



Sustainability indicators and data management for small-scale agricultural systems: the case of water resources

Elena Sánchez-Arnau¹ · Antonia Ferrer-Sapena¹ · Maria Carmen Cárcel-Mas¹

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Abstract

The management of non-industrial farming sites often lacks context-specific indicators that allow effective planning. Identifying reliable measures suited to small-scale agriculture (especially in settings with unique features such as suburban orchards) is therefore crucial for their viability. In this paper, we systematically review the indicators that can be applied in such contexts and compare them with those used in similar environments. Because the number of possible indices is as wide as the dimensions involved (social, economic, geographical, water, etc.), we narrow our scope to indicators related to sustainability and water resources. By analyzing several published time series, we show that many of these indices are strongly correlated, so tracking just one or two of them is normally sufficient, a simplification that greatly eases management in low-resource settings. We also point out that many variables can be obtained from open-data repositories or other easily accessible sources, so that producers with limited budgets can monitor the most relevant information without investing in costly data-collection systems. The literature suggests that this reduction could likewise apply to other sustainability factors.

Keywords Agriculture · Sustainability · Indicator · Local · Aggregation

Introduction

The growing interest in sustainability in agriculture has led to the emergence of various indicator-based assessment tools, designed primarily for the diagnosis and monitoring of farming systems. In the last 20 years, a new generation of composite indices has appeared as an attempt to organize the large amount of available data into actionable information for decision-making, yet there is still no consensus on a single standard (Lampridi et al. 2019; Talukder et al. 2020). These tools typically aggregate individual indices into a single

diagnostic framework (Booyesen 2002; Jiménez-Fernandez and Ruiz-Martos 2020; Greco et al. 2019). However, even these simplified frameworks remain out of reach for many end users: small producers often lack the technical, financial, and organizational capacity to process the data released by governments and multilateral bodies, so the promise of open data as a democratizing force has failed in many cases (Fairbairn and Kish 2023). As a result, predictive models and market information become tools available only to large corporations, marginalizing family farms and local food systems (Ferrer-Sapena and Sánchez-Arnau 2023). Working with concise, context-specific indicators offers a constructive way forward.

In this paper, we adopt a broad diagnostic perspective across the three recognized sustainability dimensions (environmental, economic, and social) while placing special emphasis on environmental impacts. We first provide a general overview of indicator-based approaches across all three dimensions, in order to establish the conceptual framework needed to understand what can be reduced and why. We then focus on a concrete case study: indices related to water resources, which serve as a representative domain for demonstrating that a drastic reduction in the number of monitored indicators is both mathematically justified and practically

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✉ Antonia Ferrer-Sapena
anfersa@har.upv.es

Elena Sánchez-Arnau
esanarn@upv.edu.es

Maria Carmen Cárcel-Mas
macarm10@upv.es

¹ University Institute of Pure and Applied Mathematics (Instituto Universitario de Matemática Pura y Aplicada), Polytechnic University of Valencia (Universitat Politècnica de València), Camino de Vera s/n, Valencia 46022, Valencian Community, Spain

feasible. Many sustainability indices convey overlapping information (Bathaei and Štreimikienė 2023); collecting a wide array of them demands substantial resources that small farms rarely possess. By analyzing water-related indices, we show that most are strongly correlated, meaning that monitoring one or two key indices is usually sufficient.

To this end, we apply two main mathematical tools—correlation analysis and principal component analysis (PCA), both well established for the analysis of indices and the construction of composite indicators (OECD and European Commission, Joint Research Centre 2008; Gómez-Limón and Sanchez-Fernandez 2010), although their application to water resource management at the level of small agricultural producers remains relatively unexplored (Jia et al. 2016; Li et al. 2017). We analyze time-series water data from several countries, drawing on both scientific studies and the FAO AQUASTAT database. Reducing the set of key variables to monitor can simplify and democratize the use of data; showing how to achieve this in the context of water resource management is the main contribution of this paper.

Theoretical background and literature review

In this section, we present the key concepts and discussion points surrounding the sustainability of agricultural activities. Together with these fundamental ideas, we provide an overview of the current state of research in the field, highlighting the main approaches and contributions that shape the academic and practical understanding of the topic today.

Approaches to agricultural sustainability assessment: indicators and frameworks

Although sustainability assessment in agricultural and food production is now a primary concern, standardized methodologies for its measurement are still lacking. The process of measuring sustainability through the definition of information indices was already a widespread practice at the beginning of the century. Early contributions to environmental indexing, such as the work (Sands and Podmore 2000), provided a quantitative foundation that could be adapted to local scales, making possible assessments that are sensitive to regional characteristics. Although these early indices often focused mainly on environmental data, they laid the groundwork for more context-specific and local frameworks. Nowadays, many approaches emphasize the need to integrate environmental, social, and economic factors, but it is still difficult to find a way to synthesize these ideas, already established in the initial 2000s (Morse et al. 2001). As often happens with scientific and technological advances, several methodologies have been developed to structure

indicator-based assessments (among other methods), each with varying degrees of contextual adaptation and theoretical foundation. These procedures usually aim to involve at least some of the stakeholders interested in the issue (such as scientists, farmers, policymakers, and others), who are assumed to participate in designing, developing, and evaluating potential solutions.

From an indicators-based approach, the main issue is the selection and prioritization of indicators, which have to comprehensively cover all aspects related to the problem. Although the initial analyses generally consider the three main dimensions (environmental, economic, and social), the specific approaches often depend on where the focus is placed. For example, the use of materiality analysis has been proposed as a viable method to align indicator selection with stakeholder concerns and contextual relevance. For example, in the case study (Whitehead 2017) on the wine industry in New Zealand, this technique is shown to be effective in identifying high-priority sustainability issues, revealing in that case an emergent trend to prioritize environmental indicators over economic and social ones.

Due to this state of the art, in which the search for good measurement instruments continues, the analysis of indices, reduction of redundant fundamental sets of indicators, and development and validation of composite indices can play a meaningful role in ensuring robust assessments. This also allows for adaptation to particular settings, which may differ significantly from other contexts, as in the case of the study (Valizadeh and Hayati 2021). In it, a multi-dimensional index tailored to Iranian wheat farms is proposed, combining factors such as social equity, durability, and productivity. This study demonstrates that a reliable methodology necessitates rigorous interpretation, validation, and critical analysis. When handling composite information, adhering to a clear methodological path grounded in the scientific method is vital; consequently, a drastic reduction of indices is often the most effective solution to simplify both computation and interpretation.

Similarly, in Movilla-Pateiro et al. (2021), it is argued that harmonizing sustainability indicators is crucial to support comparability across studies and reduce the dispersion of non-integrated information that could lead to analytical confusion. The authors of this paper also claim the need for consensus on the conceptualization of agricultural sustainability and emphasize the role of stakeholder participation in indicator development, especially at the local level. Essentially, the same ideas appear in Perrin et al. (2023), which highlights the relevance of integrating sustainability assessments into innovation design, while remarking that this process requires careful consideration of local dynamics and actor engagement throughout agri-food systems. Moreover, the social dimensions of sustainability, often underrepresented, are gaining increasing attention. For example, in the

context of family farmers (an area explored in the following sections), the work by Wohlenberg et al. (2022) highlights the importance of capturing the lived experiences and economic conditions of these farmers. Indicators cannot be assumed to be simple numerical measures of data-driven information; they must also reflect outcomes or practices, the well-being of human actors, and social aspects such as resilience, equity, and adaptive behavior. In this sense, sustainability encompasses more than purely ecological or economic metrics. Thus, well-founded agricultural sustainability assessment requires balancing methodological robustness with local and social relevance. A synthesis of validated indicators, stakeholder-driven prioritization, and flexibility to adapt to diverse agroecosystems is needed. The integration of all these factors is necessary for a well-established analytical methodology. In addition, providing a simple synthesis of indicators sufficient for efficient farm management is fundamental to democratizing their use and facilitating the decision-making of small farms.

The social dimension of sustainability

The sustainability of agricultural systems has traditionally focused on (primarily) environmental and (secondarily) economic dimensions. However, recent research has emphasized the essential role of social sustainability, especially in small-scale and local contexts such as those considered in this paper (Brennan et al. 2023; Janker and Mann 2020; Sannou et al. 2023). Family-based farming, as well as smallholder farming in general, contributes significantly to food production, as well as to social welfare and the cultural preservation of traditional ways of life. Therefore, social indicators are fundamental elements in the analysis of sustainability frameworks.

Thus, going beyond physical metrics and incorporating community-based indicators such as well-being, equity, and participation is fundamental for measuring sustainability issues in any context. For instance, Brennan et al. (2023) introduce quality of life and farmer well-being measures into sustainability indicators, showing that productive output alone is insufficient to characterize sustainable agriculture (see also Sannou et al. 2023). On the other hand, Janker and Mann (2020) analyze existing sustainability assessment tools, noting that many of them still marginalize social aspects, primarily due to the complexity of measuring quantities often influenced by subjective factors, and more generally, due to the lack of standardized frameworks. A holistic approach that considers the diversity of agricultural systems is therefore required. As will be seen in the next section, this complexity is particularly evident in studies of small-scale farming systems, where local context and subjective perceptions play a key role.

More methodological approaches can also be found in the scientific literature. For example, Franks and Frater (2013) adopt a pragmatic perspective and argue for the development of practical assessment tools at the farm level that balance completeness with usability. Their work supports the idea that sustainability assessments must be adapted to the operational realities of farmers and should be designed to provide actionable feedback. Similarly, Talukder et al. (2020) call for a shift towards complex models relating ecological, economic, and social subsystems. This is the reason why many authors (Movilla-Pateiro et al. 2021) propose the creation of composite indicators that are sensitive to regional variation while allowing comparison and benchmarking, as well as incorporating social and physical factors.

The relevance of these issues is particularly evident in local studies, such as the work by Puerto et al. (2021) on irrigation communities in Eastern Spain. We build upon their methodology. Complementing this perspective, making information truly useful for producers requires a deep integration of social dimensions. Beyond merely including social indicators, research results, and technical data must be tailored to the specific social environment of the users. In the same way that water resources are analyzed in our study, such adaptation requires a process of simplification to provide practical and accessible tools to small-farm managers.

Sustainability in small-scale agricultural production

As a particular case of what are considered agricultural production centers, small-scale agriculture plays a vital role in food security, rural livelihoods, and environmental stewardship, particularly in developing regions. Considering the total number of productive food centers, the majority of global food production corresponds to this type of installation. In fact, small farms, often family farms, are fundamental to global food production, although the precise estimation of their contribution varies. A 2018 study on global food security (Ricciardi et al. 2018) estimates that farms of less than two hectares produce between 28% and 31% of total crop production and between 30% and 34% of the global food supply, using 24% of the gross agricultural area. The FAO, through various reports and press releases, corroborates the importance of these farms, noting that although the figure of 70–80% has become popular, more recent and detailed research tends to place the contribution of small farms at around a third of the global total of food, while family farms (of any size) produce around 80% of the world's food (Food and Agriculture Organization of the United Nations (FAO) 2021; Ricciardi et al. 2018). The disparity in these numbers highlights the complexity of defining and quantifying small-scale production.

Focusing on small-scale farms, scientific studies on global food production consistently highlight that the sustainability

of these systems is based on a delicate interplay of economic, environmental, and social dimensions. This mirrors the general case analyzed earlier in this section. However, there is interest in the construction of specific sustainability indices for small-scale production. For example, in India, Chand et al. (2015) developed a composite sustainability index tailored to small-holder dairy farms in Rajasthan. Their analysis revealed that ecological indicators generally outperformed both economic and social indicators, with the size of the herd having a substantial effect on economic sustainability. This suggests that targeted improvements in herd and input management could improve long-term viability. Also, due to the broad diversity of cases involved in such kind of productive centers, the methods used for defining appropriate indicators vary depending on the context and the particular issues found in different environments. Thus, in Timor Leste, Moore et al. (2014) investigated the sustainability of small-scale farms through surveys and interviews. Their study emphasized the importance of integrating cultural values and local knowledge into agricultural development frameworks, identifying social cohesion and resource sharing as key enablers of sustainable outcomes.

Another interesting case of fusion between the need for food, traditional production, and the modern urban life has produced a fundamental class of production nowadays, usually labeled as urban agriculture. This kind of activity was assessed in McDougall et al. (2019), where it is reported that small-scale urban farming can achieve high yields with limited land use. However, they stress the importance of optimizing input management to avoid environmental trade-offs, thereby demonstrating that urban settings can host productive and sustainable agriculture with appropriate oversight. This case is particularly relevant for our analysis, that is focused on a suburban traditional environment, that is in the way of redefining its position in the production chain of food and the modern economical requirements of the global food economy.

On a broader scale, considering the general case of constructing a model that could be useful across different scales, Ren et al. (2019) analyzed the relationship between farm size and sustainability in China, reaching conclusions that challenge the usual way of understanding the problem. Their study found that larger farms tend to be more efficient and environmentally sound, challenging the traditional narrative that smaller is inherently more sustainable. Still, small farms can outperform when supported by effective policy measures and cooperative structures. In our case, this higher sustainability must be preserved in the context of the Valencian orchard, since this is one of the key arguments for its preservation as a suburban productive area. It is important to note that there is significant residential pressure on this zone, as in many suburban areas in developed countries, and its survival depends on a subtle equilibrium between economic factors

and citizen welfare. In this direction, in the European context, Guth et al. (2022) evaluated the technical efficiency and environmental impact of small family farms. Taking into account the fact that the Common Agricultural Policy (CAP) is one of the main pillars of strength of the European Union, their findings reinforce the idea that policy support plays a vital role in balancing environmental stewardship and economic viability for small-scale producers.

Ensuring the future sustainability of small-scale agriculture requires inclusive innovation, institutional reform, and digital infrastructure (Woodhill et al. 2020). Achieving this also demands integrated frameworks that consider local contexts and actively include smallholders in policy design. Indeed, it is now necessary to recognize that the sustainability of small-scale agricultural production is highly context-dependent. Adaptive strategies, advanced technologies, and policy environments that actively support farming activities can significantly improve the long-term viability of these systems. Given the high diversity of situations, further research should focus on region-specific sustainability frameworks that integrate economic and socio-environmental indicators, facilitating resilient agricultural development across diverse settings.

Methods

In this section, we describe the tools used for our analysis. We employ conceptual elements to define the context, indices, and numerical descriptive instruments for the agricultural systems, and the mathematical tools applied in the next section.

Indicators and indices for agricultural sustainability

In what follows, we draw a general picture of sustainability indicators in agriculture. A comprehensive assessment requires attention to all three dimensions (environmental, economic, and social Bathaei and Štreimikienė 2023; Movilla-Pateiro et al. 2021), but any practical monitoring scheme must finally be grounded in a small set of concrete, measurable indices. A broad overview of the available indicators is nevertheless useful here, as it provides the context needed to appreciate the scope of the reduction we propose and to understand why the water resource domain is a representative and informative case study for illustrating it. In what follows, we briefly describe the indicators typically used within these categories, drawing on the literature reviewed in “[Theoretical background and literature review.](#)”

- 1) Environmental indicators focus on the ecological impact of farming practices (Sands and Podmore 2000). Water

use efficiency, defined as the amount of water used relative to the production obtained, is among the most widely reported. The use of fertilizers and pesticides accounts for the quantity and type of chemical inputs applied and their environmental consequences. Greenhouse-gas emissions—mainly methane and nitrous oxide—quantify the contribution of agriculture to climate change. Soil conservation is evaluated through erosion rates, salinity, and organic matter content, while biodiversity is assessed via crop diversity, fauna and flora management, and the preservation of surrounding natural ecosystems. Although agriculture inherently modifies natural environments, careful monitoring of these indicators can support the transition toward systems that balance productivity with long-term ecological health.

- 2) Economic indicators assess the financial viability of agricultural systems (Gómez-Limón and Sanchez-Fernandez 2010; Valizadeh and Hayati 2021). Crop productivity measures yield per hectare or per unit of input, and energy use efficiency expresses the ratio of energy consumed to the production obtained. Economic profitability compares net benefits against total production costs, including income and input expenses, and is closely related to the cost-benefit ratio, which evaluates economic returns against the resources invested.
- 3) Social indicators reflect the human and community dimensions of sustainability, an aspect that has gained increasing attention in recent research (Brennan et al. 2023; Janker and Mann 2020). Labor conditions capture the quality of life for workers, including fair wages and workplace safety. Food security assesses access to sufficient and quality food for both producers and the general population. Community participation measures farmer involvement in local organizations and cooperatives, gender equity addresses decision-making access and resource distribution between men and women, and rural well-being integrates the broader impact of agricultural activities on the quality of life in rural communities.

Regarding small-scale agriculture, the analysis of sources discussed in “[Sustainability in small-scale agricultural production](#)” suggests a reduction of the most relevant indicators for locally oriented agriculture. The selection that follows is grounded in the following criteria, drawn from the literature. First, indicators are retained when they directly capture on-farm resource efficiency, ecological resilience, or livelihood outcomes, since these are the dimensions most consistently reported as critical for smallholder viability (Bathaei and Štreimikienė 2023; Hoover et al. 2023). We also prioritize indicators for which data are accessible through open repositories or low-cost measurement, given the limited technical and financial resources of small producers (Fairbairn and

Kish 2023; Gómez-Limón and Sanchez-Fernandez 2010). Finally, we exclude indicators that are highly correlated with others already in the set, in line with the redundancy analysis presented in “[Results: case studies on water resource indicators](#)” (Bathaei and Štreimikienė 2023). Applying these criteria to the indicator sets reviewed in “[Sustainability in small-scale agricultural production](#),” the following stand out as the most informative and practical for smallholder systems focused on local production and short supply chains.

- Water use efficiency and soil conservation, because water availability and soil health strongly limit productivity on small plots.
- Biodiversity, as diversified cropping systems enhance resilience, reduce input needs, and open local market niches.
- Crop productivity and economic profitability, measured at the scale of individual holdings; although these two indicators are often correlated, both are retained here because they capture distinct dimensions of viability (physical output and financial return) that are relevant for different types of management decisions.
- Food security and community participation, which reflect the direct contribution of small farms to local diets and the strength of farmer networks that facilitate knowledge exchange and collective marketing.
- Gender equity, given the frequent involvement of family labor and the need to recognize women’s decision-making roles in smallholder contexts.

Focusing on this reduced set avoids redundancy among highly correlated indicators, streamlines data collection, and highlights the specific sustainability levers that matter most in local, small-scale agricultural systems. Although the next section continues to explore general aspects and relevant variables, the one that follows will focus specifically on the first item listed above: water use efficiency.

Indicators enable a comprehensive assessment of agricultural sustainability, integrating productive performance with environmental protection and social well-being. General frameworks for their construction and selection are provided by the OECD Handbook on composite indicators (OECD and European Commission, Joint Research Centre 2008) and the systematic reviews of Bathaei and Štreimikienė (2023) and Movilla-Pateiro et al. (2021). In what follows, we present a selection of numerical indices drawn from the scientific literature, developed to quantify sustainability in agriculture across its three main dimensions (environmental, economic, and social). These indices allow for comparative analysis and continuous monitoring of agricultural systems and constitute the basis for the indicator scheme adopted in this paper. The most commonly used measurement categories in each dimension are summarized in Table 1 and described

Table 1 Main sustainability indices used in agricultural systems

Dim.	Index	Description	Ref.
Env	Carbon footprint	GHG emissions generated by agricultural activities, expressed in CO ₂ equivalent; useful for quantifying climate impact	Pandey and Agrawal (2014); Poore and Nemecek (2018)
Env	Water productivity	Agricultural output per unit of water consumed (kg/m ³); measures water use efficiency in production	Hoover et al. (2023); Puerto et al. (2021)
Env	Fertilizer and pesticide	Amount of chemical inputs applied per hectare relative to optimal usage standards; indicates sustainability of input management	Sabiha et al. (2016)
Env	Soil health and quality	Composite of organic matter content, water retention capacity, and erosion rates; determines soil quality and long-term productivity	Karlen et al. (1997); Andrews et al. (2004)
Econ	Total factor productivity	Ratio of total agricultural output to all productive inputs (land, labor, capital, materials); measures overall resource efficiency	Coelli and Prasada Rao (2005)
Econ	Profitability	Net farm income relative to total production costs; assesses economic viability at the farm level	Gómez-Limón and Sanchez-Fernandez (2010)
Econ	Energy efficiency	Ratio of energy obtained (calories or biomass) to energy consumed (fuels, electricity) in the production process	Hoover et al. (2023)
Social	Rural well-being	Integrates family income, access to basic services (health, education), and living conditions in rural areas	Brennan et al. (2023); Wohlenberg et al. (2022)
Social	Food security	Assesses access to and availability of sufficient, nutritious food for the local population based on yields and distribution	Talukder et al. (2020); FAO (2023)
Social	Community participation	Level of farmer involvement in cooperatives, community networks, and agricultural policy decisions	Movilla-Pateiro et al. (2021); Janker and Mann (2020)
Social	Gender equity	Equity in access to resources, opportunities, and participation in decision-making between men and women	Perelli et al. (2024)

in what follows. The concepts listed in this table represent the most frequently addressed sustainability dimensions in the agricultural literature; for each of them, multiple numerical indices have been proposed and validated in different contexts. A comprehensive survey of such indices and their relative prevalence can be found in Bathaei and Štreimikienė (2023).

To finish this section, we mention some composite indices found in the literature that aim to provide a unified perspective on the problem. Following the ideas on composite indices introduced in the introductory section, the use of such numerical tools seeks to simplify information management (Hoover et al. 2023). Some examples of these composite indices are the following.

The Agricultural Sustainability Index (SAI) combines environmental, economic, and social indicators to provide an integrated measure of the sustainability of an agricultural system (Valizadeh and Hayati 2021). The Composite Environmental Impact Index (CEII) focuses more specifically on

the physical aspects of the problem, using a combination of factors such as natural resource use, emissions, and biodiversity impact to assess the overall environmental impact of an agricultural operation (Sands and Podmore 2000). Finally, the Agricultural Ecological Footprint Index quantifies the amount of land and water required to sustain agricultural activities based on available resources.

These indices allow for numerical and objective evaluations, facilitating comparisons between regions, production systems, or time periods, and supporting decision-making in the context of sustainable policies and practices. However, they are built by integrating information from multiple sources through various mathematical formulas. Therefore, although they offer a synthetic way of presenting information on specific or general aspects of sustainability, their construction relies on a methodology opposite to the one proposed in this paper. Computing them requires complete (and often technically complex) procedures to obtain all the individual indices needed to calculate the aggregated ones. We provide

a concrete example of this analytical approach in the next section.

Mathematical approach and specific tools

The analysis carried out in this paper relies on two standard multivariate statistical tools: correlation analysis (Johnson and Wichern 2007) and principal component analysis (PCA) (Jolliffe 2002). Both are applied to time series of sustainability indices in order to assess the degree of redundancy among them and to identify a minimal representative subset.

Given a set of n indices observed over T time periods, each index defines a vector in \mathbb{R}^T . The Pearson correlation coefficient between two indices x and y is defined as

$$r(x, y) = \frac{\sum_{t=1}^T (x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^T (x_t - \bar{x})^2} \sqrt{\sum_{t=1}^T (y_t - \bar{y})^2}}, \quad (1)$$

where \bar{x} and \bar{y} denote the respective sample means. Values of $|r|$ close to 1 indicate near-perfect linear dependence between two indices, implying that one of them conveys no additional information beyond the other. In our analysis, we use the threshold $|r| > 0.85$ as a practical criterion for identifying redundant pairs (Bathaei and Štreimikienė 2023; Hoover et al. 2023).

PCA provides a global assessment of the dimensionality of the indicator set (OECD and European Commission, Joint Research Centre 2008; Gómez-Limón and Sanchez-Fernandez 2010). Given the $n \times T$ data matrix X (after standardization), PCA computes the eigendecomposition of the correlation matrix $R = \frac{1}{T} X X^T$. The resulting eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$ measure the variance explained by each principal component, and the proportion of total variance captured by the first component is given by

$$\pi_1 = \frac{\lambda_1}{\sum_{i=1}^n \lambda_i}. \quad (2)$$

When π_1 is close to 1, the dataset is essentially one-dimensional: a single composite index derived from the first principal component suffices to represent the information contained in the full set. The degree of multicollinearity can also be assessed directly from the eigenvalue spectrum: if all but the first eigenvalue are close to zero, the indicator vectors lie in a near-one-dimensional subspace, confirming that the set is highly redundant.

These two tools are complementary: correlation screening identifies redundant pairs and produces an interpretable reduced dashboard, while PCA provides a formal, variance-based justification for the dimensionality reduction. In each case study, the indices compared are represented as time-series vectors, which are then analyzed to determine whether their behavior follows a common pattern. We first compute

correlation matrices to reveal redundancy, supported by heat maps and other plotting tools, and then apply PCA to show that the time series can typically be described by one or two parameters. The common conclusions that can be extracted across case studies are discussed in the Discussion section.

All statistical analyses were carried out in R version 4.3. Pearson correlation matrices were computed using the base function `cor()` with the default method (`method = "pearson"`). Principal component analysis was performed using `prcomp()` with standardized data (`scale. = TRUE`), along with standard auxiliary functions for output formatting and plotting.

Results: case studies on water resource indicators

In this section, we present four case studies focused on water resource-related indices for analyzing sustainability in specific regions around the world. All of them show a high degree of redundancy, as demonstrated by analyzing the time series they define. In particular, the vectors that describe the local behavior of different indices over time are strongly correlated. This essentially means that using just one indicator is usually sufficient.

Fruit-tree orchards in the Valencian Community (Spain)

The following Table 2 has been constructed using the information of Puerto et al. (2021). The selection of indicators is assumed to be adequate for the aim of having a precise idea of the efficient use of water resources, as well as a time series representing the evolution of this efficiency.

Table 3 and Fig. 1 show the time series that can be found in this study. We analyze the series in what follows.

Both the *Relative Irrigation Supply* (RIS) and the *Relative Water Supply* (RWS) show a gradual decrease over the 5-year period, indicating a progressive alignment between the water supplied (either through irrigation or in combination with rainfall) and the actual crop water requirements (ETc). Simultaneously, the *Water Productivity* (WP) and *Irrigation Water Productivity* (IWP) indicators exhibit a modest but steady increase, reflecting a more efficient transformation of water into yield. This trend is reinforced by the economic indicators: both the *Gross Value Water Productivity* (GWP) and the *Gross Value Irrigation Water Productivity* (GIWP) have increased significantly, suggesting that the water applied—especially through irrigation—is producing higher economic returns per unit.

The mathematical analysis of these indicators given in Table 4 shows that, although they give different information,

Table 2 Irrigation performance and water productivity indicators

Indicator	Formula	Meaning	Interpretation
RIS	$RIS = \frac{I}{ET_c}$	Ratio of irrigation water applied to the crop water requirement (ETc)	RIS =approx= 1 indicates adequate irrigation; RIS > 1 suggests over-irrigation; RIS < 1 indicates deficit
RWS	$RWS = \frac{I+P}{ET_c}$	Total water supply (irrigation + precipitation) relative to ETc	Measures if total available water meets the crop demand
WP	$WP = \frac{Y}{ET_c}$	Yield per unit of crop water requirement (ETc)	Indicates physiological efficiency of water use (potential productivity)
IWP	$IWP = \frac{Y}{I}$	Yield per unit of irrigation water applied	Reflects productivity of the actual irrigation applied
GWP	$GWP = \frac{GV}{ET_c}$	Gross value per unit of crop water requirement	Evaluates economic return from optimal water use
GIWP	$GIWP = \frac{GV}{I}$	Gross value per unit of irrigation water applied	Assesses economic efficiency of the actual irrigation supplied

the final results are strongly correlated. Also, the analysis of linear dependence shows the set of eigenvalues.

Also, the analysis of linear dependence shows the set of eigenvalues of the correlation matrix

0.1938 0.0075 0.0006 0.0003 0.0000 0.0000

which shows a strong linear dependence among the indices, too.

We summarize in what follows the main findings from the principal component analysis (PCA) conducted on six irrigation and productivity indicators. Each indicator was treated as a five-dimensional vector, corresponding to yearly values from 2016 to 2020.

The PCA revealed that the first principal component (PC1) captures the vast majority of the variance. Concretely, the obtained data are as follows:

- (i) Standard deviation (PC1): 2.2139
- (ii) Proportion of variance explained (PC1): 98.02%
- (iii) Cumulative variance (PC1): 98.02%

Subsequent components account for negligible variance, confirming that the dataset is essentially one-dimensional in

Table 3 Historical values of irrigation and productivity indicators (2016–2020)

Indicator	2016	2017	2018	2019	2020
RIS	1.22	1.14	1.30	1.16	1.11
RWS	1.55	1.34	1.58	1.29	1.24
WP	2.01	2.12	2.03	2.05	2.17
IWP	3.07	3.56	3.02	3.50	3.66
GWP	1.05	1.24	1.07	1.09	1.29
GIWP	1.61	2.08	1.61	1.87	2.18

structure. On the other hand, the projection of each indicator on the first principal component is as follows:

Indicator	PC1 coordinate
RIS	−1.7214
RWS	−1.1163
WP	0.6443
IWP	4.0449
GWP	−1.8761
GIWP	0.0246

These values highlight that the IWP indicator dominates PC1, suggesting a strong contrast between indicators focused on productivity (IWP, WP) and those tied to efficiency (RIS, RWS, GWP). Finally, the eigenvalues of the covariance matrix are as follows:

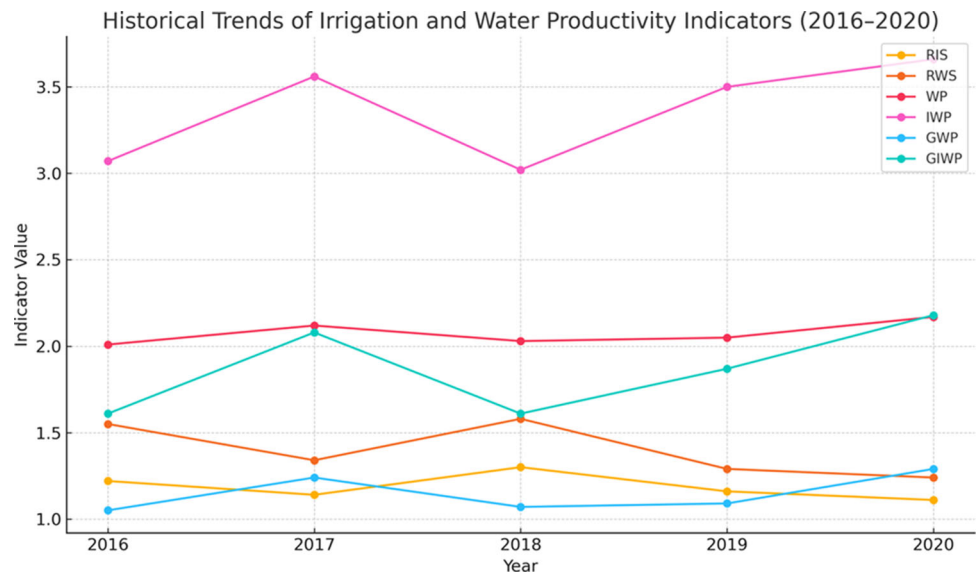
Component	1	2	3	4	5	6
Eigenvalue	0.1938	0.0075	0.0006	0.0003	0.0000	0.0000

This pattern supports the dominance of PC1 and validates the dimensionality reduction. Essentially, all the information contained in these indices can be extracted from the value of the IWP.

Macro indices on evolution of water resources in Iran

The study (Hosseini et al. 2019) evaluates the sustainability of groundwater resource management in Iran by applying five key quantitative indices in different hydrogeological regions. These indices provide a comprehensive diagnosis of groundwater conditions based on water table trends, abstraction pressure, exploitation intensity, sustainable yield, and water

Fig. 1 Historical trends of irrigation and water productivity indicators (2016–2020)



quality. Table 5 shows the values of the indices in several regions in Iran.

We will center the attention on the values of the region of Kerman. The corresponding time series can be found in Table 6 and Fig. 2 below.

Following the same procedure as in the previous section, we first compute the correlation matrix that can be seen in Table 7. An inspection of the matrix makes clear that all the variables are highly correlated.

Principal component analysis of groundwater indicators for Kerman (2002–2012)

A principal component analysis (PCA) was performed on the standardized groundwater indicator data (WDI, GWI, EI, SYI, GQI) for the province of Kerman over the period 2002–2012. The purpose of the PCA is to identify the dominant patterns and reduce the dimensionality of the dataset while retaining most of the variability.

The results can be found in Table 8 and show that the first principal component (PC1) accounts for approximately 98.46% of the total variance, indicating that most of the variability among the five indicators across the years can be

explained by this single component. The remaining components (PC2 to PC5) contribute marginally to the variance. The coordinates of each year (2002–2012) projected onto the first principal component (PC1) are given in Table 9. These values represent how strongly each year aligns with the principal pattern of variability in the dataset.

Thus, Table 9 captures the fact that the main component of the dominant direction of variation across the dataset is WDI, since the larger the absolute value of a coordinate, the greater the contribution of the corresponding indicator to the underlying structure described by PC1.

Collinearity assessment via eigenvalue analysis

To assess the degree of multicollinearity among the groundwater indicators in the Kerman dataset, we examine the eigenvalues of the correlation matrix. The presence of strong collinearity is typically indicated by one eigenvalue being significantly larger than the rest, with the remaining eigenvalues close to zero.

Table 4 Correlation matrix

	RIS	RWS	WP	IWP	GWP	GIWP
RIS	1.000	0.928	-0.792	-0.946	-0.782	-0.906
RWS	0.928	1.000	-0.795	-0.983	-0.747	-0.909
WP	-0.792	-0.795	1.000	0.861	0.991	0.961
IWP	-0.946	-0.983	0.861	1.000	0.835	0.963
GWP	-0.782	-0.747	0.991	0.835	1.000	0.952
GIWP	-0.906	-0.909	0.961	0.963	0.952	1.000

Table 5 Representative values of groundwater sustainability indices in Iran

Region	WDI	GWI	EI	SYI	GQI
Khorasan Razavi	0.85	1.12	0.94	0.42	58.3
Esfahan	0.70	1.04	0.89	0.38	63.7
Fars	0.76	1.17	0.92	0.35	51.9
Kerman	0.82	1.23	0.97	0.31	49.5
Yazd	0.90	1.30	0.99	0.27	47.0
Khuzestan	0.45	0.95	0.76	0.58	72.1
Tehran	0.67	1.10	0.85	0.44	61.2

Table 6 Groundwater sustainability indices in Kerman (2002–2012), transposed

Index	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
WDI	0.78	0.79	0.80	0.81	0.81	0.82	0.82	0.83	0.84	0.84	0.85
GWI	1.18	1.20	1.21	1.22	1.23	1.23	1.24	1.24	1.25	1.25	1.26
EI	0.94	0.95	0.95	0.96	0.96	0.97	0.97	0.97	0.98	0.98	0.99
SYI	0.36	0.35	0.34	0.33	0.32	0.32	0.31	0.30	0.30	0.29	0.28
GQI	51.1	50.8	50.4	50.0	49.6	49.3	49.0	48.7	48.3	48.0	47.6

In our analysis, the eigenvalues of the correlation matrix are as follows:

4.9228 0.0359 0.0288 0.0097 0.0028

These results show that the first eigenvalue accounts for the vast majority of the total variance (which sums to 5, as the correlation matrix is 5×5). The second, third, fourth, and fifth eigenvalues are all close to zero, indicating that the five variables are nearly linearly dependent. This suggests that the dataset lies close to a one-dimensional subspace and exhibits a high degree of multicollinearity, with most of the variance explained by a single direction in the variable space.

Taken together, these results show that the five groundwater indicators vary almost synchronously: the first principal component alone captures more than 98% of the total variance. Consequently, a single composite index derived from that dominant component would be sufficient to monitor groundwater status and to inform management decisions in Kerman, without the need to track a redundant set of highly correlated variables. Although not shown here, the analyses applied to the other time series included in this study produced comparable results.

Assessing irrigation system sustainability in Sudan through time-series analysis

The study (Ahmed 2014) evaluates the sustainability of irrigation systems by analyzing time-series data on crop yield, irrigated area, and water consumption over several years in some specific region of Sudan. The core method relies on the Theil–Sen estimator to detect trends in the time series and quantify the sustainability of water use in agriculture. A sustainability index (SUS) is proposed based on the relative trends in water consumption per hectare. The next Table 10 shows the list and explanation of the indices used in the analysis. The corresponding time series are shown in Table 11.

Again, in what follows, we analyze the use of several variables related to the use of water resources. As we can see, one variable (index) is enough to follow the evolution of these resources.

The time series presented in the cited paper can be seen in Table 11 below.

We perform principal component analysis (PCA) on four time-series variables representing irrigation performance indicators: yield (YLD), irrigated area (IA), irrigation water use (IWU), and water use efficiency (WUE). The data matrix was constructed with each indicator as a vector in \mathbb{R}^5 ,

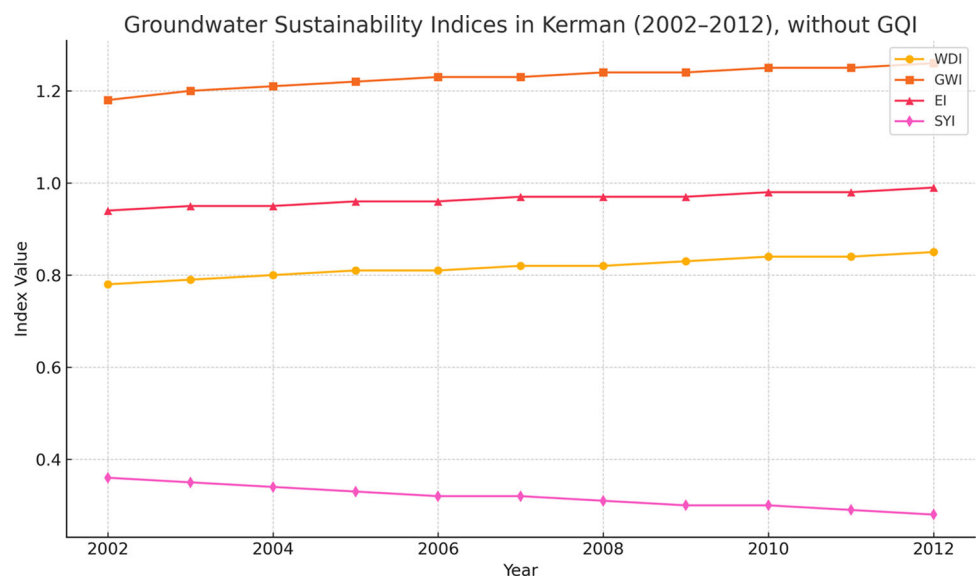
Fig. 2 Groundwater Sustainability Indices in Kerman Province (2002–2012), excluding GQI

Table 7 Correlation matrix of groundwater indicators in Kerman (2002–2012)

	WDI	GWI	EI	SYI	GQI
WDI	1.000	0.976	0.986	−0.985	−0.991
GWI	0.976	1.000	0.970	−0.980	−0.972
EI	0.986	0.970	1.000	−0.971	−0.982
SYI	−0.985	−0.980	−0.971	1.000	0.994
GQI	−0.991	−0.972	−0.982	0.994	1.000

corresponding to five time points. The correlation matrix and its eigenvalues indicate that the data are highly collinear. The following Table 12 shows the correlation matrix between the four indicators.

The strong positive correlations among YLD, IA, and WUE suggest that these indicators evolve in a similar direction, while IWU shows weak or negative correlation, indicating a different trend. On the other hand, the eigenvalues of the correlation matrix are as follows:

3.1004 0.8994 0.0001 0.0000

These values show that most of the variance (over 99%) is concentrated in the first principal component, confirming high collinearity among the original indicators.

Let us show now the results of the principal component analysis (PCA) of the data defined by the time series. To investigate the underlying dimensionality of the data formed by the four indicator vectors (yield per unit area (YLD), irrigated Area (IA), irrigation water use (IWU), and water use efficiency (WUE)), a principal component analysis (PCA) was conducted using standardized data.

The analysis revealed a highly singular structure in the data. The first principal component (PC1) accounts for 100% of the total variance, while the remaining components (PC2 to PC4) contribute virtually nothing. This is summarized in the following Table 13.

This result indicates that all the variation across the four vectors lies entirely within a one-dimensional subspace, strongly suggesting near-perfect linear dependence among them. The coordinates of the indicator vectors projected onto the principal components confirm this structure. Only PC1

Table 8 Explained variance by principal components

	PC1	PC2	PC3	PC4	PC5
Standard deviation	2.2187	0.1894	0.1698	0.0985	0.0527
Proportion of variance	0.9846	0.0072	0.0058	0.0019	0.0006
Cumulative proportion	0.9846	0.9917	0.9975	0.9994	1.0000

Table 9 Coordinates of groundwater indicators in the first principal component (PC1)

Indicator	PC1 coordinate
WDI	−3.833
GWI	−2.668
EI	−1.945
SYI	−0.926
GQI	−0.408
GIWP	0.209

carries information, and all remaining projections are numerically negligible, as can be seen in Table 14,

The dominance of PC1 and the redundancy of the other components confirm that the set of vectors is essentially collinear and can be well described by a single linear dimension in the indicator space.

In order to explore the internal structure and potential redundancy of the four selected indicators (yield per unit area (YLD), irrigated area (IA, rescaled by dividing by 1000), irrigation water use (IWU), and water use efficiency (WUE)), a principal component analysis (PCA) was carried out again but this time using standardized data. The results reveal a very strong alignment of the four indicators along a single direction in space. The first principal component (PC1) accounts for 99.84% of the total variance, while the second component (PC2) explains only 0.16%. The remaining components (PC3 and PC4) are numerically negligible. This is shown in Table 15.

These results indicate that the set of vectors is nearly collinear and that a single dimension (PC1) suffices to represent almost all variability in the data. The small contribution of PC2 suggests that there is only marginal orthogonal deviation between indicators. The projections of each original vector onto the principal components are reported in Table 16. The structure is clearly dominated by PC1, confirming that all four indicators follow a strong shared pattern, with slight contrast introduced by IWU.

The structure captured by PC1 corresponds to a coherent trend in which YLD, IA, and WUE evolve in a closely related manner, while IWU introduces an opposing effect. This confirms the dominant role of PC1 and the near-linear dependence among the indicators.

Table 10 Explanation of indicators used in the study

Indicator	Description
Yield (YLD)	Crop yield per hectare (e.g., tons/ha)
Irrigated area (IA)	Total irrigated area per year (ha)
Irrigation water use (IWU)	Total annual irrigation water use (m^3)
Water use efficiency (WUE)	Yield divided by water use (tons/m^3)
Sustainability index (SUS)	Relative trend slope of IWU/IA using Theil–Sen estimator

Water resource annual series from Aquastat (Food and Agriculture Organization of the United Nations) in Spain

In this section, we analyze a subset of long-term indicators drawn from the *AQUASTAT* database of the Food and Agriculture Organization of the United Nations (FAO). *AQUASTAT* is the Food and Agriculture Organization's global information system that collects, analyzes, and freely disseminates country-level data on water resources, water use, and agricultural water management worldwide. Of course, the data available there are not local, but the same method used in the other sections can be applied to compare the behavior of the indices involved.

Each series spans more than forty years and captures either macro-economic structure (e.g., sectoral value added), demographic pressure, land use, or water resource availability. The variables used in the study are listed in Table 17; a full description can be found in the database's metadata sheet (GDP=gross domestic product).

Figure 3 displays the Pearson correlation matrix computed from the annual time series (after standardization). The visual inspection reveals an almost block-diagonal structure in which most pairwise correlations exceed $|0.85|$ in magnitude; the red–blue color scale in the figure confirms that nearly all variables move in lockstep over the four-decade horizon. Hence, from an information-theoretic viewpoint, the set is highly redundant: adding further indicators would contribute negligible new variance once the first principal

Table 11 Time series of sustainability indicators

Indicator	2000	2002	2004	2006	2008
YLD (tons/ha)	3.2	3.5	3.8	4.0	4.2
IA (ha)	1200	1250	1300	1350	1400
IWU ($\times 10^6 m^3$)	9.5	9.7	9.8	9.6	9.4
WUE (tons/ m^3)	0.337	0.361	0.388	0.417	0.447
SUS (slope)	+0.015 (increasing efficiency)				

Table 12 Correlation matrix

	YLD	IA	IWU	WUE
YLD	1.000	0.994	−0.199	0.989
IA	0.994	1.000	−0.300	0.999
IWU	−0.199	−0.300	1.000	−0.340
WUE	0.989	0.999	−0.340	1.000

component is accounted for. In later sections, we therefore retain only a minimal subset when building predictive or clustering models.

Discussion

The results obtained from the four case studies show that the water-related sustainability indices analyzed are highly redundant: in all the cases in which this analysis is considered, the first principal component accounts for more than 98% of the total variance, and the correlation matrices reveal near-perfect linear dependence among the indicators. This finding is not incidental, since water productivity and irrigation performance indices are inherently collinear, as they share the same underlying variables (irrigated area, water applied, and crop yield). Although they may incorporate slight variations, they are combined through different but algebraically related formulas. The high correlations observed are therefore an intrinsic property of these indicator sets rather than a feature of the particular datasets chosen.

This result is consistent with current findings in the sustainability-related literature. The recent work by Bathaei and Streimikienė (2023) shows that most agricultural sustainability metrics cluster along a few collinear dimensions, and Hoover et al. (2023) demonstrate that yield-based ratios, energy inputs, and profitability tend to move in parallel across diverse agroecosystems. Our contribution is to show that the same structural redundancy holds specifically in the domain of water resource indices, and to provide concrete PCA-based evidence of this across geographically and institutionally diverse contexts, ranging from a traditional irrigation community in eastern Spain to groundwater management in Iran and irrigation systems in Sudan.

Table 13 Proportion of variance explained by each principal component

	PC1	PC2	PC3	PC4
Standard deviation	2.2361	0.0011	0.0000877	8.31×10^{-17}
Proportion of variance	1.0000	0.0000	0.0000	0.0000
Cumulative proportion	1.0000	1.0000	1.0000	1.0000

Table 14 PCA coordinates of indicator vectors

Indicator	PC1	PC2	PC3	PC4
YLD	1.121	0.001	0.000	0.000
IA	-3.354	0.000	0.000	0.000
IWU	1.101	-0.002	0.000	0.000
WUE	1.132	0.001	0.000	0.000

From a practical standpoint, the implication is clear: a small producer does not need to monitor a full battery of water indices in order to obtain a reliable picture of resource use efficiency. In the Valencian case study, the IWP (Irrigation Water Productivity) emerges as the dominant indicator, since it loads most strongly on PC1 and captures the contrast between productivity-oriented and efficiency-oriented metrics. In the Kerman groundwater case, WDI (Water Table Decline Index) plays the equivalent role. The appropriate choice of representative indicator will depend on the local context (specifically, on whether the primary management concern is irrigation scheduling, groundwater depletion, or economic return per unit of water), but in all cases, a single well-chosen index appears to suffice for routine monitoring purposes. To operationalize this selection, a simple correlation screen (for example, $|r| > 0.85$) removes redundant variables and produces a streamlined dashboard that farmers can easily interpret (Bathaei and Štreimikienė 2023; Hoover et al. 2023).

This has direct consequences for the design of sustainability monitoring tools aimed at small-scale agriculture. Small producers often lack the technical and financial capacity to collect and process large sets of indicators (Talukder et al. 2020). Our results provide a methodological justification for reducing this burden: rather than demanding compliance with complex multi-indicator frameworks, monitoring schemes could be redesigned around a minimal set of locally meaningful indices without significant loss of information. A scalable data strategy can keep requirements proportional to local resources, starting with readily available statistics, then adding plot-scale measurements, and finally incorporating targeted social surveys when capacity allows (Talukder et al. 2020). This simplification would lower the cost of data collection, ease interpretation, and make sustainability assessment accessible to smallholders.

Table 15 Proportion of variance explained by each principal component

	PC1	PC2	PC3	PC4
Standard deviation	2.2342	0.0908	0.0025	9.07×10^{-17}
Proportion of variance	0.9984	0.0017	0.0000	0.0000
Cumulative proportion	0.9984	1.0000	1.0000	1.0000

Table 16 PCA coordinates of indicator vectors

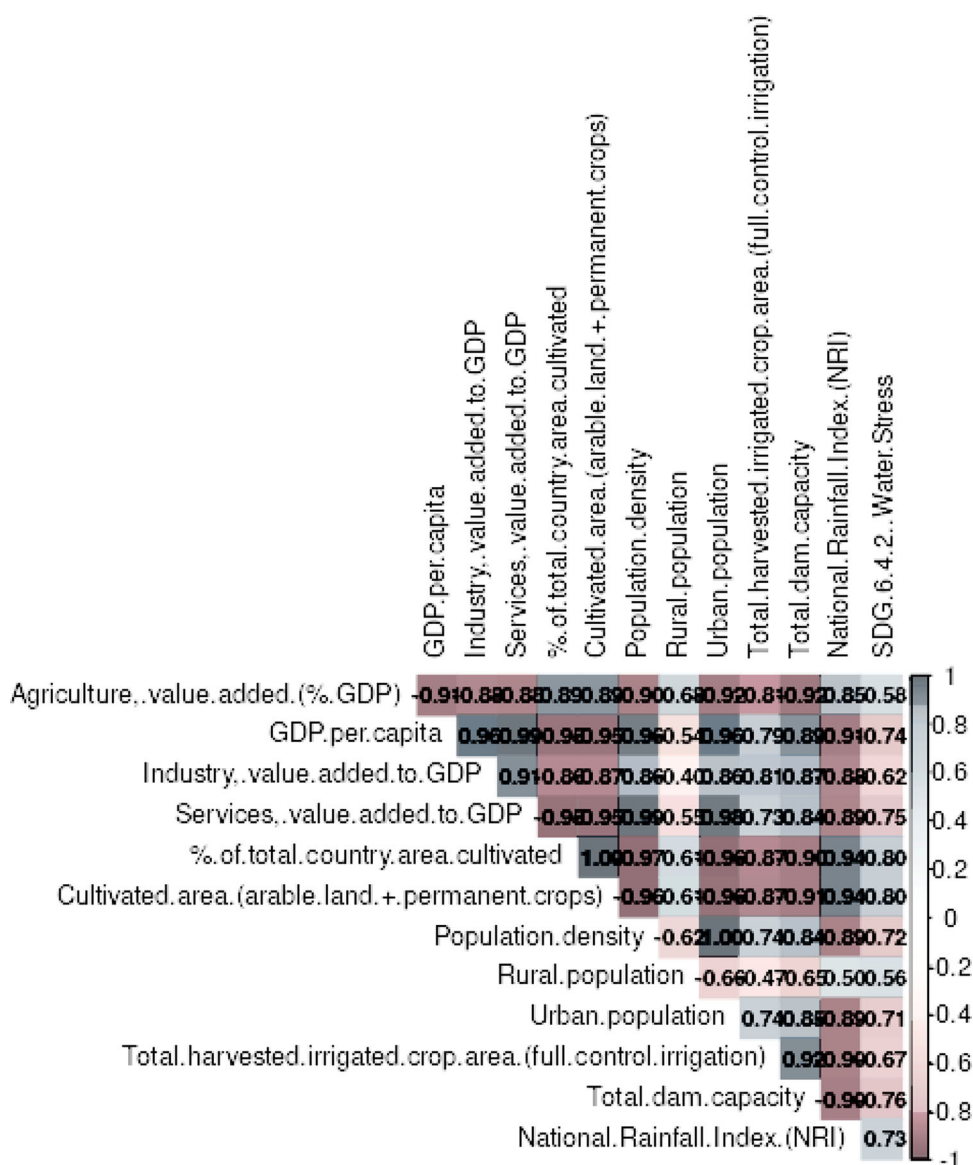
Indicator	PC1	PC2	PC3	PC4
YLD	0.008	0.136	0.000	0.000
IA	1.325	-0.033	0.003	0.000
IWU	-3.150	-0.046	0.000	0.000
WUE	1.816	-0.056	-0.003	0.000

Beyond the water domain, a comprehensive monitoring scheme for small-scale agriculture must also integrate social dimensions. Composite evaluations routinely show that food security and community participation are among the most informative sustainability variables (Talukder et al. 2020), and a cross-country study in sub-Saharan Africa links gender-balanced land rights directly to faster adoption of climate-smart practices (Perelli et al. 2024). Reviews of agri-food assessments reach the same conclusion for labor conditions and well-being metrics (Brennan et al. 2023). Embedding at least one context-sensitive social indicator (such as the proportion of women in decision-making or the strength of local cooperative networks) ensures that any monitoring system remains responsive to the full range of local sustainability levers (Jones et al. 2023; Perelli et al. 2024). Biodiversity also warrants inclusion as a complement to the core water index, since evidence from diversified farms shows that increasing crop diversity enhances both yield stability and ecological resilience (Jones et al. 2023). After the dimensionality reduction performed in the same way as for

Table 17 Indicators extracted from *Aquastat.xlsx*

Variable name (sheet label)	Meaning/description
Agriculture, value added (% GDP)	Share of agriculture in national GDP
GDP per capita	GDP divided by population; proxy for income level
Industry, value added to GDP	Share of industry in GDP
Services, value added to GDP	Share of services in GDP
% of total country area cultivated	Cultivated land as percentage of total area
Cultivated area (arable + permanent crops)	Absolute cultivated surface
Population density	Inhabitants per km ²
Rural population	People living in rural areas
Urban population	People living in urban areas
Total harvested irrigated crop area (full-control)	Harvested area under full-control irrigation
Total dam capacity	Storage capacity of reservoirs
National Rainfall Index (NRI)	Country-average rainfall index
SDG 6.4.2 Water Stress	Freshwater withdrawal as share of renewable resources

Fig. 3 Correlation matrix of the selected *AQUASTAT* indicators. Dark red (blue) denotes strong positive (negative) correlation. The near-uniform saturation illustrates that the indicators are strongly inter-dependent and convey overlapping information



the water-related indices, such social indicators should be added to a composite indicator for analysis.

Finally, although this paper focuses on water-related indices, the structural argument developed here is not specific to this domain. The sustainability literature documents similar patterns of high correlation among environmental, economic, and social indicators more broadly (Bathaei and Štreimikienė 2023; Talukder et al. 2020), suggesting that the dimensionality-reduction approach demonstrated here could be extended to other sustainability dimensions. This would potentially allow the construction of genuinely minimal yet comprehensive monitoring frameworks for small-scale agricultural systems, and we leave this extension as a direction for future work.

Conclusions

This study has addressed the challenge of making sustainability monitoring accessible and actionable for small-scale agricultural systems. By analyzing water-related sustainability indices across four geographically diverse case studies, we have shown that the most commonly used indices in this domain are highly correlated. In all cases, the first principal component captures more than 98% of the total variance. This redundancy is not a dataset-specific artifact but a consequence of the fact that the indices involved are defined using essentially the same underlying information.

The practical implication is that a small, well-chosen set of indices can capture the essential dynamics of smallholder

farming systems without requiring the collection of a large and redundant indicator battery. These indices could be for example centered on a single dominant water indicator selected via PCA or correlation screening and complemented by a soil health proxy, a measure of economic return, and at least one social metric such as food security or gender equity. This simplification lowers the cost of data collection, eases interpretation, and makes the sustainability assessment genuinely accessible to producers who lack the technical and financial resources required by conventional composite index frameworks.

Taken together, our results support a shift away from overly complex composite indices toward more accessible, context-sensitive monitoring tools. With careful indicator selection and methodological simplification, it is possible to develop robust sustainability assessment frameworks tailored to small-scale, locally oriented agriculture, offering a practical path forward to support more inclusive, resilient, and sustainable food systems. Extending this dimensionality-reduction approach beyond water resources to other sustainability dimensions, such as soil health, biodiversity, and social equity, remains an open and promising direction for future work.

Author contribution Conceptualization, E.S-A, A.F-S.; methodology, M.C.C-M., A.F-S.; software, E.S-A.; validation, M.C.C-M.; formal analysis, A.F-S., E.S-A.; investigation, A.F-S., E.S-A.; data curation, M.C.C-M.; writing—original draft preparation, A.F-S.; writing—review and editing, E.S-A., M.C.C-M.; visualization, M.C.C-M.; supervision, A.F-S. All authors have read and agreed to the published version of the manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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