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Usability of agricultural drought vulnerability and resilience indicators in planning strategies for small farms: A principal component approach

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ABSTRACT

Water-related stresses and risks of droughts, exacerbated by climate change, have been extensively documented. These studies often rely on various indicators to monitor and forecast the impacts of droughts. However, current literature on the usability of these indicators for modelling drought risk and in decision-making processes is fragmented and lacks a clear, systematic, and methodological approach. Usability, in this context, refers to the relevance, accessibility, clarity, and practicality of indicators for guiding planning strategies. To address this knowledge gap, the Management of Disaster Risk and Societal Resilience (MADIS)[1] project aims to collate and assess drought vulnerability and resilience indicators from existing literature to support decision-makers in improving policies related to agricultural droughts on small farms.

The MADIS project identified over 100 indicators, from which 36 were selected for further analysis. A global online survey using the Delphi technique was conducted, and the resulting data was used to perform a Principal Component Analysis (PCA). Findings revealed that these 36 indicators could be reduced and grouped up to ten principal components, each corresponding to a theme across five categories: relevancy, understanding, accessibility, objectivity, and temporal. This study, therefore, highlights the practical usability of these indicators for developing context-specific and efficient resilience strategies.

Indicators related to water management were found to be crucial and applicable across all five categories, as the availability, quality, and source of water are essential for monitoring and mitigating drought hazards. Conversely, indicators related to rural development and demographics, while quantifiable and collected at different temporal scales, were deemed less understandable and accessible by experts. Grouping indicators under common themes reduces the complexity of evaluating similar indicators and aids in selecting the most relevant ones for different contexts. This approach simplifies indicator selection and enables decision-makers to formulate resilience policies more efficiently and comprehensively.

Practical implications

The study simplifies a complex set of over 100 drought vulnerability and resilience indicators into 36 key indicators, further distilled into principal components across five categories: relevancy, understanding, accessibility, objectivity, and temporal characteristics. This approach helps decision-makers avoid confusion when faced with an overwhelming number of potential indicators, guiding them to focus on the most critical ones based on their specific context. This methodological framework aids policymakers in selecting the right indicators for targeted drought

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[1] Further information on the MADIS project can be found at https://sites.psu.edu/belmont/ and https://www.cranfield.ac.uk/research-projects/madis.

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resilience strategies, ensuring that policy decisions are based on clear, justified rationale.

Water management indicators emerged as highly significant across all categories, demonstrating their critical role in drought resilience. Together, these indicators stress the whole water management cycle requiring integrated practices and thinking. Indicators like groundwater levels, water quality, and the availability of drought prediction systems are essential for monitoring water resources and addressing agricultural drought impacts. Policymakers must prioritise integrated water resource management policies that ensure sustainable water use and distribution, especially in drought-prone regions. Implementing water management strategies based on these indicators can enhance the resilience of small farms, which often suffer from limited access to reliable water sources. In collaboration with national agencies, local authorities should invest in infrastructure that improves water retention, storage, and irrigation efficiency.

Indicators related to the socioeconomic aspects of farming communities, such as poverty rates, access to financing, and participation in farming cooperatives, are also crucial. These indicators reflect the vulnerability of smallholder farmers to drought, who often lack financial safety nets or social support mechanisms. By addressing these socioeconomic factors, policymakers can reduce the risks associated with drought and enhance the adaptive capacity of farming communities. Programs that provide financial support, such as crop insurance or access to credit, are vital. Policymakers should also promote cooperative farming structures, which can offer collective resilience through shared resources and knowledge. Additionally, poverty alleviation programs tailored to drought-prone regions can bolster resilience by reducing the socioeconomic vulnerabilities of farmers.

The study highlights the importance of ensuring that drought indicators are accessible and objective. Decision-makers need reliable, quantifiable data to make informed decisions. However, in many regions, data collection is inconsistent, and indicators such as land degradation or crop loss are not readily available or easily interpretable. To address this challenge, governments and international organisations should invest in building robust data collection systems that provide timely, accurate, and objective information on drought risks. Remote sensing technologies and local ground-level data collection can significantly enhance the quality and availability of drought-related information. Ensuring that this data is accessible to local decision-makers is critical for timely and effective drought response.

The study identifies the importance of community participation and policy support indicators in building drought resilience. Indicators such as public participation in local policies, technical assistance from cooperatives, and drought management policies highlight the role of governance and community engagement in effective drought risk management. Policymakers should engage local communities in the planning and implementing drought resilience strategies. By involving farmers and other stakeholders in the decision-making process, policies can be better tailored to local needs and conditions. Furthermore, strengthening local institutions and providing technical assistance can enhance the capacity of farming communities to respond to drought.

The temporal category of indicators is crucial for monitoring drought risks over time. Indicators that capture long-term trends, such as land degradation or crop water use efficiency, allow policymakers to develop proactive strategies rather than reactive responses. Longitudinal data can help identify patterns and predict future risks, enabling more effective resource allocation and planning. Policymakers should implement monitoring systems that track these long-term indicators, ensuring that data is collected at regular intervals to provide a comprehensive understanding of drought dynamics. This information can guide the development of adaptive management strategies that account for both short-term impacts and long-term resilience.

The study emphasises the need for context-specific indicators. Not all drought indicators are equally relevant across different regions or farming systems. For example, indicators related to rural demographics or land tenure may be more significant in regions where land ownership is contested or where migration patterns are influenced by drought. Policymakers should tailor their drought resilience strategies to the specific vulnerabilities of their regions. By selecting indicators that reflect an area's unique socioeconomic, environmental, and institutional conditions, decision-makers can create more effective and locally relevant policies. Regional drought management plans should, therefore, be flexible, allowing for the inclusion of context-specific indicators that may not be universally applicable.

Indicators related to sustainable agricultural practices, such as drought-resistant crop varieties or the efficiency of agricultural inputs, are vital for building resilience. By promoting sustainable farming techniques, policymakers can reduce the vulnerability of small farms to drought and enhance their long-term productivity. Governments should support research and development in drought-resistant crops and promote the adoption of water-efficient technologies in agriculture. Additionally, agricultural extension services should be strengthened to give farmers the knowledge and tools needed to implement these practices.

The PCA approach used in the study provides a holistic framework for drought management by revealing the interconnections between various indicators. This allows policymakers to move beyond isolated solutions and develop comprehensive strategies that address the multiple dimensions of drought risk. For example, water management cannot be discussed without socioeconomic factors like poverty or access to credit. Therefore, policymakers must adopt integrated approaches that consider the full range of factors contributing to drought vulnerability. Cross-sectoral collaboration between water, agriculture, and social welfare departments is essential for successfully implementing these strategies.

The study opens avenues for further research on the role of climate services in enhancing drought resilience. Policymakers and practitioners should collaborate with researchers to refine the indicators used in drought risk assessment, ensuring they stay relevant in changing climate patterns. Additionally, exploring the potential of emerging technologies, such as artificial intelligence and machine learning, in drought prediction and management could offer new opportunities for proactive resilience building.

1. Introduction

Drought is a complex and pervasive phenomenon that poses significant challenges to societies around the globe, affecting ecosystems, economies, and human well-being. Drought is often called a "creeping hazard" that unfolds gradually, making it distinct from sudden-onset hazards (Ahmad and Kam, 2024). Unlike earthquakes or hurricanes, drought events manifest through a slow and cumulative deficiency in precipitation and other meteorological issues, leading to cascading impacts on water resources, energy infrastructure, agriculture, and ecosystems. As climate change intensifies, drought events' frequency and severity amplify the urgency for effective and proactive planning strategies (Ault, 2020; Wilhite, 2000). To address these challenges, researchers and decision-makers are increasingly turning to the concept of drought resilience, a multidimensional framework that aims to enhance the capacity of communities to cope and recover from the impacts of drought (Cole et al., 2021). It is an overarching concept that encompasses the ability of ecosystems, economies, and communities to anticipate, respond to, and recover from the adverse impacts of drought (Folke et al., 2010). While the importance of drought resilience is widely acknowledged, a critical knowledge gap remains in understanding the specific drought vulnerability and resilience indicators that can guide the formulation of effective and proactive planning strategies, with an emphasis on small farms (AghaKouchak et al., 2015; Mishra and Singh, 2010).

Small farms are crucial to agricultural systems for several reasons. They produce a significant portion of the world's food supply, despite operating on small plots of land. Of the 570 million farms worldwide, 475 million are smallholder farms, and these operate about 12 % of the world's agricultural land (Fanzo, 2017). Smallholder farmers, who often work under challenging conditions with limited resources, contribute substantially to local food security and the global food market. Thus, supporting these farmers with drought-resilient solutions enhances their productivity and sustainability (Shroff, 2022). A clear understanding of the relevance of drought vulnerability and resilience indicators is crucial for formulating adaptive planning strategies that can withstand the increasing threats posed by drought to small farms in a changing climate (Muthelo et al., 2019).

'Indicators' are measurable quantities based on which analysts often assess specific outcomes (Kumar et al., 2020). Indicators have the ability to represent multidimensional constructs as quantitative variables. This enables decision-makers and planners to formulate effective policies as indicators can provide accessible and reliable information to guide the decision-making process (UNDP, 2018). While indicators can be context-specific, and care is needed in their selection, policies formulated with the aid of relevant indicators can ensure that there is a clear rationale and justification for an approach taken (World Bank, 2019; Mens et al., 2022). Existing literature on drought risk modelling is extensive and presents a large set of indicators (Wilhite and Glantz, 1985; Heim, 2002; Le et al., 2024). The danger is that the myriad range of indicators creates complexity and may well blur the line between comprehensiveness and importance (Mishra and Singh, 2010). In many cases, large sets of indicators might induce confusion among decision-makers as to 'why' the indicators were included, in the first place. For example, there may be instances where inclusion cites data availability as the reason, while in another instance, indicators may be included because they were periodically collected over time. For some, indicators that can be objectively recorded are preferred for policymaking, while other policymakers may suggest that some indicators are more relevant for understanding drought impacts than others. These conflicting views arise from the underlying reason or 'lens' through which decision-makers may view indicators as important. Considering all these selection perspectives might be crucial for decoding the importance attached to individual indicators on the part of policymakers. This paper presents a methodological approach based on Principal Component Analysis (PCA) to answer this question in the context of drought risk for small farms. The primary use case of the proposed PCA-based approach is to identify the most usable and important drought indicators from the perspectives of different stakeholders involved in drought risk management for small farms.

Analysts generally assess the importance of such indicators through pragmatic approaches, which are usually founded on practical aspects associated with data availability, procurement, or a domain focus area (Meza et al., 2020). For example, existing literature on drought vulnerability and resilience indicators primarily focuses on aspects such as meteorological, hydrological, and agricultural indicators to assess drought severity and impacts (Mishra and Singh, 2010; Meza, et al., 2019; Keyantash and Dracup, 2002). However, a comprehensive analysis of such indicators considering their relevancy, ease of understanding, objectivity, accessibility, and temporal aspects, individually or together, is seen to be lacking (King-Okumu, 2019). The 'relevancy' or the suitability of different indicators across various drought-prone regions and socio-economic contexts is often lacking (Hayes et al., 1999; Wilhite and Glantz, 1985). While existing literature discusses the technical aspects such as calculation methods and data sources of such indicators, there is a lack of emphasis on the 'understanding' of drought indicators or their clarity and interpretability, which is important for decision-makers, researchers, and practitioners (Svoboda et al., 2002; Datta and Behera, 2022). Discussions on 'accessibility' or availability of data associated with indicators are crucial for widespread adoption and application in decision-making processes, especially in developing regions or remote areas, but are often overlooked in existing studies (Svoboda et al., 2002). 'Objectivity' of indicators or quantifiable indicators is another critical aspect that has received limited attention in the literature, but it is essential for ensuring the credibility and comparability of drought risks (Heim, 2002). While some research addresses the temporal aspects of specific indicators, such as satellite-derived indices for monitoring drought progression, a comprehensive analysis of temporal features, such as frequency of data collection, temporal resolution, and the ability to capture short-term and long-term drought events across different indicators, is lacking for clear understanding of drought dynamics and trends over time.

Therefore, amidst the multitude of indicators associated with drought vulnerability and resilience, the challenge lies in distilling a manageable set that can effectively support policy and planning strategies. PCA emerges as a powerful statistical tool capable of reducing the dimensionality of complex datasets while preserving the essential information contained within them (Jolliffe, 2002). By applying PCA to a diverse set of agricultural drought vulnerability and resilience indicators, this paper seeks to identify the principal components that most significantly contribute to the overall resilience of a system vis a vis small farms. We demonstrate the process of distilling a large set of drought indicators into a concise, usable form for policymakers and analysing the relations among these indicators using PCA. The simplest approach to dealing with such importance scores about indicators is calculating averages across responses and arriving at the most important indicator (mean-based approach). However, this PCA-based approach differs from a mean-based indicator analysis where indicators are compared independently to identify the most important ones. In the context of drought analysis, we argue that the PCA-based approach offers a significant advantage over mean-based indicator analysis by reducing data dimensionality, revealing underlying patterns, and managing multicollinearity, thereby providing a comprehensive and holistic understanding of the complex interrelationships among various drought indicators. We demonstrate the process and benefits of analysing expert opinion surveys, frequently conducted in drought risk modelling and analysis, using this PCA-based approach that considers interrelationships among the indicators across multiple dimensions. By employing PCA, this study provides insights into how these indicators can be effectively grouped and used to inform policy and decision-making. PCA aids policymakers by identifying interconnections between indicators, reducing complexity, and highlighting key entry points for targeted intervention. For instance, clustering related indicators enables streamlined decision-making by emphasising themes such as water resource management or socioeconomic resilience. The usability of drought indicators – defined as their relevance, clarity, accessibility, and practicality – is critical for improving planning and resilience strategies. However, existing literature rarely emphasises usability as a criterion for evaluating indicators. In this study, we address this gap by systematically analysing the usability of drought vulnerability and resilience indicators, focusing on their applicability to small farms. This methodological analysis approach constitutes the main contribution of the paper.

The paper outlines the methodology in Section 2. The results from the PCA analysis are addressed in Section 3. The discussion in Section 4 is split into two sections: the first analyses the results around the common indicators across the categories, and the second addresses the indicators that do not fall into any of the five categories. The conclusion in Section 5 summarises the key issues and points for future research.

2. Methodology

2.1. Indicator selection and responses collected

The MADIS project created an online Delphi survey of several drought indicators to elicit their usability and importance among global domain experts on climate change, agriculture, drought hazard, disaster risk, within the water-energy-food nexus across geographically diverse regions. Responses were received from responders based in Africa, America, Asia and Europe, with the United States and India having the highest number of participants. From the existing literature, over 100 drought vulnerability and resilience indicators were collated, of which 36 were selected for the Delphi survey based on discussions among the MADIS team members and opinions from external experts working in allied areas. This was done on a 4-point scale from 'relevant' to 'not relevant at all'. The team members and external experts provided their justifications for including or excluding an indicator from the final list, after which a consensus was reached for the 36 indicators. This survey aimed to determine decision-makers' information needs for improving drought resilience and resource management policies. To do so, the online survey asked experts to rate the list of 36 drought vulnerability and resilience indicators on a 3-point scale of Low, Medium, and High from five different points of view or lenses. The five lenses were termed as 'categories' for this investigation, and they include – (1) relevancy of the indicator for improving drought resilience policies; (2) ease of understanding of the indicator by the decision-makers; (3) data accessibility or availability of the indicator; (4) data objectivity to evaluate the indicator; and (5) availability of the data over different temporal scales.

All 36 indicators (Table 1) were assessed concerning the above five categories. Appendix A shows the questions asked to the experts during the Delphi survey and the operational definitions of the options given under the 3-point scale. Details about this survey are reported in a parallel study by Sass et al. (2024) and De MacEdo et al. (2024).

The current paper builds on and extends the work of these two previous studies by offering a distinct approach to analysing drought vulnerability and resilience indicators. Sass et al. (2024) classified the 36 indicators collected from the global survey into four clusters. They proposed specific action points based on these groupings, focusing on categorising indicators and linking them directly to actionable strategies for policymakers. In contrast, De MacEdo et al. (2024) concentrated on the methodological challenges and lessons learned while creating the global Delphi survey itself, highlighting issues related to data collection, expert participation, and the survey design process. This current paper, therefore, takes a different analytical approach. Instead of focusing on challenges or clustering, authors employ Principal Component Analysis (PCA) to explore the inter-relationships between the 36 indicators. Doing so reveals underlying patterns in the dataset and groups indicators into principal components. This method emphasises the connections and shared characteristics among indicators rather than categorising them into distinct clusters, allowing for a more nuanced understanding of how different indicators contribute to drought vulnerability and resilience.

As a part of the online Delphi survey, more than 2000 questionnaires were mailed to experts, of which a total of 326 responses were received, and Table 2 shows the sample size details in the final dataset after removing all 'null' responses from each of the categories. 'Null' refers to the situation when the respondents did not answer the question. 'Don't know' was included as the last option for each category to reduce pseudo-opinions. The consistency in the experts' responses was assessed using the Fleiss Kappa score ($\kappa = 0.73$, substantial agreement range: 0.61–0.8), which was found to have adequate reliability across all five categories.

The number of fully completed questionnaires per category in this study ranged from 100 to 134. While variation in sample size across categories could influence the stability of Principal Component Analysis (PCA) results, the overall sample size was sufficient to identify meaningful patterns in the data. The PCA was conducted using only fully completed responses, ensuring that the analysis was based on reliable and consistent input without introducing artificial assumptions through imputation.

Regarding inter-category variability, it is acknowledged that differences in response distributions across categories could lead to variations

Table 1
List of 36 indicators.

No.	Indicator name	Type	Reference
1	Percentage of the contribution of crop and livestock production in the income of smallholder farming	Vulnerability	Lindoso et al. 2011
2	Crop loss	Vulnerability	Hao et al. 2012; Antwi-Agyei et al. 2012; Simelton et al. 2009; Epule 2021
3	Percentage of drought-resistance crop varieties cultivated	Resilience	Meza et al. 2019
4	Percentage of farmers who use different types of crops	Resilience	Meza et al. 2019
5	Percentage of area protected and designated for the conservation of biodiversity	Vulnerability	Meza et al. 2019
6	Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery)	Vulnerability	Meza et al. 2019
7	Crop water use efficiency (WUE)	Vulnerability	Meza et al. 2019
8	Degree of land degradation and desertification	Vulnerability	Meza et al. 2019
9	Land rights clearly defined (yes/no)	Resilience	Lindoso et al. 2011; Leguízamo et al., 2020
10	Existence of drought management policies (mitigation/adaptation/prevention/preparedness)	Resilience	Kampragou et al. 2015
11	Technical assistance from local entities (e.g., cooperatives/NGO/government)	Resilience	Leguízamo et al., 2020
12	Percentage of farmers with crop, livestock, or drought insurance	Resilience	Meza et al. 2019
13	Water use rights clearly defined	Resilience	Kampragou et al. 2015
14	Availability of drought prediction and warning systems or climatic predictions	Resilience	Lee and Yoo 2021; Xu et al. 2021; Leguízamo et al., 2020
15	Produce storage and transportation capacity	Resilience	Simelton et al. 2009
16	Access to energy	Resilience	Meza et al. 2019
17	Prevalence of conflict/insecurity	Vulnerability	Meza et al. 2019
18	Percentage of the population without access to (improved) sanitation	Vulnerability	Meza et al. 2019
19	Gender inequality	Vulnerability	Meza et al. 2019
20	Percentage of the rural population	Vulnerability	Meza et al. 2019
21	Unemployment rate and/or proportion of formal work	Vulnerability	Meza et al. 2019
22	Percentage of population ages 15–64	Vulnerability	Meza et al. 2019
23	Percentage of population displaced internally or transboundary	Vulnerability	Meza et al. 2019
24	Presence of drivers of migration and displacement	Vulnerability	Meza et al. 2019
25	Poverty rate	Vulnerability	Antwi-Agyei et al. 2012; Epule 2021
26	Food source reliability and diversity	Resilience	Luetkemeier and Liehr 2018
27	Level of public participation in local policy	Resilience	Meza et al. 2019
28	Participation in farming cooperatives or associations	Resilience	Lindoso et al. 2011
29	Percentage of the population employed in farms	Vulnerability	Lindoso et al. 2011; Kampragou et al. 2015
30	Access to financing and credit	Resilience	Huai 2017; Leguízamo et al., 2020

(continued on next page)

Table 1 (*continued*)

No.	Indicator name	Type	Reference
31	Ratio of annual withdrawals to available water	Vulnerability	Meza et al. 2019
32	Water quality	Vulnerability	Meza et al. 2019
33	Groundwater level/sources	Vulnerability	Kampragou et al. 2015; Wu and Yang, 2013; Alonso et al. 2019; Murthy and Yadav, 2015
34	Integrated land and water management policies	Resilience	Lerner et al. 2018
35	Percentage of retained renewable water	Resilience	Meza et al. 2019
36	Total dam capacity	Resilience	Meza et al. 2019

Table 2
Details of responses considered for the analysis.

No.	Category	Total responses received	Complete responses received
1	Relevancy	326	134
2	Understanding	326	125
3	Accessibility	326	115
4	Objectivity	326	117
5	Temporal	326	100

in factor loadings. However, the extracted principal components align with theoretical expectations and exhibit meaningful interpretability, suggesting that the variability did not distort the underlying structure of the data. Additionally, the selection of components was guided by eigenvalue criteria and scree plot analysis, ensuring that the retained factors were representative of the overall dataset.

While minor fluctuations in PCA results due to sample variability cannot be ruled out, the consistency of the identified components supports the robustness of the findings. Future studies with larger and more balanced sample sizes could further validate these results.

2.2. Analysis of the responses

Principal Component Analysis (PCA) is a statistical technique used to reduce the dimensionality of a dataset while preserving as much variability as possible by transforming the original indicators into a new set of uncorrelated indicators called principal components. However, the responses were analysed before conducting PCA by assessing their correlations. This was carried out as a first step because a correlation analysis helps confirm sufficient correlation among the indicators to justify the use of PCA. By understanding which indicators are highly correlated, one can ensure that the principal components derived from PCA explain the maximum variance with fewer components, leading to more meaningful and interpretable results. On the other hand, analysing indicator pairs with low correlation could be a crucial initial position for developing improved drought policies.

The collected responses were analysed using PCA to study the variance in responses related to indicators. PCA was, therefore, employed to distil the 36 drought vulnerability and resilience indicators into thematic groups that policymakers can use to prioritize actions. PCA identifies patterns in data by revealing correlations and clustering indicators into components that explain the largest variance. This study also highlights the importance of integrating indicators to reflect systemic resilience, emphasising how PCA facilitates such integration by combining correlated indicators into cohesive themes. However, the current study focused more on water-energy-food indicators, which are policy-relevant with widely available data and excluded indicators such as Days to Day Zero (DDZ) (as proposed by Lankford et al., 2023). This limitation emphasises the need for future work to incorporate indicators like DDZ to enhance the scope and applicability of the study further. The current methodology enables policymakers to focus on actionable themes rather than individual indicators, offering a practical roadmap for resilience planning.

Five PCA models were run independently using the responses for each category (relevancy, understanding, etc.). This was done to identify principal components that explain the largest variance in each category, which were ranked based on their relative ability to explain the total variance, called the eigenvalue of the component. To identify important principal components, all components with an eigenvalue of more than 1 were retained (Bucherie et al., 2022; Faisal and Shaker, 2017). To do this, a 'scree-plot' was prepared highlighting the principal components and the eigenvalue. To understand which indicators influence connected principal components the most, 'loading' values were analysed. 'Loading' refers to the coefficients or weights that quantify the contribution of each original indicator to a particular principal component. These values vary between -1 to $+1$ and to decide which indicator is represented by each principal component, a cut-off point is selected. For clinical studies, the cut-off usually varies between 0.3 and 0.5, magnitude-wise (Zhang and Castelló, 2017); however, for vulnerability and resilience studies, PCA usually uses the cut-off of 0.4 and above, magnitude-wise (Uddin et al., 2019; Wu, 2021).

The results obtained in this study satisfy Bartlett's test of sphericity ($p = 0.012$, i.e., $p < 0.05$), indicating that the interpretations are statistically significant. This is true for all five categories considered in this study. Based on the orthogonal (varimax) rotated component matrix results generated from PCA, indicators with a loading of more than 0.5 were grouped under one common theme to interpret associations between indicators better and classify them into appropriate groups for each of the five categories.

3. Results

3.1. Correlations among responses

Correlation coefficients were calculated between the 36 indicators across all five categories. Table 3 presents the top three highest and lowest correlated indicator pairs. The values of the highly correlated indicator pairs ranged between 0.625 and 0.752, making them suitable candidates for furthering the PCA. In the 'objectivity' category, the highest correlation of 0.752 was observed for the Unemployment rate and/or proportion of formal work (O_21) & Percentage of the population ages 15–64 (O_22). It was also noted that Percentage of retained renewable water (35) was seen to be highly correlated with other indicators in all five categories. This indicator may be capturing the same or similar information that other indicators are also conveying, and therefore, might be redundant. For example, the strong correlation between the Unemployment rate (21) and the % of population ages 15–64 (22) suggests a socioeconomic dimension critical for addressing drought vulnerability. While the correlation between indicators (21) and (22) is inherent due to their mathematical relationship, its significance in the context of drought vulnerability extends beyond this dependency. A high proportion of the working-age population coupled with high unemployment reflects economic instability and limited livelihood opportunities, which can exacerbate social vulnerability during drought events. In such scenarios, unemployed individuals and their households face financial constraints, reducing their capacity to adapt to drought-induced economic disruptions, such as increased food and water prices or reduced agricultural productivity. Therefore, rather than viewing this correlation as merely a statistical artefact, it serves as an indicator of economic resilience or fragility in drought-prone regions. To further substantiate this argument, additional analysis incorporating employment types and income distribution can be explored to reinforce the socioeconomic dimension of drought vulnerability.

Weak correlations, such as between the Existence of drought management policies (10) and the Ratio of annual withdrawals to available water (31), highlight areas where further integration of policies and dynamic water management practices could enhance resilience. This

Table 3
Highest and lowest correlation (magnitude-wise) for each category.

Category	Indicator pairs	Correlation value (Highest)	Indicator pairs	Correlation value (Lowest)
Relevancy (R)	Integrated land and water management policies (34) & % of retained renewable water (35)	0.711	% of population ages 15–64 (22) & Water quality (32)	0.009
	Groundwater level/sources (33) & % of retained renewable water (35)	0.645	Use of agricultural inputs (6) & Unemployment rate and/or proportion of formal work (21)	0.016
	% of retained renewable water (35) & Total dam capacity (36)	0.637	Use of agricultural inputs (6) & Total dam capacity (36)	0.021
Understanding (U)	Integrated land and water management policies (34) & % of retained renewable water (35)	0.669	% of drought-resistance crop varieties cultivated (3) & % of the population without access to sanitation (18)	0.008
	Produce storage and transportation capacity (15) & Access to energy (16)	0.632	Existence of drought management policies (10) & % of population ages 15–64 (22)	0.010
	Ratio of annual withdrawals to available water (31) & Water quality (32)	0.625	Crop water use efficiency (7) & % of population displaced (23)	0.020
Accessibility (A)	% of the rural population (20) & % of population ages 15–64 (22)	0.725	Prevalence of conflict/insecurity (17) & Groundwater level/sources (33)	0.005
	Ratio of annual withdrawals to available water (31) & % of retained renewable water (35)	0.680	% of the rural population (20) & Ratio of annual withdrawals to available water (31)	0.017
	% of drought-resistance crop varieties cultivated (3) & % of farmers who use different types of crops (4)	0.653	% of the rural population (20) & Integrated land and water management policies (34)	0.024
Objectivity (O)	Unemployment rate (21) & % of population ages 15–64 (22)	0.752	Existence of drought management policies (10) & Ratio of annual withdrawals to available water (31)	0.013
	Groundwater level/sources (33) & % of retained renewable water (35)	0.725	Water use rights clearly defined (13) & Ratio of annual withdrawals to available water (31)	0.035
	Existence of drought management policies (10) & Availability of drought prediction and warning systems (14)	0.683	Prevalence of conflict/insecurity (17) & Ratio of annual withdrawals to available water (31)	0.035
Temporal (T)	% of population displaced (23) & Presence of drivers of migration and displacement (24)	0.739	% of farmers with crops, livestock or drought insurance (12) & Presence of drivers of migration and displacement (24)	0.033
	Ratio of annual withdrawals to available water (31) & % of retained renewable water (35)	0.729	Prevalence of conflict/insecurity (17) & Total dam capacity (36)	0.052
	Groundwater level/sources (33) & % of retained renewable water (35)	0.713	Produce storage and transportation capacity (15) & Poverty rate (25)	0.064

weak correlation in the analysis does not diminish their practical relevance. Rather, it suggests a dynamic approach to integrate policies with real-time water resource monitoring, allowing policymakers to adapt withdrawal strategies based on changing supply conditions. By highlighting such nuances, PCA simplifies complex datasets and identifies areas where policy interventions can be most impactful. Similar findings

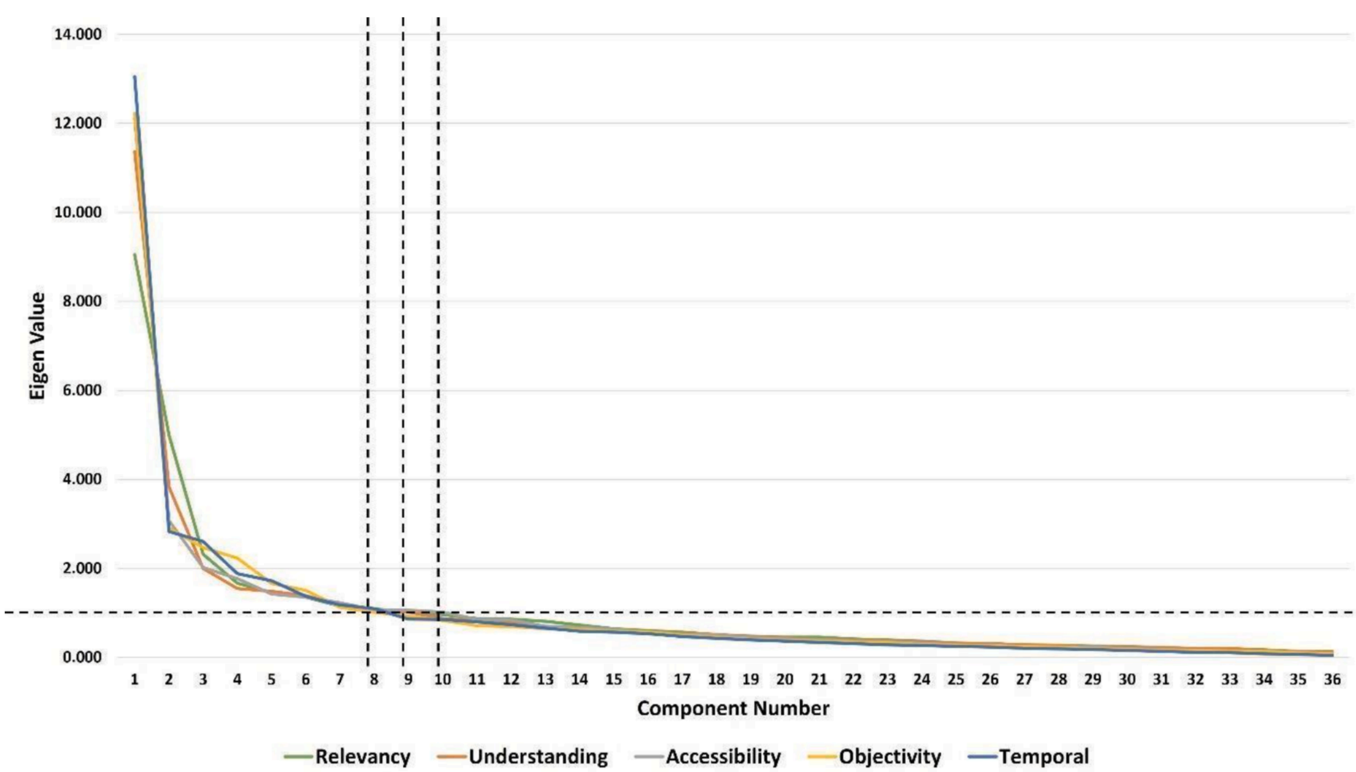

Fig. 1. Scree plot for all the categories showing the number of principal components with their corresponding eigenvalues.

were further investigated using the PCA results in subsequent sections.

3.2. Principal components derived

Fig. 1 presents the 'scree-plot' showing the relationship between individual components and their corresponding eigenvalue for each category. At least eight components had an eigenvalue of more than 1 for each category. Implications for each category are discussed in later sections. The vertical dotted lines in the figure that cross the horizontal line (showing the eigenvalues = 1), represent the total number of components for the categories.

When the data points for 'relevancy' and 'understanding' were analysed, PCA provided nine components for each category, explaining the highest variability (66.98 % and 69.08 %, respectively) among the responses. For 'accessibility' the data points were analysed which provided ten components that explained 72.65 % of the variability. Similarly, for 'objectivity' and 'temporal' the data points provided eight principal components for each category which explained 69.86 % and 71.53 % of the variability, respectively. The association of indicators with these principal components is taken forward for interpretation in the next sections. The principal component groupings derived for each of the five categories, along with the total variance and cumulative percentages, are shown in Appendix B to F.

To simplify the PCA models, we used only the top principal components with the highest eigenvalues. This still provides a good level of predictability. The cumulative explained variance ratio was calculated to show how much of the total variability in the responses is explained by these principal components. In the 'relevancy' category (Appendix B), the top four principal components explain > 50 % of the total variability, which indicates that the model, despite its simplicity, can still capture a significant portion of the response's variance and hence maintain good predictability. Similarly, in the 'understanding', 'accessibility', and 'objectivity' categories too (Appendix C to E), the top four principal components explain > 50 % of the total variability. For the 'temporal' category (Appendix F) the top three components explain > 50 % of the total variability, thus showing that the 'temporal' category is well explained in only three components as compared to the other four categories. This shows that at least three components (for each category) could explain variability and help policymakers focus only on the most important and usable indicators.

3.3. Interpretation of themes assigned towards principal components

The most influential Component 1 (See Table 4, yellow highlights) in the 'relevancy' category includes the following seven indicators – Percentage of retained renewable water (35); Integrated land and water management policies (34); Groundwater level/sources (33); Total dam capacity (36); Ratio of annual withdrawals to available water (31); Availability of drought prediction and warning systems or climatic predictions (14); Water quality (32). Looking at the nature of the seven indicators in Table 4, they may be interpreted as being related to the theme *'Drought Preparedness and Water Resource Management'* because this group signifies a collection deemed highly relevant to drought indicators influencing water-related policies. The indicator loadings highlighted in red in Table 4 do not fall under any principal component. Also see Fig. 2 for a graphical representation of the PCA loadings according to indicators (adapted from Fig. 5 in Ermitão et al., 2023).

In the 'relevancy' category, Component 2: *'Socioeconomic and Agricultural Development'* (explaining 13.8 % variance) indicators exhibit greater statistical explanatory power than Component 4: *'Infrastructure and Policy Support'* (explaining 4.6 % variance). However, both sets of indicators broadly relate to the types of assistance provided by cooperatives or decision-makers to support small-scale farming communities against the severe impacts of droughts. This points out that experts think that indicators grouped under Component 2 [Poverty Rate (25); Participation in farming cooperatives or associations (28); Access to financing and credit (30); Food source reliability and diversity (26)] are more relevant for drought resilience as compared to indicators under Component 4 [Access to energy (16); Produce storage and transportation capacity (15); Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10); Technical assistance from local entities (e.g., cooperatives/NGO/government) (11).] These statistical interpretations of components do not necessarily dictate which indicators policymakers should prioritise; they provide a framework to identify themes with significant data-driven backing. For policymakers, this means considering the broader context of all components while recognising that higher variance components, such as Component 2, may offer a more substantial statistical basis for initial exploration. All theme names and associated components across the five categories have been listed in Appendix B to F.

4. Discussions

The objective of PCA was to filter out only the most important and usable indicators for this context. Indicators were evaluated not only for their scientific validity but also for their practical application in real-world scenarios. PCA revealed that integrating usability-focused criteria – such as clarity for decision-makers and ease of data access – enhances the relevance and applicability of indicators. For example, water management indicators like groundwater levels and drought prediction systems scored highly across all five categories, emphasising their role in developing robust resilience strategies. It was found that under each category, some indicators were not associated with any principal component. 'Relevancy' and 'understanding' had nine components each; therefore, three and seven indicators could be excluded. This exclusion resulted in only 33 and 29 indicators for these two categories, respectively, instead of the initial 36 indicators. Similarly, 'accessibility' consisted of 26 out of 36 indicators. Furthermore, 'objectivity' and 'temporal' comprised 32 and 33 indicators, respectively.

4.1. Indicators common across all five categories

Explaining which common indicators across all five categories are important for monitoring drought vulnerability and resilience. As discussed before, drought vulnerability and resilience are influenced by multiple factors, including environmental, social, economic, institutional, and infrastructural aspects. Identifying common indicators provides a comprehensive understanding of these interconnected factors.

In relation to Component 1, indicators, Ratio of annual withdrawals to available water (31), Water quality (32), Groundwater level/sources (33), and Percentage of retained renewable water (35), appear across all the five categories (Table 5). This shows that Component 1 pertains to integrated water management across all five categories. Unsurprisingly, the availability of water, its quality, and its source are a prerequisite for monitoring and mitigating drought hazards and is recognised by other scholars (Alonso et al., 2019; Kampragou et al., 2015; Meza et al., 2019; Murthy and Yadav, 2015; Wu and Yang, 2013). Thus, Component 1, which clusters indicators like "Groundwater level" (33), "Water quality" (32), and "Drought prediction systems" (14), underscores the critical role of integrated water management. PCA, therefore, provides policymakers with actionable insights by grouping indicators into principal components, each representing a cohesive theme such as water resource management, socioeconomic development, or governance. Policymakers can use this component to prioritize investments in monitoring systems and sustainable water use policies.

In Tables 6 and 7, Components 2 and 3 each had three indicators, which were identified as common across three categories. With respect to Component 2 (Table 6), Percentage of drought-resistance crop varieties cultivated (3), Percentage of farmers who use different types of crops (4), and Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6) appear common across accessibility, objectivity, and temporal categories and are indicators that relate to

Table 4
Loading values highlighting indicator grouping for 'relevancy'.

Indicators	Component and Loadings								
	1	2	3	4	5	6	7	8	9
% of retained renewable water (35)	.862	.101	.018	.019	.094	.054	.170	.040	-.070
Integrated land and water management policies (34)	.793	.055	.062	.005	.163	.113	.117	-.118	.107
Groundwater level/sources (33)	.773	.154	-.048	.244	-.134	-.033	-.002	.138	-.006
Total dam capacity (36)	.753	.146	-.081	-.062	-.091	.179	.077	.069	-.035
Ratio of annual withdrawals to available water (31)	.627	.430	-.075	-.072	-.046	-.025	-.056	-.059	.167
Availability of drought prediction and warning systems (14)	.572	.036	.029	.334	-.231	.338	.129	.046	.100
Water quality (32)	.570	.252	-.039	.341	.081	-.275	-.030	.161	-.068
Poverty rate (25)	.094	.684	.438	-.007	.156	.058	-.042	.007	.054
Participation in farming cooperatives (28)	.237	.672	.173	.224	.012	-.087	.223	.110	.109
Access to financing and credit (30)	.198	.661	.028	.303	.157	.074	.123	.206	.071
food source reliability and diversity (26)	.279	.576	.193	.109	-.044	.243	.175	.034	.018
% of the rural population (20)	-.063	.047	.764	.296	.153	.042	.024	.025	-.172
Unemployment rate (21)	-.055	.123	.694	.302	.182	.159	-.155	.166	-.075
Presence of drivers of migration and displacement (24)	-.091	.200	.636	-.178	.426	.007	.292	-.153	.111
% of population displaced (23)	.009	.209	.603	-.155	.323	-.137	.229	.063	.192
% of population ages 15-64 (22)	-.203	.364	.590	-.104	.144	-.069	-.080	.361	.219
% of the population employed in farms (29)	.324	.473	.547	.084	.010	.045	.053	.060	-.033
Access to energy (16)	.076	.326	.052	.694	.136	.141	.028	.065	.154
Produce storage and transportation capacity (15)	.057	.230	.260	.617	.299	.139	.173	.146	.159

(continued on next page)

Table 4 (*continued*)

Existence of drought management policies (10)	.410	-.088	-.013	.521	-.239	.320	.168	-.016	.122
Technical assistance from local entities (11)	.131	.375	.175	.504	-.248	.172	.173	.205	.109
% of population without access to sanitation (18)	.057	-.016	.187	.158	.821	.108	.050	.046	.047
Gender inequality (19)	-.145	.178	.317	.008	.716	.109	.074	.103	-.148
Prevalence of conflict/insecurity (17)	.038	.075	.240	-.017	.648	-.231	-.031	.287	.261
Crop loss (2)	.202	-.030	-.071	.238	.003	.690	-.024	.027	.201
% of the contribution of crop and livestock production in the income of smallholder farming (1)	-.096	.427	.168	.072	.103	.572	-.011	.082	-.035
% of farmers with crop, livestock, or drought insurance (12)	.262	.357	-.019	.215	.055	.503	.130	.239	.091
% of area protected and designated for the conservation of biodiversity (5)	.108	.168	.021	.111	.104	-.022	.831	.103	.051
% of drought resistance crop varieties cultivated (3)	.334	.105	-.023	.174	-.221	.249	.527	.296	.210
Level of public participation in local policy (27)	.252	.470	.168	.162	.179	.090	.485	-.092	.060
Land rights clearly defined (9)	.035	.205	.093	.239	.196	.062	.025	.740	-.039
% of farmers who use different types of crops (4)	.108	-.040	.224	-.149	.050	.425	.233	.532	.093
Water use rights clearly defined (13)	.385	.047	.109	.376	.123	.055	.296	.464	.132
Degree of land degradation and desertification (8)	.098	.095	.109	.108	.057	.120	.070	-.115	.815
Use of agricultural inputs (6)	-.150	.172	-.204	.164	.114	.073	.075	.303	.576
Crop water use efficiency (7)	.400	-.106	.003	.266	-.254	.230	.159	.155	.448

sustainable agricultural development. Component 3 (Table 7) have indicators that relate to rural development and demographics, namely, Percentage of the rural population (20), Unemployment rate and/or proportion of formal work (21), and Percentage of population ages 15–64 (22) appear common across relevancy, objectivity, and temporal categories. This is in agreement with the fact that population and employment-related data are indeed available from the Census and Government databases. These indicators are quantifiable in nature and are collected at different temporal scales (Meza et al., 2019) but surprisingly are not understandable or the data is inaccessible, as rated during the survey.

Further, there was commonality noted in relation to Component 4 (Table 8) where indicator (10) – Existence of drought management policies (mitigation/adaptation/prevention/preparedness) – appeared to be relevant, having data that is objective or quantifiable, and also available across different temporal scales. This also suggests that

Fig. 2. Principal Component (PC) loadings as per indicators.

Table 5
Component 1 indicators common across all five categories.

Comp.	Indicators	R	U	A	O	T
1	Crop water use efficiency (WUE) (7)		yellow		yellow	yellow
	Degree of land degradation and desertification (8)					red
	Availability of drought prediction and warning systems or climatic predictions (14)	orange	orange			
	Participation in farming cooperatives or associations (28)					red
	Ratio of annual withdrawals to available water (31)	green	green	green	green	green
	Water quality (32)	green	green	green	green	green
	Groundwater level/sources (33)	green	green	green	green	green
	Integrated land and water management policies (34)	light green	light green		light green	light green
	Percentage of retained renewable water (35)	green	green	green	green	green
	Total dam capacity (36)	yellow			yellow	yellow

Legend	
R=Relevancy; U=Understanding; A=Accessibility; O=Objectivity; T=Temporal	
green	Indicator appearing across all 5 categories
light green	Indicator appearing across any 4 categories
yellow	Indicator appearing across any 3 categories
orange	Indicator appearing across any 2 categories
red	Indicator appearing across only 1 category

indicator (10) is not easy to understand and thereby making data accessibility difficult. However, Kampragou et al. (2015) state that regions and countries with drought management policies are proactive towards drought resilience and develop better predictive mechanisms.

Additionally, it was seen that when the total variance explained decreased from Component 2 to 10 (1 explaining the most variance), the number of common indicators across the components also decreased. This points to the fact that indicators in the low variance components were stand-alone indicators, which may not be important for all categories.

From Components 5 to 10, there was no common indicator across at least three categories. For example, in relation to Component 5 across all categories, indicator Prevalence of conflict/insecurity (17) was rated as relevant and the availability of its data over different temporal scales, whereas the indicator was not easily understandable, its data were inaccessible, and difficulty in finding data that is quantifiable. This is in accordance with a study by Meza et al. (2019) where it was concluded that more than 50 % of the 124 experts considered by Meza et al. (2019) rated this indicator as relevant at the global level (out of total 64 indicators). On the other hand, in the current study, indicators Percentage of population displaced internally or transboundary (23) and Presence of drivers of migration and displacement (24) (Component 5) were rated as easy to understand as well as available over different temporal scales. These indicators were observed to be irrelevant, inaccessible, and difficult to quantify. This is unexpected as the relevancy of these indicators to drought resilience has been shown in a similar study conducted by Meza et al. (2019). It is also contrary to the experiences and perceptions of small-scale farmers who have reported migration and displacement as the primary impacts of droughts and hence require proactive adaptive measures to mitigate the same (Lottering et al., 2021). Table 9 summarises the common indicators across all categories as discussed in the above sections.

PCA identifies thematic components that represent integrated dimensions of drought resilience. These integration of correlated

Table 6
Component 2 indicators common across at least three categories.

Comp.	Indicators	R	U	A	O	T
2	Percentage of the contribution of crop and livestock production in the income of smallholder farming (1)					
	Crop loss (2)					
	Percentage of drought-resistance crop varieties cultivated (3)					
	Percentage of farmers who use different types of crops (4)					
	Percentage of area protected and designated for the conservation of biodiversity (5)					
	Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6)					
	Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10)					
	Percentage of farmers with crop, livestock, or drought insurance (12)					
	Water use rights clearly defined (13)					
	Poverty Rate (25)					
	Food source reliability and diversity (26)					
	Level of public participation in local policy (27)					
	Participation in farming cooperatives or associations (28)					
	Access to financing and credit (30)					

Table 7
Component 3 indicators common across at least three categories.

Comp.	Indicators	R	U	A	O	T
3	Percentage of farmers with crop, livestock, or drought insurance (12)					
	Produce storage and transportation capacity (15)					
	Access to energy (16)					
	Percentage of the rural population (20)					
	Unemployment rate and/or proportion of formal work (21)					
	Percentage of population ages 15-64 (22)					
	Percentage of population displaced internally or transboundary (23)					
	Presence of drivers of migration and displacement (24)					
	Poverty rate (25)					
	Percentage of the population employed in farms (29)					
	Access to financing and credit (30)					

indicators offers a context for policymakers to assess and carry out a comparative analysis, such as assessing whether "System A is more resilient than System B." Thematic components, enable pathway to determine actionable strategies because a multitude of indicators are looked at from a holistic point of view, as a component, rather than in silos or individually. For instance, if a system scores lower on socio-economic indicators clustered under a specific component (say Component 2), policymakers can prioritise interventions like increasing access to financing and credit or promoting farming cooperatives to improve resilience. By addressing these dimensions together, PCA provides a pathway to enhance resilience by guiding specific improvements in indicator clusters rather than isolated metrics.

Water resource-related indicators exhibited consistent significance across all five categories. This suggests that water access and usage patterns are foundational and spatially ubiquitous drivers of regional differentiation. For example, given the agrarian nature of many Indian and African regions and the critical role of water in sustaining both agriculture and domestic needs, water-related indicators tend to exhibit relatively high variance and correlation with multiple developmental and environmental variables, thereby influencing several components. In contrast, socioeconomic indicators such as the percentage of the rural population (20) and poverty rate (25) are context-dependent. They may not exhibit the same level of statistical variation or correlation across all regions. Their partial significance in specific components suggests that these variables strongly influence only certain developmental typologies or clusters (e.g., components emphasizing rural backwardness or urbanization levels) rather than universally affecting all regional dynamics. This contrast highlights how the availability of natural resources (e.g., water) serves as a fundamental driver of regional development patterns. At the same time, socioeconomic factors may be more selectively influential, depending on the local context and existing infrastructure.

4.2. Indicators not identified with any principal component across all five categories

The following three indicators did not fall under any principal component in the 'relevancy' category – Level of public participation in

Table 8
Component 4 indicators common across at least three categories.

Comp.	Indicators	R	U	A	O	T
4	Land rights clearly defined (yes/no) (9)					(red)
	Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10)	(yellow)			(yellow)	(yellow)
	Technical assistance from local entities (e.g., cooperatives/NGO/government) (11)	(orange)				(orange)
	Water use rights clearly defined (13)				(orange)	(orange)
	Availability of drought prediction and warning systems or climatic predictions (14)				(red)	
	Produce storage and transportation capacity (15)	(red)				
	Access to energy (16)	(red)				
	Percentage of the rural population (20)			(red)		
	Unemployment rate and/or proportion of formal work (21)		(orange)	(orange)		
	Percentage of population ages 15-64 (22)			(red)		
	Participation in farming cooperatives or associations (28)		(red)			
	Total dam capacity (36)		(red)			

Table 9
List of indicators common across categories.

Comp.	Relevancy (R)	Understanding (U)	Accessibility (A)	Objectivity (O)	Temporal (T)	Common
1	**35**, 34, **33**, 36, **31**, 14, **32**	**35**, 34, 7, **31**, **32**, 14, **33**	**32, 33, 31, 35**	**33**, **35**, **32**, **31**, 36, 34, 7	**35**, **33**, **31**, 34, **32**, 7, 8, 28, 36	31, 32, 33, 35
2	25, 28, 30, 26	10, 26, 5, 13, 27	**4, 6, 3**	**3**, **4**, 1, 5, 2, **6**	1, **4**, 2, **6**, **3**, 12	3, 4, 6 (A, O, T)
3	**20**, **21**, 24, 23, **22**, 29	16, 15	30, 15, 16, 12	**22, 21, 20,** 25	**22**, 25, **20**, **21**, 29	20, 21, 22 (R, O, T)
4	16, 15, **10**, 11	36, 28, 21	22, 20, 21	**10**, 14, 13	9, 13, **10**, 11	10 (R, O, T)
5	18, 19, 17	23, 24	34, 10	28, 27, 29, 30, 26	24, 23, 17	–-
6	2, 1, 12	17, 18	19, 17	15, 16, 12	18, 19	–-
7	5, 3	19, 1, 25, 20	26, 25	19, 17	14, 15	–-
8	9, 4	6, 4	14, 13	23, 9	26, 27	–-
9	8, 6	2, 8	23, 24			–-
10			9, 5			–-

local policy (27), Water use rights clearly defined (13), and Crop water use efficiency (WUE) (7). Indicators (27) and (13) both represent rights or norms within governance and legal systems, with engagement and ownership being considered fundamental to being heard and represented in policies affecting them. It may be that these indicators were considered too remote from drought, but further investigation is warranted. Indicators (13) and (7) are also water-related indicators, but according to the analysis, do not fall within the most relevant Component 1, broadly pertaining to *integrated water management policies*. This is unexpected as the importance of these indicators to drought management has been shown in the past (Kampragou et al. 2015; Meza et al., 2019) and the reason they were selected for inclusion in the MADIS project. It is also contrary to anecdotal experience within the MADIS team, where small-scale farmers are seeking better irrigation and water use efficiency, for example. The reason may be that experts do not perceive the information on these indicators being relevant for the specific job of formulating drought related mitigation strategies. Regarding the indicator Crop water use efficiency (WUE) (7), while the PCA analysis identified WUE as a less significant independent factor for policymaking when integrated into targeted tools or calculators, WUE can become highly actionable. For instance, its use in dynamic modelling frameworks or resource allocation systems enables policymakers to optimise water use in agriculture. This highlights the need for contextual applications of WUE, whose relevance depends on its integration into broader decision-making frameworks. This may warrant further investigation in future research. Due to the low variability in responses between Components 7 to 9, and their similarity, it is arguable these could be integrated into a single component of *sustainable agriculture*.

'Understanding' and 'accessibility' had a maximum number of indicators that did not relate to any principal component (seven and ten indicators, respectively) owing to the experts either rating them as 'not known' or 'low'. Percentage of drought-resistance crop varieties cultivated (3), Land rights clearly defined (yes/no) (9), Access to financing and credit (30), Technical assistance from local entities (e.g., cooperatives/NGO/government) (11), Percentage of farmers with crop, livestock, or drought insurance (12), Percentage of population ages 15–64 (22), and Percentage of the population employed in farms (29) were the indicators that were excluded from the 'understanding' category. This may be because the experts regard these as too broad an indicator for clear 'understanding', the indicators did not fall under the research area of the experts rating them, or these indicators are not directly related to a policy objective for delivering it to the broader public. For the 'accessibility' category, along with indicator (29), nine more indicators were not included, namely, Total dam capacity (36), Crop loss (2), Percentage of the contribution of crop and livestock production in the income of smallholder farming (1), Technical assistance from local entities (e.g., cooperatives/NGO/government) (11), Participation in farming cooperatives or associations (28), Percentage of the population without access to (improved) sanitation (18), Level of public participation in local policy (27), Crop water use efficiency (WUE) (7), and Degree of land degradation and desertification (8). This may be because the data of these ten indicators is not easily accessible or available, and collecting and processing the data requires significant time and effort. This was an interesting note because for drought management policies to be formulated and implemented contextually, it is imperative that the indicators are understood well and data are accessible to be able to be monitored in a timely manner (Lindoso et al., 2011; Kampragou et al., 2015). Looking back at the questions asked for rating indicators under these two categories of 'understanding' and 'accessibility', this may be because the indicators were interpreted differently by various decision-makers and the indicator data is not easily accessible or available, as best known by the experts.

Similarly, Degree of land degradation and desertification (8), Technical assistance from local entities (e.g., cooperatives/NGO/government) (11), Percentage of the population without access to (improved) sanitation (18), and Presence of drivers of migration and displacement (24) were excluded from the 'objectivity' category hinting that the data of these four indicators is subjective and requires expert judgement to be quantitatively evaluated or interpreted (Leguízamo et al., 2020; Meza et al., 2019). Whereas for the 'temporal' category, Access to financing and credit (30), Percentage of area protected and designated for the conservation of biodiversity (5), and Access to energy (16) were not included. This may be due to the reason that the data of these three indicators is collected in an ad-hoc manner, limiting the ability to monitor and compare the indicator over different temporal scales (Huai, 2017; Leguízamo et al., 2020; Meza et al., 2019). Of all indicators, Technical assistance from local entities (e.g., cooperatives/NGO/government) (11) does not associate with any of the three categories namely, understanding, accessibility, and objectivity, because experts feel that data on indicator (11) is qualitative, less understandable, and if the data exists it is not accessible to all. However, this indicator is relevant and can be collected at different temporal scales.

To reiterate, it was interesting to note that Crop water use efficiency (WUE) (7) did not relate to any of the components with the 'relevancy' and 'accessibility' categories. Whereas this same indicator is related to Component 1 in the 'objectivity' category. This may indicate that while WUE could be easily quantified with low ambiguity, it is perceived as not relevant to the context of droughts, which makes the data for this indicator unavailable or inaccessible (Meza et al., 2019). Although WUE is a very related indicator for droughts, policy makers must be aware that this indicator may be highly unreliable for developing drought mitigation strategies. Fig. 3 summarises the indicators that were not identified under any principal component for all the five categories.

5. Conclusion

This study underscores the importance of indicator usability in drought resilience planning. By systematically evaluating indicators across multiple dimensions, this study employs a PCA-based approach to analyse 36 drought vulnerability and resilience indicators, grouped into five categories – relevancy, ease of understanding, data accessibility, data objectivity, and temporal data availability for decision-makers to select the most practical and impactful indicators. Analysis shows that not all the 36 indicators were grouped under the themes of the principal components and fewer indicators can be considered to be used in the decision-making process by policymakers. The analysis highlights the significant role of water-related indicators, consistently prominent in Component 1 across all categories, underscoring the critical importance of integrated water management in mitigating agricultural drought impacts, particularly for small-scale farming communities. It was also seen that at least three components (for each category) could explain > 50 % of the variability and thereby help policymakers contextually focus only on the most important and usable indicators, offering a more concise framework for drought assessment in small farms.

Unlike traditional mean-based indicator analysis, PCA provides a nuanced understanding of the interrelationships between indicators, allowing for the identification of core components that drive drought vulnerability and resilience. This methodological advantage enables a more holistic and interconnected view, facilitating the development of comprehensive and effective drought management strategies. PCA thus aids policymakers by reducing complexity, revealing interconnections, and grouping indicators into actionable themes. The simplicity of using mean-based analysis does not help uncover the interrelationships between indicators, nor does it help to categorise indicator information into usable groups for decision-making.

Small farms can integrate these drought resilience indicators into their planning by focusing on the most relevant and practical components identified through PCA. By prioritising key water-related indicators, such as crop water use efficiency and access to water resources, small farms can implement water conservation strategies and optimize irrigation systems to mitigate drought impacts. These indicators help farmers adopt efficient practices like rainwater harvesting and soil moisture monitoring, vital for maintaining productivity during drought conditions. Additionally, incorporating socioeconomic indicators, such as the unemployment rate and the percentage of the population aged 15–64, allows small farms to assess community vulnerability and ensure economic preparedness for drought recovery. By focusing on the most actionable indicators, based on the PCA results, small farms can streamline their decision-making processes, making them more efficient and effective in building resilience to drought.

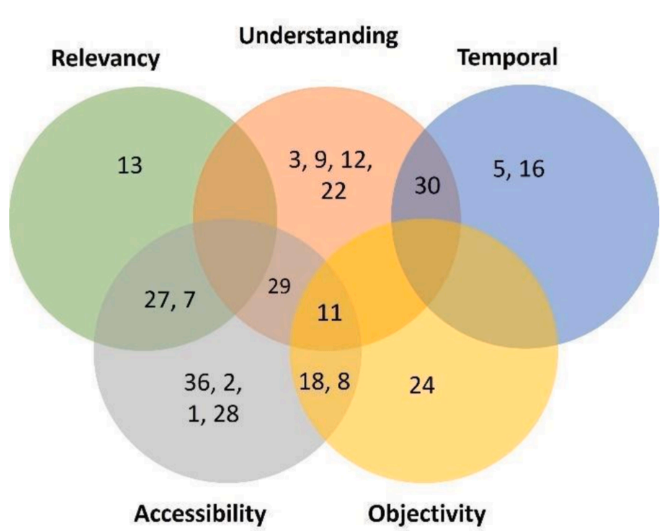

Fig. 3. Representation of indicators (depicted by their numbers) not identified under any principal component.

The findings offer practical implications for decision-makers, planners, water resource managers, and community stakeholders, guiding the creation of targeted and context-specific interventions. By focusing on integrated water management policies and viewing individual indicators within the broader water cycle, policymakers can better address the multifaceted challenges of drought. The findings emphasize the need for clear, accessible, and relevant data to support effective policy-making, particularly for small-scale farmers. PCA's combinatorial (or reducing data dimensionality) nature helps policymakers understand systemic resilience by grouping indicators. For example, the clustering of indicators like "Unemployment rate" (21) and "% of population ages 15-64″ (22) into socioeconomic components highlights their collective relevance in addressing vulnerabilities. Meanwhile, the analysis of weak correlations, such as between the "Existence of drought management policies" (10) and the "Ratio of annual withdrawals to available water" (31), offers valuable insights for designing integrated policies that dynamically respond to drought conditions. The nuanced treatment of Crop water use efficiency (7) further demonstrates how specific indicators, while less influential on their own, gain policy relevance when integrated into targeted tools or calculators. Using PCA results, policymakers can compare resilience between systems, identify weaknesses, and implement targeted measures that improve the overall resilience of that system (vis a vis small farms in the current study). Policymakers are thus equipped with both a strategic overview and detailed guidance for implementation, making the framework both scientifically robust and practically usable.

Furthermore, this study opens avenues for future research, suggesting the inclusion of additional lenses, such as indicators' susceptibility to climate patterns and their cascading risks across the water-energy-food nexus. For example, indicators linked to the water-energy-food nexus – such as Crop water use efficiency (7), Access to energy (16), Food source reliability and diversity (26), etc. – were included to capture the interconnected challenges and opportunities within this methodology. Research on such topics will provide a valuable resource for refining drought resilience strategies, ultimately aiding policymakers in making informed decisions that bolster community resilience to drought events.

Also to be noted is that the relevance and applicability of these indicators can vary significantly depending on geographical location. Water-related indicators will be especially crucial in regions facing water scarcity or recurrent droughts, where efficient water management is central to maintaining crop yields. In contrast, farms in areas with more stable rainfall patterns or better access to water resources might emphasise crop diversification and food source reliability more than direct water management. Socioeconomic indicators also vary in relevance based on local conditions, with regions experiencing high unemployment or labour migration benefitting from integrating these into their drought preparedness strategies. The PCA framework allows small farms to tailor their resilience plans to their specific environmental, economic, and social contexts, helping policymakers and farmers address regional challenges effectively and focus on the most impactful indicators for their unique circumstances.

CRediT authorship contribution statement

Tanaya Sarmah: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nazmiye Balta-Ozkan:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Abdullah Konak:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Elisabeth Shrimpton:** Writing – review & editing. **Karina Simone Sass:** Writing – review & editing. **Marina Batalini De Macedo:** Writing – review & editing. **Eduardo Mario Mendiondo:** Writing – review & editing. **Adelaide Cassia Nardocci:** Writing – review & editing. **Da Huo:** Writing – review & editing. **Michael Gregory Jacobson:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors 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:. Questionnaire design

No.	Category	Question	Scale		
			Low	Medium	High
1	Relevancy	How relevant are the indicators in terms of the information needs of decision-makers for improving drought resilience policies and better managing resources?	The indicator is irrelevant to the information needs of decision-makers.	The indicator is moderately relevant to the information needs of decision-makers.	The indicator is highly relevant to the information needs of decision-makers.
2	Understanding	How easy to understand are the indicators by decision-makers to be used in a drought resilience index for small to medium size farms?	The indicator may be interpreted differently by various decision-makers. The indicator is not clearly connected to a policy objective.	The indicator is understood by most decision-makers with some clarification. The indicator conveys useful information.	The indicator is readily understood by decision-makers and, preferably, the broad audience. The indicator conveys useful, relevant information for decision-makers on a specific policy objective.
3	Accessibility	How easy is the data accessibility of the indicators for reasonable cost or level of effort?	The indicator data is not easily accessible or available. Collecting and processing the data requires significant time and effort.	The indicator data is mostly available, but processing the data requires some effort.	The indicator data is publicly accessible and readily available. Processing the data requires minimal effort.
4	Objectivity	How objective or subjective is the available data for ease of interpretation?	A subjective measure that requires expert judgment to evaluate the indicator.	Requires some degree of expert judgment to interpret	An objective measure is based on quantifiable, impartial, and recorded data.

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No.	Category	Question	Scale Low	Medium	High
				quantitative or qualitative data.	
5	Temporal	How consistent is the data availability over different temporal scales to be used in a drought resilience index for small to medium size farms?	The indicator data is collected in an ad-hoc manner, limiting the ability to monitor and compare the indicator over different temporal scales.	The indicator data is collected periodically but not frequently enough for comparing the indicator in different temporal scales.	The indicator data is collected regularly and available over different time scales, allowing for monitoring and comparing the indicator over different temporal scales.

Appendix B:. 'Relevancy' category principal components

Component no. and name	Total	% Variance	Cumulative %	Indicator grouping
1: Drought Preparedness and Water Resource Management	9.04	25.133	25.133	Percentage of retained renewable water (35); Integrated land and water management policies (34); Groundwater level/sources (33); Total dam capacity (36); Ratio of annual withdrawals to available water (31); Availability of drought prediction and warning systems or climatic predictions (14); Water quality (32)
2: Socioeconomic and Agricultural Development	4.99	13.870	39.004	Poverty Rate (25); Participation in farming cooperatives or associations (28); Access to financing and credit (30); Food source reliability and diversity (26)
3: Demographic and Labor Market Dynamics	2.31	6.440	45.444	Percentage of the rural population (20); Unemployment rate and/or proportion of formal work (21); Presence of drivers of migration and displacement (24); Percentage of population displaced internally or transboundary (23); Percentage of population ages 15–64 (22); Percentage of the population employed in farms (29)
4: Infrastructure and Policy Support	1.66	4.627	50.071	Access to energy (16); Produce storage and transportation capacity (15); Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10); Technical assistance from local entities (e.g., cooperatives/NGO/government) (11)
5: Social Vulnerability and Equity	1.45	4.048	54.118	Percentage of the population without access to (improved) sanitation (18); Gender inequality (19); Prevalence of conflict/insecurity (17)
6: Agricultural Livelihood and Risk Management	1.35	3.769	57.887	Crop loss (2); Percentage of the contribution of crop and livestock production in the income of smallholder farming (1); Percentage of farmers with crop, livestock, or drought insurance (12)
7: Ecological Resilience and Conservation	1.15	3.203	61.090	Percentage of area protected and designated for the conservation of biodiversity (5); Percentage of drought-resistance crop varieties cultivated (3)
8: Agricultural Diversity and Land Tenure	1.09	3.035	64.125	Land rights clearly defined (yes/no) (9); Percentage of farmers who use different types of crops (4)
9: Agricultural Intensification and Land Health	1.03	2.862	**66.987**	Degree of land degradation and desertification (8); Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6)

Appendix C:. 'Understanding' category principal components

Component no. and name	Total	% Variance	Cumulative %	Indicator grouping
1: Water Resource Management and Efficiency	11.36	31.572	31.572	Percentage of retained renewable water (35); Integrated land and water management policies (34); Crop water use efficiency (WUE) (7); Ratio of annual withdrawals to available water (31); Water quality (32); Availability of drought prediction and warning systems or climatic predictions (14); Groundwater level/sources (33)
2: Environmental Policy and Community Engagement	3.83	10.645	42.217	Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10); Food source reliability and diversity (26); Percentage of area protected and designated for the conservation of biodiversity (5); Water use rights clearly defined (13); Level of public participation in local policy (27)
3: Infrastructure and Energy Access	2.00	5.565	47.782	Access to energy (16); Produce storage and transportation capacity (15)
4: Economic and Institutional Capacity	1.54	4.304	52.086	Total dam capacity (36); Participation in farming cooperatives or associations (28); Unemployment rate and/or proportion of formal work (21)
5: Population Displacement and Migration Drivers	1.48	4.124	56.210	Percentage of population displaced internally or transboundary (23); Presence of drivers of migration and displacement (24)
6: Human Security and Public Health	1.39	3.862	60.073	Prevalence of conflict/insecurity (17); Percentage of the population without access to (improved) sanitation (18)
7: Rural Livelihood and Social Equity	1.17	3.263	63.336	Gender inequality (19); Percentage of the contribution of crop and livestock production in the income of smallholder farming (1); Poverty Rate (25); Percentage of the rural population (20)
8: Agricultural Practices and Crop Diversity	1.05	2.921	66.257	Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6); Percentage of farmers who use different types of crops (4)
9: Agricultural Resilience and Land Health	1.01	2.829	**69.086**	Crop loss (2); Degree of land degradation and desertification (8)

Appendix D:. 'Accessibility' category principal components

Component no. and name	Total	% Variance	Cumulative %	Indicator grouping
1: Water Resource Availability and Quality	12.11	33.662	33.662	Water quality (32); Groundwater level/sources (33); Ratio of annual withdrawals to available water (31); Percentage of retained renewable water (35)
2: Crop Diversity and Agricultural Practices	3.07	8.544	42.206	Percentage of farmers who use different types of crops (4); Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6); Percentage of drought-resistance crop varieties cultivated (3)
3: Agricultural Risk Management and Infrastructure	2.02	5.619	47.825	Access to financing and credit (30); Produce storage and transportation capacity (15); Access to energy (16); Percentage of farmers with crop, livestock, or drought insurance (12)
4: Rural Demographic and Labor Market	1.77	4.927	52.752	Percentage of population ages 15–64 (22); Percentage of the rural population (20); Unemployment rate and/or proportion of formal work (21)
5: Policy Frameworks for Drought and Water Management	1.42	3.961	56.713	Integrated land and water management policies (34); Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10)
6: Social Vulnerability and Gender Equity	1.35	3.769	60.482	Gender inequality (19); Prevalence of conflict/insecurity (17)
7: Food Security and Poverty	1.22	3.406	63.888	Food source reliability and diversity (26); Poverty Rate (25)
8: Water Governance and Predictive Capabilities	1.07	2.978	66.865	Availability of drought prediction and warning systems or climatic predictions (14); Water use rights clearly defined (13)
9: Migration and Displacement Risk	1.06	2.954	69.819	Percentage of population displaced internally or transboundary (23); Presence of drivers of migration and displacement (24)
10: Biodiversity Conservation and Land Tenure	1.02	2.840	**72.659**	Land rights clearly defined (yes/no) (9); Percentage of area protected and designated for the conservation of biodiversity (5)

Appendix E:. 'Objectivity' category principal components

Component no. and name	Total	% Variance	Cumulative %	Indicator grouping
1: Water Resource Management and Efficiency	12.22	33.946	33.946	Groundwater level/sources (33); Percentage of retained renewable water (35); Water quality (32); Ratio of annual withdrawals to available water (31); Total dam capacity (36); Integrated land and water management policies (34); Crop water use efficiency (WUE) (7)
2: Agricultural Sustainability and Resilience	2.91	8.099	42.045	Percentage of drought-resistance crop varieties cultivated (3); Percentage of farmers who use different types of crops (4); Percentage of the contribution of crop and livestock production in the income of smallholder farming (1); Percentage of area protected and designated for the conservation of biodiversity (5); Crop loss (2); Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6)
3: Rural Socioeconomic Development	2.46	6.858	48.903	Percentage of population ages 15–64 (22); Unemployment rate and/or proportion of formal work (21); Percentage of the rural population (20); Poverty Rate (25)
4: Drought Governance and Preparedness	2.23	6.208	55.111	Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10); Availability of drought prediction and warning systems or climatic predictions (14); Water use rights clearly defined (13)
5: Agricultural and Community Resilience	1.66	4.615	59.725	Participation in farming cooperatives or associations (28); Level of public participation in local policy (27); Percentage of the population employed in farms (29); Access to financing and credit (30); Food source reliability and diversity (26)
6: Agricultural Infrastructure and Risk Management	1.51	4.197	63.922	Produce storage and transportation capacity (15); Access to energy (16); Percentage of farmers with crop, livestock, or drought insurance (12)
7: Social Equity and Security	1.12	3.127	67.049	Gender inequality (19); Prevalence of conflict/insecurity (17)
8: Land Tenure and Displacement	1.01	2.815	**69.864**	Percentage of population displaced internally or transboundary (23); Land rights clearly defined (yes/no) (9)

Appendix F:. 'Temporal' category principal components

Component no. and name	Total	% Variance	Cumulative %	Indicator grouping
1: Sustainable Agriculture and Water Management	13.05	36.269	36.269	Percentage of retained renewable water (35); Groundwater level/sources (33); Ratio of annual withdrawals to available water (31); Integrated land and water management policies (34); Water quality (32); Crop water use efficiency (WUE) (7); Degree of land degradation and desertification (8); Participation in farming cooperatives or associations (28); Total dam capacity (36)
2: Agricultural Productivity and Resilience	2.82	7.859	44.128	Percentage of the contribution of crop and livestock production in the income of smallholder farming (1); Percentage of farmers who use different types of crops (4); Crop loss (2); Use of agricultural inputs (e.g., insecticides, pesticides, fertilizer, machinery) (6); Percentage of drought-resistance crop varieties cultivated (3); Percentage of farmers with crop, livestock, or drought insurance (12)
3: Land and Water Governance	2.60	7.243	51.371	Percentage of population ages 15–64 (22); Poverty Rate (25); Percentage of the rural population (20); Unemployment rate and/or proportion of formal work (21); Percentage of the population employed in farms (29)
4: Natural Resource Governance	1.88	5.228	56.598	Land rights clearly defined (yes/no) (9); Water use rights clearly defined (13); Existence of drought management policies (mitigation/adaptation/prevention/preparedness) (10); Technical assistance from local entities (e.g., cooperatives/NGO/government) (11)

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Component no. and name	Total	% Variance	Cumulative %	Indicator grouping
5: Human Security and Displacement	1.72	4.779	61.378	Presence of drivers of migration and displacement (24); Percentage of population displaced internally or transboundary (23); Prevalence of conflict/insecurity (17)
6: Social Equity and Public Health	1.37	3.815	65.193	Percentage of the population without access to (improved) sanitation (18); Gender inequality (19)
7: Infrastructure and Resilience Planning	1.18	3.289	68.481	Availability of drought prediction and warning systems or climatic predictions (14); Produce storage and transportation capacity (15)
8: Community Food Security and Governance	1.09	3.053	**71.534**	Food source reliability and diversity (26); Level of public participation in local policy (27)

Data availability

Data supporting this study are openly available at https://sites.psu.edu/belmont/files/2024/08/PCA_Paper.zip

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