated as a DMU. To ensure consistency, we use the term DMU when referring to the optimization model, while the term farm household is used in the descriptive analysis.

As previously explained, we employed the DEA method to assess the technical efficiency of water resource utilization by different DMU. We opted for an output-oriented DEA model, motivated by the need to determine to what extent a unit can increase its outputs while keeping its inputs constant (O'Donnell et al., 2008). In other words, this approach aims to maximize production without altering the quantity of resources used, thereby evaluating the relative efficiency of the units in an optimal productivity context (Yu and Chen, 2020; O'Donnell et al., 2008).

The selection of inputs and outputs reflects the key resources and production activities characterizing farm households in the Chtouka-Massa plain (Table 2). These variables were used in both the DEA model and the meta-frontier analysis to assess efficiency at both the group and overall levels. Our study applies the VRS model introduced by Banker et al., 1984, as farms in the sample differ considerably in size and resources. Unlike the CRS model, which assumes proportionality between inputs and outputs, the VRS model accounts for increasing or decreasing returns to scale, making it more suitable for capturing efficiency in this heterogeneous context. This approach is particularly useful when DMU differ in size, as it avoids comparing small units directly with much larger ones (Chen, 2005).

To evaluate the output-oriented technical efficiency of the DMU, we employed a linear programming model proposed by Färe et al. (1994). This model aims to maximize the potential output of each DMU while keeping inputs constant. The mathematical formulation is as follows:

$$Max\theta$$

$$Subject\ to:$$

$$\theta y_{jm} \leq \Sigma z_j \cdot y_{jm}, \quad \forall \quad m \tag{1}$$

Table 2
Specification of inputs and outputs used in the DEA Model.

Category	Variable	Description
Output	Gross Margin of cereal crops	Represents the gross margin generated from cereal production, providing a measure of cereal crop profitability (MAD/ha).
Output	Gross margin of vegetable crops	Measures the gross margin obtained from vegetable production, reflecting productivity and profitability in vegetable farming (MAD/ha).
Output	Gross margin of arboriculture crop	Captures the gross margin from tree crops, representing returns from perennial agriculture (MAD/ha).
Output	Gross margin per water unit for cereal	Gross margin efficiency per unit of water for cereals, defined as the gross economic margin relative to water use (MAD/m3).
Output	Gross margin per water unit for vegetable	Gross margin efficiency per unit of water for vegetables (MAD/m3).
Output	Gross margin per water unit for arboriculture crop	Gross margin efficiency per unit of water for arboriculture crop (MAD/m3).
Input	Land (terre)	Total agricultural area cultivated by each household, highlighting land use intensity.
Input	Drip Irrigation Water (GaG)	Volume of water applied through drip irrigation systems, indicating water efficiency.
Input	Flood Irrigation Water (Surf)	Amount of water used through flood irrigation methods, reflecting traditional water management practices.
Input	NPK Fertilizer for Cereals (NPKcer)	Amount of NPK fertilizer applied to cereal crops, influencing crop yield.
Input	NPK Fertilizer for Vegetables (NPKmar)	NPK fertilizer used in vegetable production, contributing to yield quality and quantity.
Input	NPK Fertilizer for Arboriculture Crops (NPKarb)	NPK fertilizer applied to Arboriculture crops, relevant for orchard management and productivity.
Input	Total Labor	Sum of permanent, seasonal and family labor per farm

$$\Sigma z_j \cdot x_{jn} \leq \quad x_{jn}, \quad \forall \quad n \tag{2}$$

In order to calculate changes in scale efficiency, we also calculate distance functions under variable returns to scale by adding the VRS restriction:

$$\Sigma z_j = \quad 1 \quad (\quad VRS\ condition) \tag{3}$$

$$z_j \geq \quad 0, \quad \forall \tag{4}$$

where:
θ = output technical efficiency measure,
y_{jm}= quantity of output m produced by DMU j,
x_{jn} = quantity of input n produced by DMU j, and
z_j = intensity variable for DMU j.

2.3.2. *Meta-frontier analysis*

2.3.2.1. Group-Frontier and Meta-Frontier. To assess technical efficiency while accounting for technological heterogeneity, we applied a group-frontier DEA approach combined with a meta-frontier analysis. The classification of DMU into homogeneous types was already established in the typology analysis. Based on this predefined classification, we directly assigned each farm to its respective type in the DEA model.

For each type, we applied an output-oriented DEA model to estimate group-specific frontiers, assuming that all units within a given category share similar technological conditions. In this phase each DMU was compared within its own type. In the second stage, we constructed a meta-frontier, encompassing all types, allowing for inter-type efficiency comparisons. In this phase each DMU was compared to the best technology available. This approach follows the principles of the group-frontier DEA which we implemented using a linear programming-based DEA method. Instead of relying on a theoretical approach based on technological sets, we formulated the problem as a linear optimization model. The DEA model was written in GAMS (General Algebraic Modeling System), version 43.4.1, based on the framework developed by Walden and Kirkley (2000). The mathematical formulation remains the same as in the output-oriented DEA model, with the only difference being:

- In the group-frontier DEA, a DMU is compared only to other DMU within its own type.
- In the meta-frontier DEA, a DMU is compared to all DMU across all types.

2.3.2.2. Technological gap ratio. In order to assess the sources of efficiency and inefficiency at the type level, we calculated the TGR. The TGR measures the gap between the group-frontier and the meta-frontier, indicating the technological disparity between them, such that a higher TGR value signifies that the DMU is closer to the meta-frontier and therefore operates at a higher production technology level (O'Donnell et al., 2008; Huang and Zhao, 2024). The TGR is constructed as follows, based on the approach proposed by O'Donnell et al. (2008):

$$TGR_{k(x,y)} = \frac{TE(x,y)}{TE_{k(x,y)}} \tag{5}$$

With:
TE(x, y): Technical Efficiency of the DMU relative to the meta-frontier
$TE_{k(x,\ y)}$: Technical efficiency of the DMU relative to the group-*k* frontier
x: Input vector
y: Output vector
The value of the TGR is between 0 and 1. A TGR close to 1 indicates minimal technological disparity, implying that the group frontier is almost aligned with the meta-frontier. Conversely, a TGR close to

0 indicates greater technological heterogeneity, highlighting significant differences in environmental efficiency between the two frontiers (Ding et al., 2020). The meta-efficiency scores are lower than the group efficiency score, because the meta-frontier envelops the group frontiers (Yu and Chen, 2020). It should be emphasized that the TGR does not directly measure inefficiency, but rather captures technological gaps between the group-frontier and the meta-frontier. The inefficiencies are inferred indirectly by comparing farms' efficiency scores relative to their group-frontier and the meta-frontier, as well as through the TGR (Chiu et al., 2012; Yu and Chen, 2020).

To provide a comprehensive understanding of the technological efficiency of each type, we calculated the average Technological Gap Ratio (TGR) for the DMU belonging to each farm type. These averages — denoted as $MOY_i i = 1, 2 or 3$ — offer insights into the overall performance of each type relative to the meta-frontier. These values provide an overview of the average technological gaps for each farm type. The averages MOY_i are calculated as follows:

$$MOY_i = \frac{\sum_i TGR_{ki}}{n_{ki}} \tag{6}$$

Where:

- TRG_{ki} is the Technological Gap Ratio for DMU_k in type i
- n_{ki} represents the total number of DMU k in type i.

2.3.3. Technical Inefficiencies Decomposition

To identify the sources of inefficiency for each farm household at the meta-frontier level, we relied on the approach proposed by Chiu et al. (2012) and Yu and Chen (2020). This approach decomposes the overall inefficiency (OI) of each DMU into technical gap inefficiency (TIE) and management inefficiency (MIE) as follow:

$$TIE = Group\ Efficiency - Meta\ Efficiency \tag{7}$$

$$MIE = \quad 1 - Group\ Efficiency \tag{8}$$

$$OI = 1 - MIE = TIE + MIE \tag{9}$$

Ding et al. (2020) underline that inefficiency among DMU within the same type mainly arises from management inefficiency, as they share the same technological framework. The TIE reflects inefficiency due to the technological gap between the meta-frontier and group-specific frontiers, while the MIE captures inefficiency within the group frontier caused by input excess, undesirable outputs, and shortfalls in desirable outputs (Chiu et al., 2012). Thus, overall inefficiency can be reduced through better technologies and practices (TIE) and/or improved management, training, and resource allocation (MIE).

3. Results

This section presents the results in three key stages. First, we describe the farming and cropping systems in the study area, highlighting the diversity of agricultural practices and resource use patterns among farm households. Next, we analyze the classification of farms using PCA and HCA to identify distinct farm typologies. Finally, we assess the technical efficiency using a meta-frontier DEA approach, comparing group-specific and global efficiency scores to assess technological disparities across different farm types. This analysis enables us to quantify the technological gaps and identify opportunities to improve water use management within each farm typology.

3.1. Description of the farming and cropping systems in the study area

The analysis of data collected from the surveys revealed that the mean farming area is 7.04 ha, ranging from 0.5 ha to 29.5 ha. Cumulative frequency analysis reveals that 55 % of farm operate on less than 5 ha, while 27.5 % manage between 5 and 10 ha, and 17 % exceed 10 ha (Fig. 3). The surveyed sample predominantly consists of small-scale agricultural farms, characterized by limited land size but also exhibits variability in terms of farm size. The large majority of farmers own their farmland, and each farm is divided into several plots. The age of the respondents ranges from 23 to 68 years, and all of them are male. Around 80 % of the respondents are educated, their educational levels ranging from primary school to university. Farm household incomes are primarily derived from agricultural activities. The vast majority of surveyed farmers grow vegetables under greenhouses. Farmers with the smallest farmland areas (between 0.5 and 2 ha) are located in the south and southwest of the zone. In contrast, those with larger agricultural areas are situated in the northern and northeastern parts, which include both public and private irrigated perimeters, meaning these farmers rely on irrigation. These farmers rely on permanent and seasonal salaried workforce, whereas small-scale farmers primarily depend on family labor. In the entire sample, various crops have been grouped into three main categories: vegetables, arboriculture, and cereals, as detailed in the Table 3. This classification simplifies the categorization of farmers within the typology.

3.2. Results of data analysis

The PCA was applied to data from 40 farms to identify key variables and better understand the diversity of farming systems. PCA was used to reduce the number of variables into uncorrelated principal components, retaining only those with eigenvalues greater than 1 (Kaur et al., 2021). The first two axes of the PCA explain 44.73 % of the total variability across 21 variables, with Axis 1 accounting for 31.48 % (Dim 1) and Axis 2 for 13.25 % (Dim 2) (Fig. 4). The third and fourth components explain an additional 11.51 % and 8.54 % of the total variability, respectively.

Axis 1 had 12 significant loadings (values higher than 0.5), indicating that this principal component captures a substantial portion of the total variance in the data (Table 4, Appendix A). Variables contributing positively to Axis 1 include the size of the irrigated plot, total quantity of irrigation water used, total water costs, quantity of water applied through drip irrigation systems, cultivated area of vegetable farming, seed costs, number of seasonal workers, total quantity of NPK, overall farming area, the gross margin and the gross margin per unit of water. Notably, one variable, the number of family workers, contributed negatively to this component.

Axis 2 presented 4 significant loadings, primarily associated with the volume of water drawn from the dam, the amount of water used through sprinkler systems, the cultivated area of cereal farming, and the total number of workers on the farm.

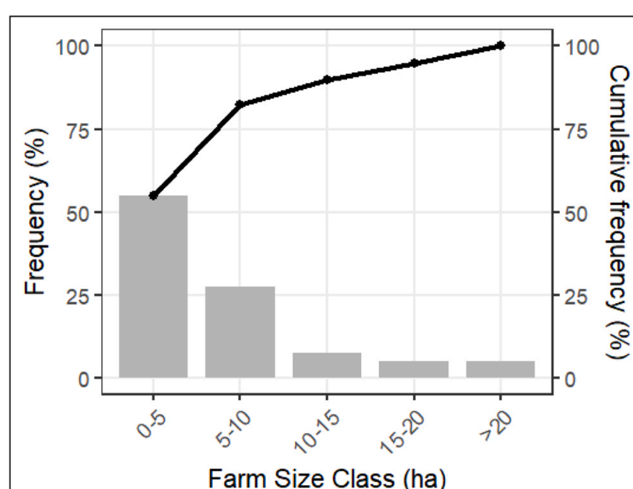

Fig. 3. Frequency distribution of farms by size of land holding.

Table 3
Classification of crop types in the sample.

Categories	Crops
Vegetables	Tomato, bell pepper, green bean, pea, zucchini, turnip, blueberry, raspberry, blackberry, potato, melon, carrot, fava bean, cucumber
Arboriculture	Lemon, carob tree, olive trees
Cereals	Corn, alfalfa, durum wheat, soft wheat, barley

The PCA biplot (Fig. 4) visualizes the positioning of the individuals (farms) based on their characteristics along the first two principal components, Dim1 (31.48 %) and Dim2 (13.25 %). This plot provides insights into the variability and relationships between different farms.

Based on the distribution of the farmers, we observe that farms are dispersed across the four quadrants, indicating variability in their characteristics. This dispersion suggests that the farms differ significantly in their practices. The clustering of several farms around the origin (0,0) suggests that these farms have average characteristics relative to the dataset, meaning they do not strongly differ in the dimensions defined by Dim1 and Dim2. Farm household 7 is positioned far to the right along Dim1, suggesting that it has distinct characteristics compared to the other farm households. This farmer has the largest agricultural area, covering 29.5 ha, and bears the highest water costs compared to the rest of the sample. He cultivates raspberries, blackberries, and blueberries, irrigated by a drip system sourced from his private well. The use of electricity as the primary energy source further contributes to the high-water costs.

The classification of farm households is based on the factor coordinates obtained from the PCA. The two principal components were used as input data for the HCA. The approach of agglomerative hierarchical clustering involves calculating the distances between farm households and clustering those with minimal distances to form a dendrogram (Appendix A, Fig. 5). The dendrogram resulting from the HCA illustrates the hierarchical structure of the farms (labeled H1, H2, etc.) based on their similarity. The closer two individuals in the dendrogram, the more similar they are. The branches of the dendrogram represent the successive groupings of farms. At each level of fusion, farms or groups of farms are combined into a larger group. For example, farms H7 and H17 are very similar as they merge at a low level. To determine the number of clusters (groups), we choose to cut the dendrogram at a height of 10, which results in three main types of farms. The cluster plot as shown in the Fig. 6 illustrates the grouping of data points into three clusters (Cluster 1, Cluster 2, and Cluster 3) based on their coordinates on the two principal components (Dim 1 and Dim 2). Cluster 1 (red) is located on the far left, Cluster 2 (green) is central but elongated, and Cluster 3 (blue) is on the right.

The identified farm household types were designed as follows: (1) extensive cereal-arboriculture farming household, (2) semi-intensive mixed cereal-vegetables farming household, and (3) intensive vegetable farming household. A detailed description of each farm household type is provided below:

- Extensive cereal-arboriculture farming household

  Type 1 farm households primarily focus on cereal cultivation, complemented by arboriculture. This category includes 11 units, which have the smallest average irrigated plot size of about 1.31 ha. These farm households use the least amount of water for irrigation because their cereal cultivation is rainfed. The total water used

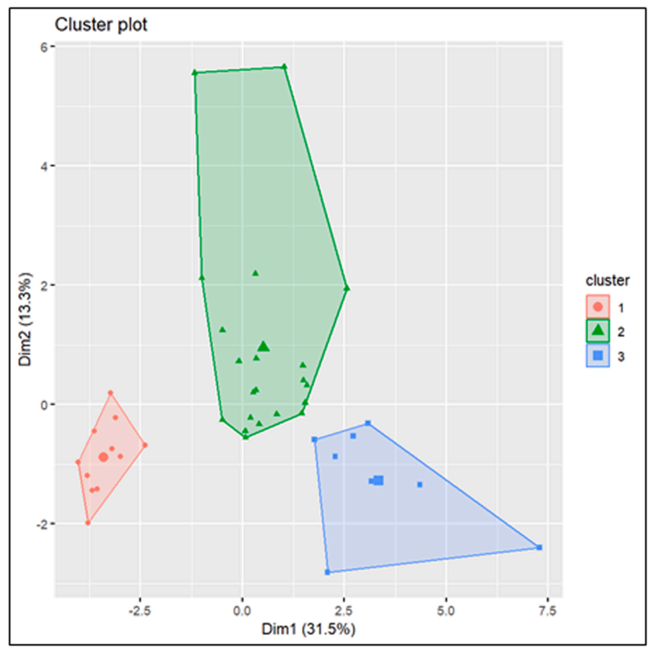

Fig. 6. Cluster plot of PCA Results with hierarchical clustering.

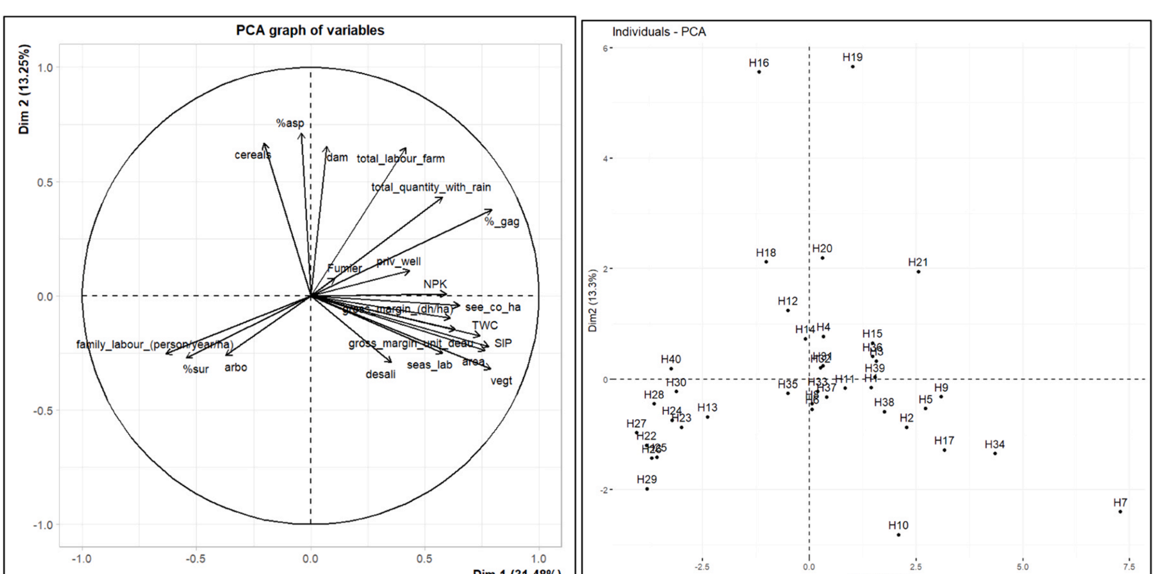

Fig. 4. Representation of variables, correlation circle and projection of farm households on factorial plane 1–2 of PCA.

amounts to 5945 m^3 per year per hectare, to which an estimated 3000 m^3 of rainfall per year per hectare is added They neither use water from the dam nor from the desalination plant, relying instead on their private wells for irrigating arboriculture. The irrigation technique employed is flood irrigation.

Cereal cultivation in these farm households heavily depends on family labor, unlike the other two types where family labor contribution is minimal. In Type 1 farms, family labor amounts to 2 persons per year per hectare. These farm households have the lowest gross margin per unit of water, calculated at 4.97 MAD/m^3 , as well as the lowest overall gross margin. They also use the smallest amount of NPK fertilizer, approximately 36 kg per hectare. Their dependence on family labor and reliance on rainfall for irrigation contribute to keeping the overall farming costs at a minimum.

- Semi-intensive mixed cereal-vegetables farming household

Semi-intensive mixed cereal-vegetable farming households (Type 2) are characterized by a combination of cereals and vegetables cultivation, with no engagement in arboriculture. On average, they cultivate larger irrigated plots (5.91 ha). This type represents the largest cluster, comprising 21 farm households.

The average water usage for irrigation is approximately 11,800 m^3 per year per hectare. These farm households primarily rely on water from private wells and dams. The irrigation technique used is drip irrigation. They are characterized by their reliance on permanent labor and for using the largest amount of manure, averaging 272 kg of N per hectare. The average gross margin per unit of water is around 72 MAD per m^3 .

- Intensive vegetable farming household

Intensive vegetable farming households (Type 3) specialize exclusively in vegetable production. This category includes 21 households and has the largest average irrigated plot size, measuring 17.18 ha. They use a significant amount of water for irrigation, averaging 10,728 m^3 per year per hectare, and face the highest water costs. This is primarily due to their reliance on desalinated water, which costs 5 MAD per cubic meter—substantially higher than water sourced from dams, priced at 0.85 MAD per cubic meter. The primary irrigation method employed is drip irrigation, which is efficient but entails high operational costs. These farm households also incur elevated costs due to the high price of seeds and the need for both seasonal labor (10 persons per year per hectare) and permanent labor. They use the highest quantity of NPK fertilizer, averaging 1887 kg per hectare. Despite these higher costs, they achieve the highest gross margin and the highest gross margin per unit of water, with an average of 152 MAD per m^3 .

These three farm typologies — extensive cereal-arboriculture farming households, semi-intensive mixed cereal-vegetables farming households and intensive vegetable farming households — differ significantly in their resource use, production strategies, and input intensity. These differences are reflected in their water usage, labor dependency, fertilizer application, and gross margins, which underline the diversity in production systems and their challenges. Given this diversity, it becomes essential to assess the technical efficiency of these farm types to determine how effectively they utilize their resources compared to their potential output levels.

3.3. Data envelopment analysis and meta-frontier

3.3.1. Meta-Frontier and group-Frontier

Having identified the distinct characteristics and resource use patterns of each farm household, the next step involves evaluating their technical efficiency within their respective types and in comparison, to the overall technological potential. The meta-frontier analysis provides a robust framework for assessing efficiency across heterogeneous groups.

To evaluate and compare the technical efficiencies of the group-frontiers to the meta-frontiers, we used an output-oriented DEA model. This model is designed to maximize outputs while keeping inputs constant, aligning with the objective of improving resource efficiency across farm households. By doing so, we can identify farm households that utilize resources optimally and those that face significant inefficiencies.

Fig. 7 illustrates the variations in the three efficiency indicators (meta-frontier, group-frontier, and TGR) for the 40 farm households. The results highlight significant disparities: while some achieve high efficiency levels, others require substantial interventions to improve their resource utilization and reduce the technological gap.

Analyzing efficiency by type, we observe distinct patterns. Type 1 (extensive cereals-arboriculture farming households) shows efficiency scores ranging from 0.199 to 1.000, with several farms operating at full efficiency (score = 1.000), suggesting that some units fully exploit their available technology while others lag behind. Type 2 (semi-intensive mixed cereals-vegetables farming household) shows a greater dispersion of scores (0.201–1.000), indicating significant heterogeneity in resource utilization among farms within this type. Finally, Type 3 (intensive vegetables farming household) demonstrates relatively high efficiency overall, with scores ranging from 0.430 to 1.000, suggesting that the majority of farms in this type operate closer to the efficiency frontier.

3.3.2. Technological gap ratio (TGR)

The TGR quantifies the technological gap between farm household performance and the global potential, where a value close to 1 indicates minimal technological disparity. The results of the average TGR calculations (Eqs. (5) and (6), Table 5) and the efficiency analysis (Fig. 8) reveal significant heterogeneity among the three farm types. For Type 1 farms (extensive cereals-arboriculture), all farm households exhibit a TGR of 1.000, leading to an average MOY_1 of 1.000. This indicates that these farm households consistently achieve full efficiency, fully aligning with the meta-frontier. Despite their lower efficiency scores compared to other groups, they have fully reached their technological potential within their category and relative to the meta-frontier. According to Battese et al. (2004), this means their efficiency is not constrained by technological limitations but rather by structural or environmental factors, such as their reliance on rainfed cereal cultivation and minimal external inputs. Their farming system is inherently less intensive, which explains why they operate at full technological potential despite lower overall productivity.

In contrast, Type 2 farm household (semi-intensive mixed cereals-vegetables) demonstrate heterogeneous technological efficiency, with TGR values ranging from 0.744 to 1.000, leading to an average MOY_2 of 0.944. This suggests that these farms are close to the meta-frontier, with only minor technological disparities. Many farm households in this type utilize their resources effectively, but some fail to fully exploit available technological advancements. For example, farm households 32 and 37 have TGR values close to 1 (0.995 and 0.997, respectively), while others, such as farm 19 (TGR = 0.744) and farm 33 (TGR = 0.781), exhibit technological gaps. These disparities suggest opportunities for improvement through the adoption of advanced irrigation systems, optimized fertilization methods, and better resource management strategies

The Type 3 farm household (intensive vegetables) exhibit the highest variability in technological efficiency, with TGR values ranging from 0.221 to 1.000, resulting in an average MOY_3 of only 0.761. This pronounced inefficiency suggests that while some farm households in this type operate at their maximum potential (e.g., farm 10 and farm 2, both with TGR = 1.000), others experience significant technological lag (farm 34: TGR = 0.221, farm household 38: TGR = 0.293). The low MOY_3 score reflects that, on average, farm households this type struggle to integrate advanced technologies, likely due to high input costs (e.g., desalinated water and fertilizers) and the labor-intensive nature of their operations. While intensive vegetables production is highly profitable, its reliance on expensive inputs and skilled labor creates barriers to efficiency improvements. Farms with lower TGR values may need support

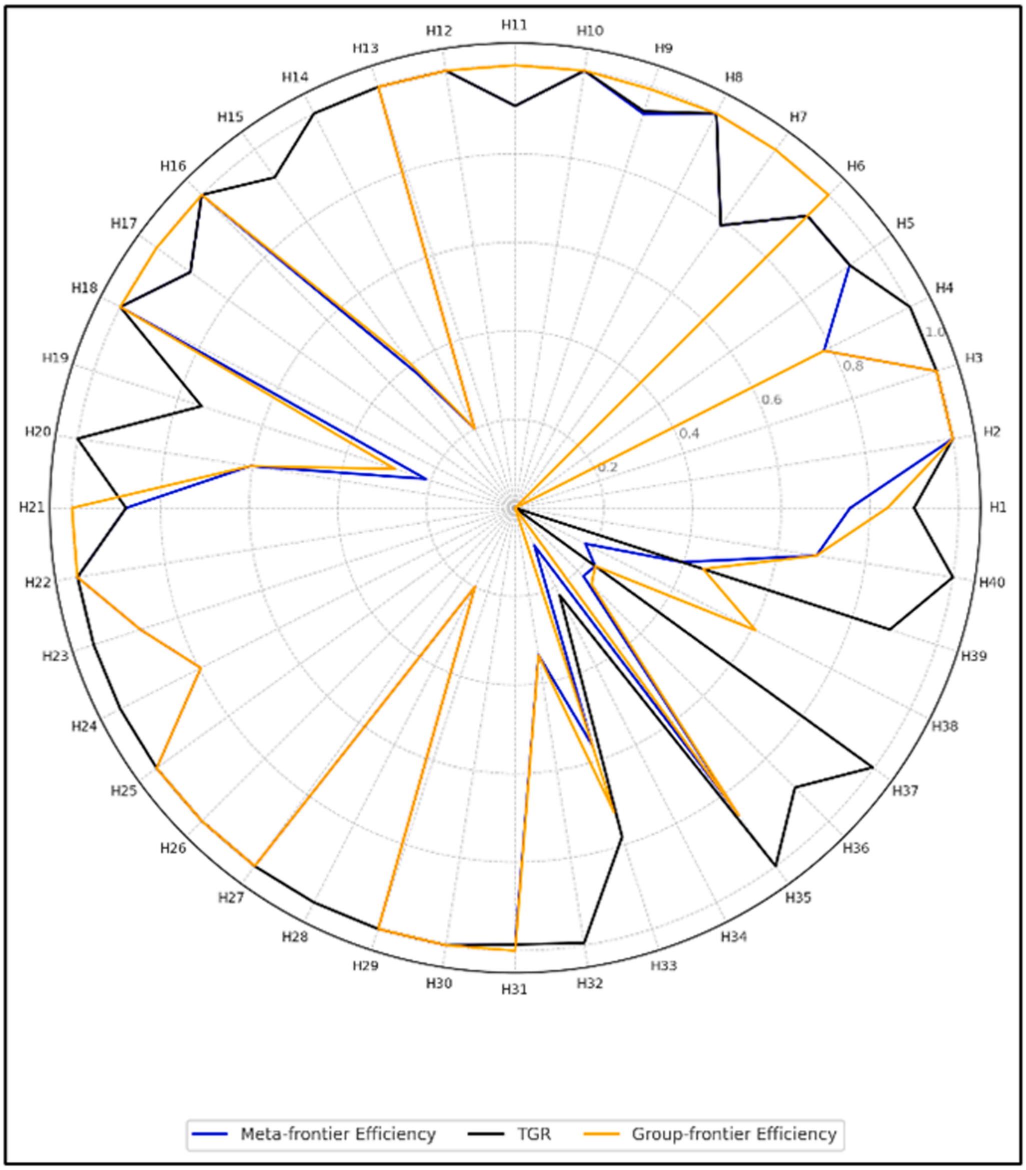

Fig. 7. Meta-Frontier, Group Frontier and TGR of each farm household.

Table 5
Average Technological Gap Ratio (TGR) by farm type.

Farm Type	Average TGR (MOY_i)
1. Extensive Cereal-Arboriculture	1.0
2. Semi-Intensive Mixed Cereal-Vegetable	0.944
3. Intensive Vegetables	0.761

in adopting cost-effective irrigation strategies, optimizing fertilization techniques, and improving labor efficiency to bridge the gap with the meta-frontier. This analysis highlights the importance of designing targeted solutions that address the specific challenges and resource constraints of each farm household type to enhance overall efficiency.

3.4. Technical inefficiency analysis

This part identifies the internal factors that contribute to inefficiencies across farm households. The detailed inefficiency scores are presented in Table 6 (Appendix A), which reports also meta-frontier and group-frontier efficiency levels together with the decomposition of the overall inefficiency (OI) into technological (TIE) and managerial (MIE) inefficiencies. Fig. 9 complements these results by providing a visual representation of the decomposition, highlighting the relative contribution of managerial versus technological inefficiencies across farm households.

The inefficiency analysis shows that managerial inefficiency (MIE) is the most common source of inefficiency, affecting 10 farm households in total (6 from Type 2 and 4 from Type 1). Technological inefficiency (TIE) was observed in 6 farm households (3 from Type 2 and 3 from Type 3). A smaller group of 4 farm households (2 from Type 2 and 2 from Type 3) exhibited both technological and managerial inefficiencies simultaneously. In contrast, 16 farm households were found to be fully efficient, comprising 7 from Type 1, 7 from Type 2, and 2 from Type 3. These results underline that inefficiencies are not uniformly distributed: Type 1 farm households are mostly constrained by managerial issues, Type 2 farm households display both managerial and technological gaps, while Type 3 farm households face primarily technological challenges, especially related to irrigation and input management. This heterogeneity highlights the need for targeted interventions tailored to the constraints of each farm type.

It is observed that both managerial and technological challenges can coexist within the same type of farm households, leading to the presence of multiple types of inefficiencies rather than a singular issue. At the meta-frontier level, Type 3 farm households must focus on achieving

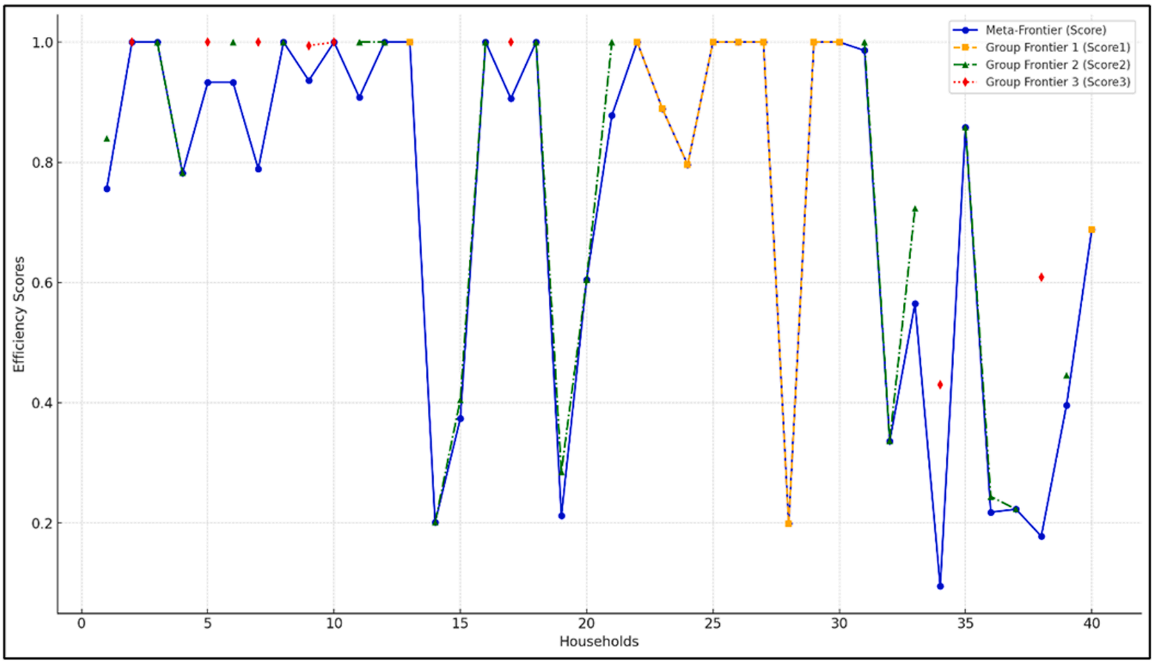

Fig. 8. Meta-Frontier and group-frontier for farm households.

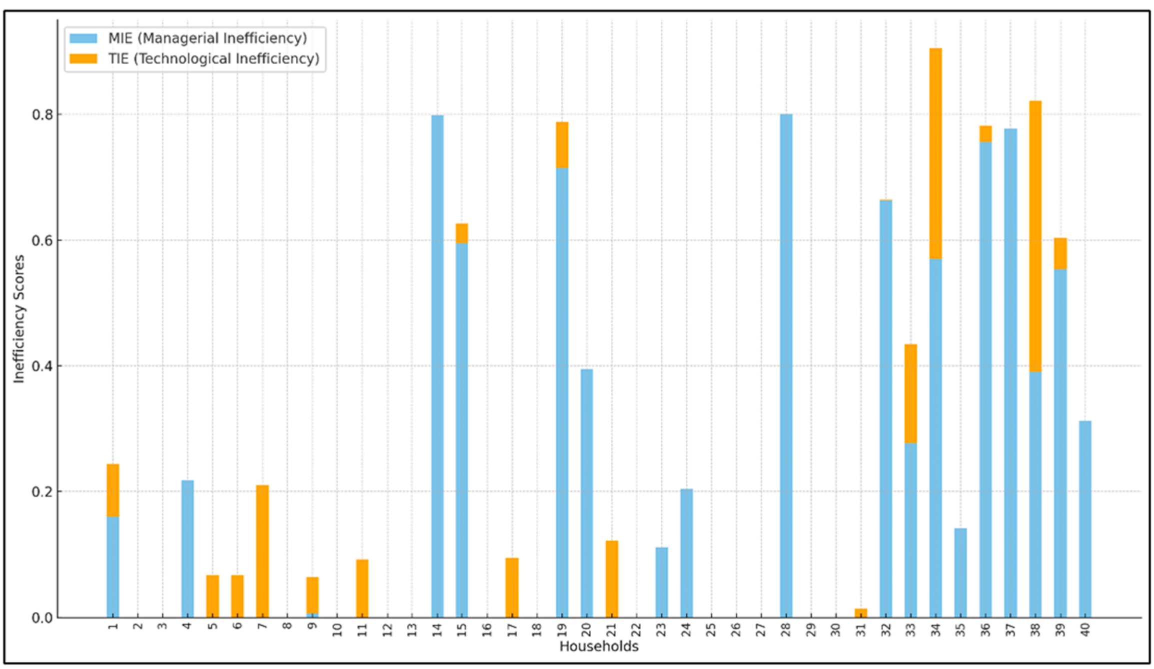

Fig. 9. Decomposition of Inefficiency in farm households

technological advancements to reach the meta-frontier. However, at the group-frontier level, where farm households share similar technologies, inefficiencies are generally linked to resource management. In this context, inefficient farm households should prioritize optimizing their resource use and improving managerial practices to enhance their overall performance. Type 1 include farm households 13, 22–30, and 40. Among them, farm households 23, 24, 28, and 40 are inefficient due to managerial issues rather than technological gaps. This suggests that their low efficiency scores within the type result from suboptimal resource allocation, ineffective management strategies, or lack of operational optimization, rather than a lack of access to advanced farming technologies.

Based on the study by Ding et al. (2020), our recommendations will follow a structured approach. If a farm household is found to be inefficient under the group-frontier, it should focus on improving its resource management practices to align more closely with the benchmarks established within its type. Conversely, if a farm household is efficient within its type but remains inefficient under the meta-frontier, it should work towards further enhancing its resource management to meet the broader overall benchmark, thereby improving its performance relative to all types.

4. Discussion

This study highlights significant inefficiencies in water use among different farm types in the Chtouka-Massa region, revealing crucial trade-offs between economic profitability and resource sustainability. Farm households engaged in intensive vegetables farming are strongly supported by public authorities in Morocco (El Ansari et al., 2020; Saoud, 2011). The GMP has prioritized the large-scale production of fruit and vegetables, with high-value crops such as early vegetables and citrus fruits primarily targeting export markets, thereby generating significant foreign currency revenues (Sraïri, 2021). However, some studies contend that the GMP overlooked the negative consequences of agricultural intensification and monoculture (Akesbi, 2015; Faysse, 2015). The specialization of crops, without diversification in crop rotation, can progressively increase their vulnerability to water scarcity.

In that sense, our findings showed that intensive vegetables farm households (Type 3) achieve the highest gross margins due to the profitability of these crops. However, based on our data analysis, they also exhibit the highest consumption of NPK fertilizers, permanent labor, land, and seeds. These results align with previous studies, which have also pointed out that while intensive vegetables farming can be economically profitable, it requires substantial input use and labor (El Ansari., 2018; Amichi et al., 2012). This type of farming faces sustainability challenges, especially in the context of climate change and water scarcity. Its heavy reliance on irrigation, specialization, and lack of crop diversification undermines the resilience of these agricultural systems in Morocco and other arid and semi-arid regions. This type of farm household also cultivates the largest agricultural areas, primarily dedicated to vegetables farming, often in greenhouses (Dugué et al., 2015). Their access to land is facilitated by subsidies and the relaxed regulations for land and water access introduced under the GMP, which aims to intensify agriculture as part of its broader objectives (Kuper and Molle, 2017).

Another critical aspect of our findings is that intensive vegetables farming heavily relies on desalinated water from the Agadir desalination plant, constructed under the GMP framework to reduce aquifer pressure. Although Type 3 farm households are highly intensive in terms of inputs (fertilizers, labor, seeds, land), their water use per hectare is lower than that of semi-intensive farm households of Type 2. This is largely explained by the much higher price of desalinated water compared to groundwater and by their stronger market orientation, which creates an economic incentive to control irrigation volumes and maximize water productivity. However, our results raise important concerns about the long-term sustainability of this approach. Morocco's strategy remains heavily supply-driven, prioritizing new water sources rather than implementing demand-side measures such as improved irrigation efficiency, crop rotation, and groundwater governance (Benblidia, 2011; Del Vecchio, 2020). Our study supports this critique by demonstrating that despite the introduction of desalination, Type 3 farms continue to exhibit unsustainable water use patterns. Furthermore, as previously highlighted by Lattemann and El-Habr (2009), seawater desalination has serious environmental externalities, including marine habitat disturbances and high energy consumption, leading to increased CO_2 and NO_x emissions. The environmental trade-offs of desalination must therefore be fully integrated into Morocco's water governance strategies to avoid exacerbating climate-related challenges.

The evaluation of the technical efficiency reveals that Type 3 farm housholds are the least efficient among the three types of agricultural systems, with an average TGR of 0.761. This inefficiency persists despite the use of drip irrigation for parcel irrigation, raising significant questions about the relevance of this technology. Our findings contribute to the ongoing debate about drip irrigation efficiency in Morocco where import taxes on micro-irrigation equipment have been reduced or completely eliminated since 1982 (Laamari et al., 2011), even though the role of drip irrigation in water conservation remains highly controversial. While widely promoted as a water-saving technology, its actual efficiency is often called into question. In practice, the efficiency of drip irrigation in farmers' fields frequently falls short of expectations due to several factors, including over-irrigation caused by uneven pressure and irregular dripper discharge, resulting from poor system design or inadequate maintenance. To compensate for these distribution problems and avoid crop stress, farmers often apply more water than required. In addition, inadequate irrigation scheduling, linked to a lack of knowledge or tools to match irrigation with crop water needs, further contributes to the reduced efficiency of drip systems (Benouniche et al., 2014). This technique has revealed significant environmental and social drawbacks. On the environmental scale, it has led to issues such as increased evapotranspiration, aquifer depletion, and higher crop density, which in turn result in greater water consumption (Molle et Tanouti, 2017).

For intensive vegetables farm households, it is crucial to raise awareness among farmers about the importance of sustainable water and resource management practices, emphasizing the efficiency of inputs to maintain profitability while protecting the environment (OECD, 2010). Farmers can improve water efficiency by understanding the factors that influence crop water requirements, allowing them to optimize irrigation schedules while adequately meeting crop needs (Tuninetti et al., 2015). Additionally, it is recommended to introduce crops that are less water-intensive and contribute to soil conservation.

Semi-intensive mixed cereals-vegetables farm households (Type 2) are the largest consumers of water, primarily sourced through groundwater pumping using private wells. This method of water access has been directly incentivized by substantial subsidies for wells and drilling provided under the GMP (Molle et Mayaux, 2023). Because groundwater is considerably cheaper than desalinated water, these farms face no effective economic limit on pumped volumes, which leads to higher water use per hectare compared to household farms of Type 3 that rely on costly desalinated water and therefore have a financial incentive to limit and optimize irrigation. Furthermore, the Moroccan Economic, Social, and Environmental Council (CESE) underscores that public authorities lack the capacity to implement effective measures to regulate groundwater extraction (Conseil Économique, Social et Environnemental (CESE), 2014). These private wells can be either authorized or unauthorized, and according to Molle and Mayaux (2023), only 10 % of wells are officially registered in Morocco. Our study provides new insights into this issue by demonstrating that Type 2 farms, despite their substantial water use, still face efficiency challenges, suggesting that water overuse is not necessarily linked to economic returns. This supports the argument that groundwater depletion in Morocco is driven by both policy incentives and weak enforcement mechanisms, reinforcing the need for stronger regulatory oversight.

In contrast, extensive cereal-arboriculture farm households (Type 1) operate with the lowest input intensities, making them most efficient in resource use, particularly in water, nitrogen, and labor and the most diversified in the region, but with the lowest net margins compared to the two other farm types. These household farms primarily rely on rainfed cereals cultivation and flood irrigation (basin) for arboriculture, leading to low water use but also low gross margins per unit of water. Their limited access to advanced irrigation technologies and strong dependence on family labor contribute to their lower efficiency scores in some cases. However, agricultural policies in Morocco, particularly the GMP, have not prioritized or promoted cereals cultivation, as it is considered less profitable and lacking high economic value. On the contrary, it has actively encouraged the conversion of cereal farmland to arboriculture (Saidi et al., 2023). Consequently, Morocco's cereals production has stagnated, showing little to no growth since the launch of the GMP (Bishaw et al., 2019). This has left the country heavily dependent on substantial cereal imports to meet its domestic demand (Sraïri, 2021). The key challenge for these agricultural systems lies in increasing their gross margins or income by improving access to nitrogen (Tilman et al., 2002), water, and labor. However, such an increase would likely come at the expense of their technical efficiency, as is the case for Type 2 farm households and Type 1 farm households.

The GMP has led to a major transformation in Moroccan agriculture by encouraging farmers, particularly those of Type 1, to shift from traditional cereal cultivation to higher-value crops. This program aimed to convert one million hectares of cereals farmland into fruit arboriculture (Agence pour le Développement Agricole (ADA), 2012). This transition has resulted in significant financial gains for farmers, reinforcing the adoption of intensive agricultural practices. However, this structural shift has also made it economically and practically challenging to revert to less intensive, traditional farming systems. Farmers who continue to rely on rainfed cereals cultivation face low profitability, despite their efficient use of natural resources, particularly water. While these traditional systems may be more sustainable from an environmental perspective, they do not generate sufficient income to remain competitive.

Given the challenges faced by different farm types, it is essential to consider climate adaptation strategies. The literature classifies these into three categories: expansive, which aims to increase production efforts (e.g., developing new water sources such as desalinated water); accommodating, which focuses on changing and adopting new water management practices; and contractive, which seeks to reduce resource use (Wheeler et al., 2013). Based on these three categories, our study focuses on accommodating strategies. For farm types 2 and 3, we propose implementing crop rotation with less water-intensive crops, introducing new drought-resistant varieties, and promoting diversification (Deressa et al., 2009).

5. Conclusion

This study provides a comprehensive analysis of groundwater resource management and water use efficiency in agricultural systems in Morocco's Chtouka-Massa region, a critical area facing increasing water scarcity and aquifer depletion. Using a meta-frontier approach combined with Data Envelopment Analysis, we assessed the efficiency of three distinct farm households' types: extensive cereal-arboriculture farm households (Type 1), semi-intensive mixed cereal-vegetable farm households (Type 2), and intensive vegetables farm households (Type 3). Our findings reveal significant trade-offs between economic profitability and resource efficiency. Type 3 farm households, while generating the highest gross margins, suffer from low efficiency, driven by high input consumption, labor demands, and reliance on costly desalinated water. Type 2 farm households show moderate efficiency but are the largest consumers of groundwater, exacerbating aquifer depletion. Type 1 farm households, though the most resource-efficient, struggle with low profitability, limiting their economic viability. The meta-frontier DEA analysis further revealed technological disparities across these farm households' types, quantified through the TGR. While extensive farm households operate at their full technological potential, intensive farm households display significant inefficiencies due to structural and technological constraints. The decomposition of inefficiencies into TIE and MIE suggests that resource optimization and improved management practices could significantly enhance farm households' performance. The results underscore the limitations of the GMP, which prioritized agricultural intensification and export-oriented production without fully addressing the long-term sustainability of water resources. Policies encouraging monoculture, high-input farming, and subsidized groundwater extraction have intensified environmental pressures and widened the technological gap between farm households' types.

By combining farm typology with efficiency analysis, this study contributes new empirical evidence to the debate on agricultural sustainability in the dryland regions. Unlike previous research that has primarily focused on groundwater depletion (Hssaisoune et al., 2020) or policy assessments (Moha et al., 2016), our study bridges the gap by quantifying the efficiency trade-offs associated with different farming systems. Our findings underscore the urgent need for integrated policies that balance economic viability with resource sustainability, ensuring that Morocco's agricultural sector remains resilient in an era of increasing water scarcity. The results of this study can serve as a foundation for discussions with policymakers and local stakeholders to define strategies for more efficient and sustainable production systems that consider both farm household viability and environmental sustainability.

6. Limitations and future research

This study provides new empirical insights into the efficiency of farming systems and water use in Morocco's Chtouka-Massa region, yet several limitations should be acknowledged. The sample size is relatively small (40 households), which may not fully capture the diversity of practices in the area. Survey data can also be affected by recall or reporting bias, although we cross-checked responses with official statistics. Methodologically, DEA and the meta-frontier approach do not separate inefficiency from external shocks, and the TGR indicator does not explain the drivers of technological gaps. Future studies could combine DEA with stochastic models (e.g., SFA) and use direct water-use measurements to improve robustness. Finally, the analysis focuses mainly on technical and economic efficiency and does not fully address long-term environmental sustainability (e.g., soil health, emissions, biodiversity). Including these aspects in future research would provide a more comprehensive evaluation of farming systems under water scarcity. Finally, these findings are not limited to the case study of the Chtouka-Massa plain and could be adapted to other dryland regions in the South Mediterranean facing similar agricultural and water management challenges.

CRediT authorship contribution statement

Nour Nsiri: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Georgios Kleftodimos:** Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Sophie Drogué:** Writing – review & editing, Validation, Supervision, Software, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests. Nour Nsiri reports financial support was provided by AgreeMed Project. 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.

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Appendix A

Table 4
Loadings and percentage of the cumulative variance explained of 21 variables on the five components

Eigen value	**6.61**	**2.78**	2.41	1.79	1.48
Variance (%)	31.47	13.25	11.51	8.54	7.07
Cumulative variance (%)	31.47	44.73	56.24	64.78	71.86
Variable	**Dim 1**	**Dim 2**	**Dim 3**	**Dim 4**	**Dim 5**
SIP	**0.78**	−0.22	−0.50	0.02	0.19
total_quantity_with_rain	**0.57**	0.43	0.31	0.47	0.09
gross_margin_unit_deau	**0.63**	−0.14	**0.58**	−0.35	0.02
TWC	**0.74**	−0.17	0.30	0.19	0.42
priv_well	0.43	0.10	0.31	**0.79**	−0.07
Dam	0.07	**0.65**	−0.22	−0.26	0.10
desali	0.35	−0.29	0.49	−0.44	0.41
%_gag	**0.79**	0.37	0.02	−0.14	−0.35
%sur	−0.54	−0.27	0.01	0.29	0.43
%asp	−0.04	**0.71**	−0.15	−0.13	0.36
Cereals	−0.20	**0.66**	−0.02	0.24	**0.54**
Veg	**0.78**	−0.32	−0.47	−0.04	0.08
Arbo	−0.37	−0.26	−0.03	0.04	0.05
see_co_ha	**0.65**	−0.04	−0.37	0.13	0.04
total_labour_farm	0.41	**0.64**	−0.08	−0.32	−0.06
family_labour_(person/year/ha)	**−0.63**	−0.25	−0.03	−0.00	0.13
seas_lab	**0.57**	−0.25	−0.35	−0.02	0.08
NPK	**0.59**	0.00	0.19	0.35	−0.38
Fumier	0.10	0.07	−0.04	−0.08	−0.27
gross_margin_(MAD/ha)	**0.61**	−0.09	**0.64**	−0.24	0.14
Area	**0.76**	−0.23	**−0.51**	0.01	0.19

Note: Bold numbers refer to loadings higher than 0.5

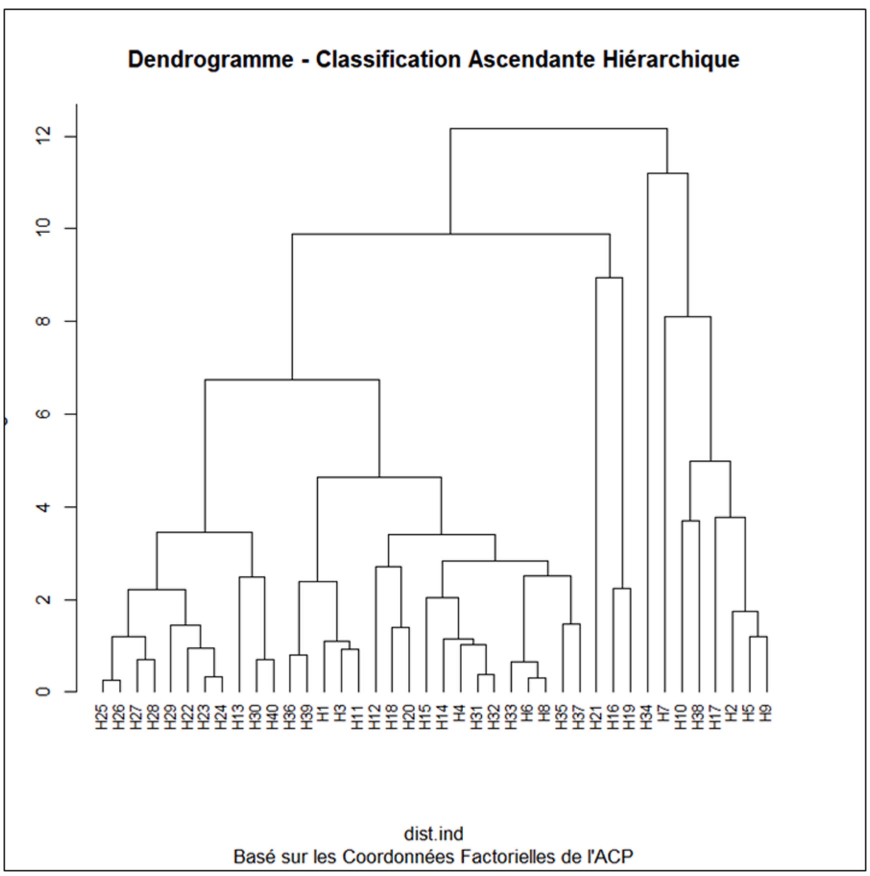

Fig. 5. Dendrogram of individuals from Agglomerative Hierarchical Clustering based on PCA factorial coordinates

Table 6
Technical Inefficiency Results

Household	Meta_Frontier	Group_Frontier	TIE	MIE	OI
1	0.756	0.84	0.08	0.16	0.24
2	1.0	1.0	0.0	0.0	0.0
3	1.0	1.0	0.0	0.0	0.0
4	0.782	0.782	0.0	0.21	0.21
5	0.933	1.0	0.06	0.0	0.06
6	0.933	1.0	0.06	0.0	0.06
7	0.789	1.0	0.21	0.0	0.21
8	1.0	1.0	0.0	0.0	0.0
9	0.936	0.994	0.05	0.006	0.06
10	1.0	1.0	0.0	0.0	0.0
11	0.908	1.0	0.09	0.0	0.09
12	1.0	1.0	0.0	0.0	0.0
13	1.0	1.0	0.0	0.0	0.0
14	0.201	0.201	0.0	0.798	0.79
15	0.374	0.405	0.03	0.595	0.626
16	1.0	1.0	0.0	0.0	0.0
17	0.906	1.0	0.09	0.0	0.09
18	1.0	1.0	0.0	0.0	0.0
19	0.212	0.285	0.07	0.71	0.788
20	0.605	0.605	0.0	0.395	0.395
21	0.878	1.0	0.122	0.0	0.122
22	1.0	1.0	0.0	0.0	0.0
23	0.889	0.889	0.0	0.11	0.11
24	0.796	0.796	0.0	0.20	0.20
25	1.0	1.0	0.0	0.0	0.0
26	1.0	1.0	0.0	0.0	0.0
27	1.0	1.0	0.0	0.0	0.0
28	0.199	0.199	0.0	0.80	0.80
29	1.0	1.0	0.0	0.0	0.0
30	1.0	1.0	0.0	0.0	0.0
31	0.986	1.0	0.014	0.0	0.014
32	0.336	0.337	0.001	0.663	0.664
33	0.565	0.723	0.158	0.277	0.435
34	0.095	0.43	0.334	0.570	0.905
35	0.858	0.858	0.0	0.142	0.142
36	0.218	0.244	0.025	0.756	0.782
37	0.223	0.223	0.0	0.777	0.777
38	0.178	0.609	0.431	0.391	0.82
39	0.396	0.446	0.049	0.554	0.604
40	0.688	0.688	0.0	0.312	0.312

Data availability

Data will be made available on request.

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