African Journal of
Agricultural and Resource Economics
Volume 21, Number 2 (2026), pp 152–174

Impacts of water reservoir valorisation on agro-pastoralists' drought response capacity in Northern and Central Benin

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Received: September 2025
Published: June 2026

DOI: https://doi.org/10.53936/afjare.2025.21(2).7

Abstract

This study analyses the impacts of water reservoir valorisation on the drought response capacity of agro-pastoralists in northern and central Benin, based on a survey of 428 respondents. It relies on the construction of the response capacity index (RCI) and the reservoir valorisation index (RVI), combined with the estimation of a robust two-step regression model. The results indicate a significant improvement in response capacity among beneficiaries, with the RVI exerting a positive and significant effect on the RCI (β = 0.714; p < 0.01). Further analysis shows that risk management knowledge (C2) and access to water infrastructure (C4) account for more than 55% of the cumulative effect. However, impacts vary across activities (agriculture, livestock, aquaculture) and territories, highlighting differentiated vulnerabilities. These findings emphasise the need for integrated and context-specific approaches, combining physical access to water with cognitive, organisational and material capacities to effectively strengthen drought resilience.

Key words: agro-pastoralists, Benin, impacts, response capacity index, water reservoir valorisation

1. Introduction

Climate change is intensifying rainfall variability and droughts in West Africa, threatening vulnerable agropastoral systems (Pörtner *et al*. 2022). These disruptions reduce water availability, agricultural productivity and food security (Zampieri *et al*. 2017; Sultan *et al*. 2019; Vallejos Mihotek 2020). Water reservoirs are promoted as technical solutions to secure water access, diversify livelihoods and improve rural households' socioeconomic conditions (Venot *et al*. 2012; Owusu *et al*. 2022).

In Benin, the proliferation of such infrastructure since the 1970s has affected the central and northern regions in particular (Pelebe *et al*. 2019). Initially intended for livestock watering, reservoirs now support irrigation, aquaculture and processing (Kpéra *et al*. 2012; Cecchi *et al*. 2020). However, research shows that their actual effectiveness depends less on their physical presence than on the conditions under which they are valorised. In this study, reservoir valorisation refers to the set of productive, organisational and operational practices through which users optimise the multifunctional use of water – irrigation, fish farming, livestock watering, collective management arrangements and maintenance activities. This valorisation is quantified using a reservoir valorisation index (RVI) that is empirically constructed from standardised sector-specific indicators aggregated through principal component Analysis (PCA). The performance of these infrastructures, however, can be undermined by rapid sedimentation, weak irrigation systems, inadequate maintenance or exclusive community management (De Fraiture *et al*. 2014; Cecchi *et al*. 2020). Their adaptive effects are neither systematic nor uniform, but shaped by local socioeconomic dynamics and organisational capacities (Speranza *et al*. 2014; Zarafshani *et al*. 2016). To analyse these dynamics, the study adopts the concept of *response capacity*, defined as the ability of agro-pastoralists to mobilise resources, knowledge and infrastructure against drought. This capacity is assessed through four key components: (i) risk prevention and organisation, (ii) knowledge level for hazard management, (iii) available resources and tools for intervention, and (iv) infrastructure and equipment deployable in emergencies (COPECO & IHCIT 2022). We hypothesise that the valorisation of water reservoirs significantly enhances this capacity.

However, despite the recognised role of reservoirs in strengthening agropastoral resilience (Ayantunde *et al*. 2018; Moussa & Laffly 2021), few studies have simultaneously assessed the quality of reservoir valorisation, the specific practices associated with it, and their measurable impacts on drought response capacity. Analyses by Venot *et al*. (2012) and Saruchera and Lautze (2019) further show that small reservoirs in sub-Saharan Africa often remain underperforming despite substantial investments, highlighting a persistent gap between infrastructural availability and its effective use, particularly in drought-prone regions. Against this background, it becomes necessary to evaluate the extent to which reservoir valorisation enhances the drought response capacity of agro-pastoralists in central and northern Benin.

This study proposes an empirical method to quantify reservoir valorisation through a PCA-based synthetic index. It also examines how this valorisation translates into response capacity using a structured analytical framework that can be replicated in other water-stressed contexts. Furthermore, it highlights sectoral and territorial disparities, offering operational insights for water governance and climate adaptation policies. Preliminary results indicate a positive and significant impact of reservoir valorisation on response capacity, with risk management knowledge and access to water infrastructure emerging as key drivers. This study thus contributes to the literature on climate adaptation under water stress and provides useful insights for policymakers, practitioners and rural communities.

2. Materials and methods

2.1 Study area

The study was conducted in five municipalities located in the departments of Borgou, Collines and Donga in northern and central Benin: Nikki, Tchaourou, Bassila, Dassa-Zoume and Ouesse. These areas account for approximately 57% of the water reservoirs identified nationwide (Pelebe *et al*. 2019) and are characterised by a high density of farmers and cattle herders (Abdoulaye *et al*. 2020). The selected municipalities were chosen for their permanent reservoirs used for agricultural, pastoral and fishery purposes (Figure 1).

Within these municipalities, six multifunctional water reservoirs (used for agriculture, livestock watering and aquaculture) that remain active during the dry season were selected for the study. These reservoirs were stratified by volume into three categories: small (≤ 31 063 m³), medium (31 063 to 69 135 m³) and large (> 69 135 m³), with two reservoirs randomly selected from each stratum (Sugunan 1995; Downing *et al*. 2006; Easter *et al*. 2018; Busker *et al*. 2019).

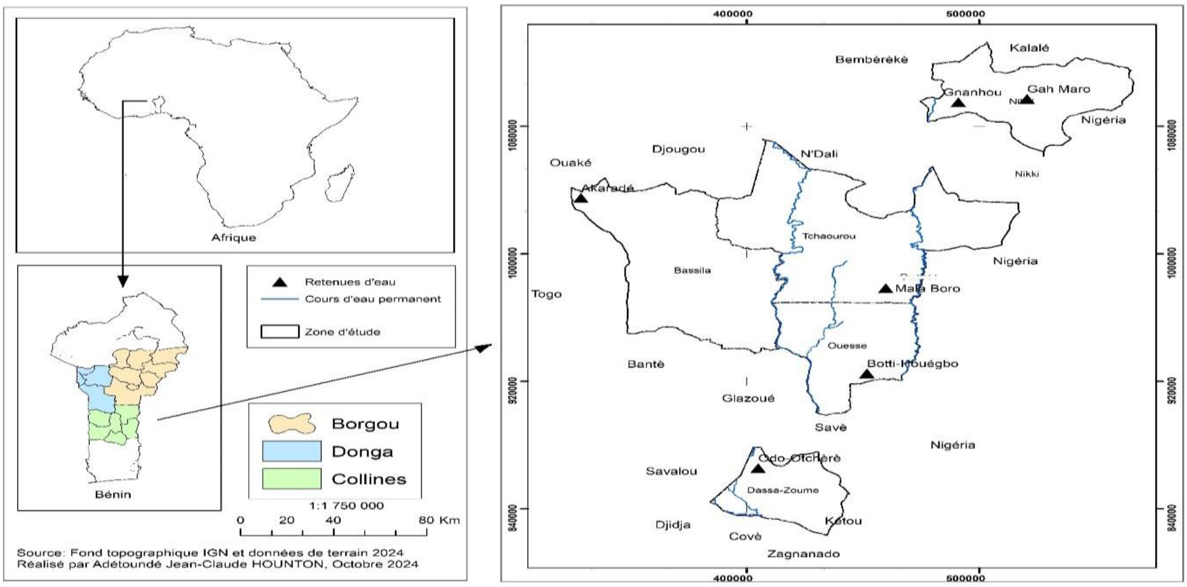

Figure 1: Map of the study area

2.2 Sampling

The study involved 428 respondents, including users (farmers, livestock breeders and fish farmers) and institutional actors involved in the management of water reservoirs. In each village, 35 agro-pastoralists were randomly selected from lists provided by the local agricultural services. Institutional agents were purposively selected based on their roles and administrative status. The sample size meets statistical standards (Kwak & Kim 2017).

2.3 Data collection

Primary data were collected using smartphones via the KoboCollect platform (Ouko *et al*. 2022) between January and March 2025, through direct surveys conducted with agro-pastoralists engaged in farming, livestock rearing and aquaculture, as well as with local government officials and representatives of decentralised agricultural services. The data collected include socioeconomic and demographic characteristics (age, gender, education level, literacy, cooperative membership, agroecological zone, etc.), along with information used to construct composite indices such as the water reservoir valorisation index (RVI) and the response capacity index (RCI) of agro-pastoralists. Additional data covered governance arrangements, stakeholder responsibilities, resource availability and types of institutional support. Variables related to the RVI and RCI vary according to the respondent's primary activity (farming, livestock or fish farming).

2.4 Methods and analytical tools

2.4.1 Descriptive statistics

Data collected with KoboCollect were cleaned in Excel and analysed using measures of central tendency and dispersion for the response capacity index (RCI) and the reservoir valorisation index (RVI), disaggregated by beneficiary status and type of activity. Mean comparison tests were applied to assess differences in RCI components, complemented by relative improvement indicators and efficiency thresholds (d'Errico 2017; Spake *et al*. 2022). Descriptive statistics and a robust MM-type regression were conducted in R 4.4.2 (Maechler *et al*. 2024; Malek-Ahmadi *et al*. 2024), with model significance evaluated through a pseudo-F statistic. The Shapiro–Wilk test checked the normality of the RCI (De Souza *et al*. 2023), Pearson correlations examined relationships between RCI, its components and RVI (Asadzadeh *et al*. 2025), and multicollinearity was assessed with the variance inflation factor (Salmerón *et al*. 2018; Marcoulides & Raykov 2019). Finally, a Pareto diagram ranked the RCI components (Sahu *et al*. 2024; Tagaram & Chen 2025), and scatterplots illustrated the RCI–RVI relationships (Pariasca-Tanaka *et al*. 2022).

2.4.2 Composite indices

Two different composite indices were constructed in this study: the response capacity index (RCI) of agro-pastoralists (used as the dependent variable) and the water reservoir valorisation index (RVI) (used as an explanatory variable). The RVI was constructed from variables characterising the intensity of reservoir use in three activity sectors: agriculture, livestock and fish farming. Principal component analysis (PCA) was employed in an exploratory way to assess the internal coherence of the variables selected for building the RVI within each activity sector. Following the methodologies of Abdi and Williams (2010), Hair (2011), Verma *et al*. (2020), Broby and Smyth (2025) and Santos *et al*. (2025), only the first principal component (PC1) was retained for each sector, as it explains the majority of the total variance and captures the common direction of the most influential variables. A component is considered a valid index when its contribution to the total variance exceeds 50%, ideally above 60%. This threshold guided the selection of variables within each domain, ensuring sufficient structural coherence to interpret the extracted component as a valid synthetic measure of reservoir valorisation.

Before conducting the PCA, all variables were normalised on a scale of 0 to 1 to ensure comparability (OECD *et al*. 2008). Several normalisation methods exist (min-max, z-score transformation, distance to a reference point, balanced opinion aggregation), each with varying suitability depending on the nature of the data and the aggregation strategy (Marzi *et al*. 2018). In this study, min-max normalisation was applied, following Vincent (2007), Hahn *et al*. (2009), Ide *et al*. (2021) and Moreira *et al*. (2021). However, some variables, such as annual production, showed strong skewness. To improve normality and stabilise variance, a logarithmic transformation was applied prior to normalisation and PCA (West 2021). This approach adheres to consistent methodological logic. For each respondent, the score on PC1 was then extracted and rescaled to an interval from 0 to 1, yielding a sector-specific index where 0 represents minimal and 1 maximal observed valorisation; the final RVI corresponds to this normalised PC1 score for the respondent's main activity. The PCA approach has the advantage of generating empirically grounded weights, reducing the bias introduced by arbitrary aggregations and improving the statistical robustness of the synthetic indices used in the econometric analyses (Jolliffe & Cadima 2016). Details results of the principal component analysis (PCA), including sector-specific loadings and explained variance, are presented in the supplementary material. All computations rely exclusively on cross-sectional (non-chronological) data describing the current level of water reservoir valorisation.

The methodology used to collect and analyse data for the RCI follows approaches adopted in the assessment of institutional and structural capacities of municipalities to respond to natural and biological disasters. Typically, data are collected at the territorial level, often municipal, based on standardised indicators (Bernhard *et al*. 2022). In this study, contextualisation of the RCI matrix led to the identification of four components comprising 16 indicators and 55 questions. These components align with the RCI framework and focus on risk prevention and organisational readiness (C1), knowledge level for risk management (C2), available resources and tools (C3), and services, infrastructure and equipment available during water emergencies (C4).

For the calculation of RCI, a three-level scoring system was adopted: 'Yes' = 2 points (high capacity), 'Partially' = 1 point (moderate capacity) and 'No' = 0 points (low capacity). This simplified approach is derived from the official methodology of the Honduran Institute of Earth Sciences (IHCIT) (COPECO & IHCIT 2022). The RCI was constructed in three sequential steps, from individual indicator scores to the overall index for each agro-pastoralist.

Step 1: For each elementary indicator d_{ik} within component C_i, an individual score was calculated for each respondent j, using Equation (1):

$$S_{dikj}\ (\%) = (P_{ikj}/P_{dik}max)\ x\ 100, \tag{1}$$

where S_{dikj} is the score of indicator k in component Ci for respondent j; P_{ikj} indicates the total points obtained; and P_{dikj} is the maximum possible score for that indicator. This method follows Diessana (2024), who assessed resilience capacity by integrating multiple dimensions, such as access to basic services, adaptive capacity, assets and social protection.

Step 2: The component score for each respondent, $Scij$, was obtained as the average of the scores of its indicators in Equation (2):

$$Sc_{ij} = (1/m_i)(\sum_{j=1}^{m_i} S_{dikj}), \tag{2}$$

where m_i is the number of indicators in component C_i and Sc_{ij} is the score of components C_i for respondent j.

This is consistent with Diessana's (2024) approach for aggregating dimension scores to obtain pillar-level indices.

Step 3: The overall response capacity index for each respondent, RCI_j, was calculated using a weighted average of the four components in Equation (3):

$$ICR_j = (\sum_{i=1}^{n} Sc_{ij}\ .wi)/(\sum_{i=1}^{n} w_i), \tag{3}$$

where w_i is the weight of component C_i and n is the number of components (here, $n\ = 44$). This method draws on Vallejos Mihotek (2020) and INSAE (2020), who applied similar weighted composite indices at the community or territorial scale.

The classification of RCI scores was done using quartiles (Q1, Q2, Q3), following the method of Vincent (2007), Deressa *et al*. (2008), Hahn *et al*. (2009) and Acheampong *et al*. (2018). Based on this approach, three levels of response capacity were defined: low level (red colour) in Equation (4); moderate level (yellow colour) in Equation (5); and high level (green colour[1]) in Equation (6):

$$0 \leq RCI \leq 0.270 \tag{4}$$

$$0.270 \leq RCI \leq 0.590 \tag{5}$$

$$0.590 \leq RCI \leq 1.00 \tag{6}$$

This classification supported the mapping of agro-pastoralists' response capacity to drought. In addition, efficiency thresholds were calculated for each component of the RCI (C1 to C4), based on the previous classification. The efficiency threshold is defined as the minimum observed level of a component from which agro-pastoralists transition to a high level of response capacity ($RCI > 0.590$). The threshold is defined as the average component score among respondents whose RCI falls within the critical transition interval [0.590; 0.610] according to the following formula:

$$(1/n) \sum_{j=1}^{n} C_{ij}, \tag{7}$$

where C_{ij} is the score of components C_i for respondent j; $RCI_j \in [0.590; 0.610]$; and n is the number of respondents within that interval. This approach identifies the functional efficiency level required for each component to transition respondents to high response capacity. These thresholds were then compared across low, moderate and high RCI groups to assess the margin of progress (total progress) by component. All computations were performed in R (version 4.4.2).

The variables used to calculate the RCI and RVI are detailed in Tables 1 and 2, respectively.

Table 1: Variables used in the construction of the response capacity index (RCI)

Components	Variables
Risk prevention related to drought events and organisational aspects (C1)	Existence of a water reservoir management committee
	Formalisation of roles and responsibilities
	Regularity of meetings
	Representation of different types of agro-pastoralists in management committees
	Inclusion of women and vulnerable groups
	User consultation mechanisms
	Existence of a reservoir management plan
	Clear rules for access and use
	Conflict-resolution mechanisms
	Linkages with agricultural technical services
	Relations with local authorities
	Integration into local policies
Level of knowledge for managing drought-related risks (C2)	Training and awareness on efficient water use (agriculture, livestock and aquaculture)
	Knowledge of drought-tolerant crops/species (resistant plants, local livestock breeds, drought-tolerant fish species)
	Training in and awareness of storage techniques for crops, livestock feed and aquaculture feed during the dry season for agro-pastoralists
	Use of climate information for seasonal planning
	Monitoring water levels
	Monitoring systems for forage availability for livestock
	Early-warning mechanisms on drought and water availability

[1] The colours are illustrated in Table 4.

	Effective and context-adapted communication channels
	Experience-sharing among farmers, livestock keepers and fish farmers/fishers
	Documentation of best practices adapted to each value chain
	Integration of traditional knowledge in water management
	Intersectoral exchange networks (agriculture–livestock–aquaculture)
	Sharing of technological innovations adapted to each sector
	Diversification of production (crops, livestock and aquaculture species)
	Soil and water conservation techniques adapted to shared water resources
	Adaptive production planning based on climate forecasts
	Integrated agro-silvo-pastoral and aquaculture systems
	Management strategies
Resources and tools available to cope with drought (C3)	Budget allocated to infrastructure maintenance
	User contribution mechanisms
	Capacity to mobilise external funding
	Diversity of productive activities
	Complementarity among agriculture, livestock and aquaculture
	Development of non-agricultural activities
	Creation of food reserves
	Savings or insurance against climate shocks
	Stocks of agricultural inputs
	Monitoring water levels
	Assessment of impacts on production
	Documentation of lessons learned
Services, infrastructure and equipment that can be mobilised in the event of a water emergency (C4)	Condition of water reservoirs
	Storage capacity
	Distribution systems
	Water-saving irrigation systems
	Pumping equipment
	Measurement and control tools
	Availability of technical assistance
	Access to adapted inputs
	Alternative water sources
	Infrastructure for crops, fodder and fish storage
	Livestock watering points
	Shelters for livestock

Table 2: Variables used in the construction of the reservoir valorisation index (RVI)

Type of activity	Variables	Variable type	Description
Agriculture	Total irrigated area	C[a]	Agricultural surface effectively irrigated thanks to the reservoir or water source, expressed in hectares.
	Number of months of continuous access to irrigation water	D[b]	Number of consecutive months during which the farmer has sufficient access to irrigation water during the dry season (number of months).
	Number of cropping cycles	D	Number of cropping campaigns or cycles achieved per year thanks to water availability (number of cycles/year).
Livestock farming	Annual number of seasonal movements	D	Number of livestock movements or transhumance events carried out each year in response to variations in water resources and grazing availability (number of movements/year).
	Frequency of animal watering per day/month	D	Average number of times animals are watered over a given period (day, week or month), reflecting the intensity of reservoir use for livestock watering (number of times/day/ month).
Fish farming	Number of fish reproduction/production cycles per year	D	Number of stocking and harvesting cycles achieved annually in fish farming (number of cycles/year).
	Annual fish production	C	Total quantity of fish produced per year, expressed in kilograms (kg/year).

Note: [a] = Continuous variable; [b] = Dichotomous variable

2.4.3 Justification for choosing the robust regression model

To analyse the impact of water reservoir valorisation on agro-pastoralists' response capacity to drought, several regression models can be considered: ordinary least squares (OLS), quantile regression, penalised models (lasso, ridge) and robust models (Finger 2010; Mukhtar *et al*. 2021; Shoukat *et al*. 2024). OLS regression has the advantage of simplicity but assumes residual normality and homoscedasticity, which limits its reliability in the presence of outliers or heteroscedasticity (Montgomery *et al*., 2021). Quantile regression, as proposed by Koenker *et al*. (2018), allows the estimation of effects across different points of the distribution but remains more complex to interpret. Penalised models such as ridge and lasso are useful in cases of multicollinearity or high-dimensional data, but they require careful tuning of regularisation parameters (Mukhtar *et al*. 2021). The robust MM-type regression model is particularly well suited for heterogeneous data, as it reduces the influence of outliers while retaining all observations (Shoukat *et al*. 2024). In this study, the MM-type robust regression model was chosen due to the non-normal distribution of residuals, the presence of influential outliers, and the absence of problematic multicollinearity among explanatory variables.

2.4.4 Specification and estimation of the MM-type robust regression model

The aim of this study was to evaluate the impact of water reservoir valorisation on the response capacity of agro-pastoralists to drought. This relationship was modelled using a robust regression of the MM-type, with the valorisation index (RVI) as the main explanatory variable and the response capacity index (RCI) as the continuous dependent variable. Table 1 presents the description of the variables included in the model.

The regression model is specified as follows:

$$RCI_j = \beta^0 + \beta^1 \cdot RVI_j + \beta^2 \cdot TYPACT_j + \beta^3 \cdot SEX_j + \beta^4 \cdot EXPACT_j + \beta^5 \cdot EFMOF_j + \beta^6 \cdot APCOOP_j + \beta^7 \cdot ALPHABET_j + \beta^8 \cdot ZAE_j + \varepsilon, \quad (8)$$

with:

- *RCI* being the response capacity index of agro-pastoralist *j* (dependent variable);
- *RVI*, *TYPACT*, *SEX*, *EXPACT*, *EFMOF*, *APCOOP*, *ALPHABET* and *ZAE* being the explanatory variables;
- β_0 being the intercept (constant term);
- $\beta_1, \beta_2, \ldots, \beta_k$ being the regression coefficients associated with each explanatory variable; and
- ε being the error term capturing unexplained variability in the response.

The description of the explanatory variables included in the robust MM-type regression model is presented in Table 3.

Table 3: **Explanatory variables introduced into the MM-type robust regression model and expected signs**

Variables	Types of variables	Description	Expected sign
RVI	C [a]	Water reservoir valorisation index (continuous scale from 0 to 1)	+
TYPACT	D [b]	Type of actor (non-beneficiary = 0; beneficiary = 1)	+
SEX	D	Gender of the agro-pastoralist (male = 1; female = 0)	+
EXPACT	C	Number of years of experience in the main activity	+
EFMOF	D	Size of the family labour force used	+
APCOOP	D	Cooperative membership (yes = 1; no = 0)	+
ALPHABET	D	Literacy (1 = literate; 0 = illiterate)	+
ZAE	D	Agro-ecological zones 3, 4 and 5 (yes = 1; no = 0)	+

Note: [a] = Continuous variable; [b] = Dichotomous variable

3. Results

3.1 Characterisation of the response capacity index (RCI) and the water reservoir valorisation index (RVI)

3.1.1 Principal component analysis (PCA)

Preliminary principal component analyses confirmed the structural coherence of the variables used to construct the reservoir valorisation index (RVI). The first principal component captured most of the shared variance across sectors – 66.15% in agriculture, 64.37% in livestock and 71.34% in aquaculture – demonstrating a strong latent structure. Loadings ranged from 0.80 to 0.88, indicating consistent contributions of all indicators and supporting the use of PC1 scores as synthetic sectoral indices in subsequent analyses.

3.1.2 Relationship between RCI and RVI by beneficiary status and type of activity

The results indicate that the beneficiaries of water reservoirs have a significantly higher response capacity index (RCI) (0.64 ± 0.15) compared to non-beneficiaries (0.13 ± 0.07), reflecting a stronger adaptive capacity to drought. Similarly, their water reservoir valorisation index (RVI) is also higher (0.58 ± 0.22 versus 0.41 ± 0.13). These findings suggest that certain groups use water reservoirs more effectively.

In terms of activity type, farmers reported the highest RVI (0.58 ± 0.16) and a moderate RCI (0.41 ± 0.30), whereas livestock herders displayed the lowest RVI (0.33 ± 0.18) and RCI (0.36 ± 0.25)

levels. Fish farmers exhibited relatively high levels in both RVI (0.57 ± 0.22) and RCI (0.40 ± 0.29). This highlights a more limited use of, or less favourable access to, water reservoirs for livestock herders compared to farmers and fish farmers. These disparities in use and impact according to stakeholder profiles underscore the need for targeted support to strengthen the response capacity of all agropastoral groups.

3.1.3 Differential effects of the RCI components

The analysis of average gaps by component (Table 4) reveals a differentiated contribution of water reservoir valorisation to agro-pastoralists' response capacity to drought. Component C2, related to knowledge and drought risk management, exhibits the largest gap between beneficiaries and non-beneficiaries (0.32 points), representing an improvement of 96.97%. This highlights the critical role of knowledge acquisition and adaptation strategies in enhancing response capacity. Component C4, which refers to access to water-related services, infrastructure and equipment, follows with a 63.16% improvement, suggesting that a well-equipped environment also facilitates a stronger response to drought. Components C1 (risk prevention and organisational aspects) and C3 (resources and response tools) display more moderate yet significant improvements, with increases of 37.62% and 21.43%, respectively. Their smaller relative variation implies that, while they support response capacity, they are less directly influenced by reservoir valorisation interventions. Figure 2 clearly illustrates these relationships by showing the trends between each component (C1 to C4) and the overall RCI. The regression curves show steeper slopes for beneficiaries, confirming a positive relationship between reservoir valorisation and response capacity, especially for components C2 and C4. Altogether, these results demonstrate that components related to information and infrastructure (C2 and C4) are the most powerful levers for strengthening agro-pastoralists' response capacity to climate stresses such as droughts.

Table 4: Average component gaps between beneficiaries and non-beneficiaries

Components	Non-beneficiaries	Beneficiaries	Difference	% Improvement [a]
C2	0.33	0.65	0.32***	96.97
C4	0.38	0.62	0.24***	63.16
C1	0.47	0.64	0.18***	38.30
C3	0.54	0.66	0.12***	22.22

Notes: *** = Significant at 1% ($p < 0.01$); [a] = % improvement = (difference / non-beneficiaries) × 100

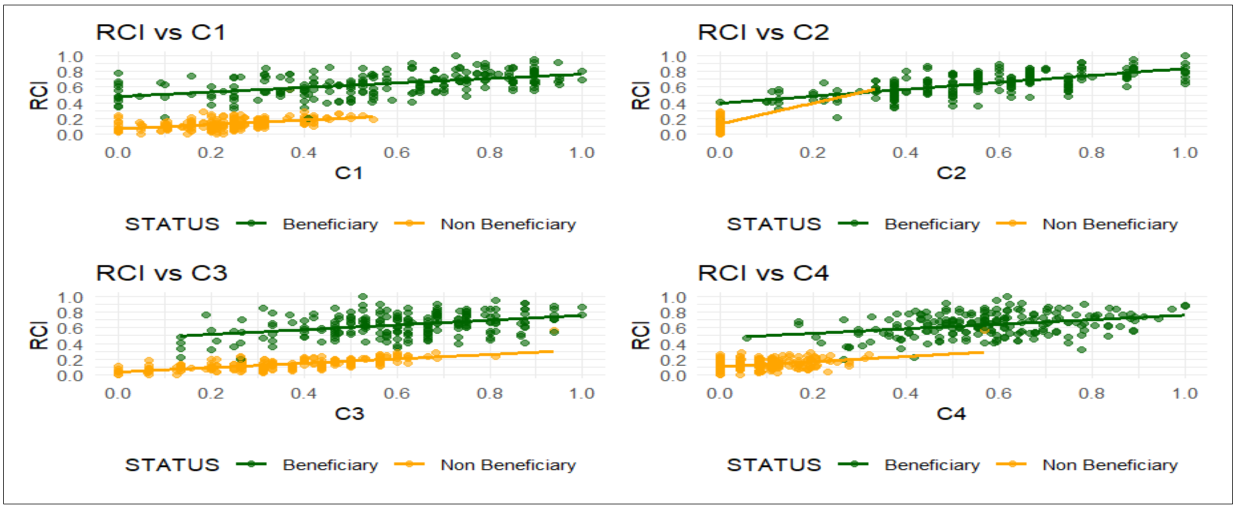

Figure 2: Relationship between valorisation components (C1 to C4) and the response capacity index (RCI) by beneficiary status

3.1.4 Efficiency thresholds of the RCI components

The analysis of efficiency thresholds and progression margins (Table 5) reveals contrasting dynamics among the components of the response capacity index (RCI). Components C2 (knowledge of risk management) and C4 (access to infrastructure) exhibit the highest progression margins, with gaps of 0.648 and 0.516, respectively. For C2, the index increases from 0.001 (low level) to 0.649 (high level), exceeding the efficiency threshold, which was set at 0.554. Similarly, C4 progresses from 0.095 to 0.611, surpassing the threshold of 0.522. These gaps reflect a strong potential for improvement, highlighting the key role of information, training and infrastructure in enhancing agro-pastoralists' response capacity. These two components thus appear as priority intervention levers.

In contrast, component C1 (risk prevention) shows a more moderate progression (0.406), with a high level (0.644) that only slightly exceeds the efficiency threshold (0.531), indicating a persistent vulnerability, particularly in some areas. Although the high level of Component C3 (material resources), at 0.658, exceeds the threshold of 0.615, it displays a more limited progression (0.315), reflecting relatively homogeneous but generally insufficient access to inputs and equipment.

Table 5: Efficiency thresholds and progression by component

Components	Low level	Moderate level	High level	Efficiency threshold	Total progression [a]
C1	0.238	0.402	0.644	0.531	0.406
C2	0.001	0.379	0.649	0.554	0.648
C3	0.343	0.547	0.658	0.615	0.315
C4	0.095	0.519	0.611	0.522	0.516

Note: [a] = total progression = high level – low level

3.1.5 Prioritisation of RCI components based on Pareto analysis

According to the Pareto analysis (Figure 3), components C2 and C4 alone account for more than half of the cumulative impact on the response capacity index (RCI), with respective contributions of 28.7% and 26.9%. These components thus emerge as the most effective for enhancing agro-pastoralists' response capacity. C1 and C3 complete the hierarchy, with respective impacts of 22.5% and 21.9%, though their contributions remain secondary. Together, components C2, C4 and C1 approach the 80% threshold. This prioritisation provides guidance for intervention planning by focusing on the most relevant components to optimise the effects of water reservoir development policies on local resilience.

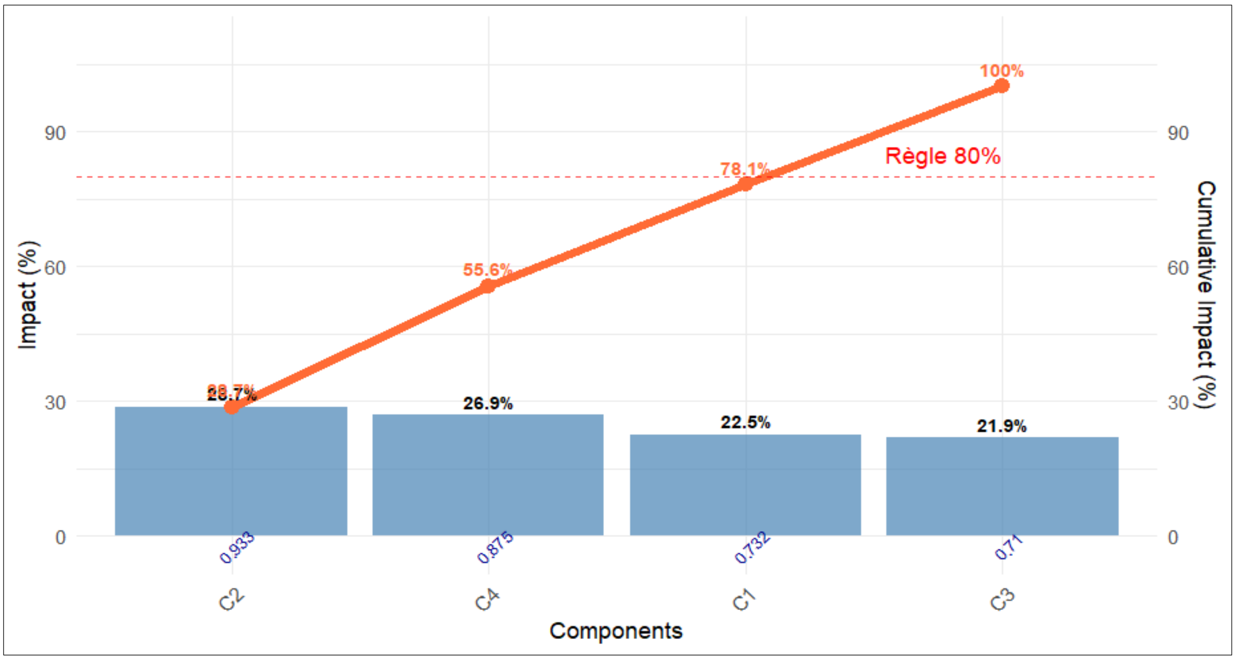

Figure 3: **RCI components according to Pareto analysis**

3.1.6 Correlation between the RCI components

The positive correlation between the components of the response capacity index (RCI) reflects a structural coherence in the index's construction. The strongest correlation is observed between component C2 (knowledge level for risk management) and C4 (services and infrastructure), with a coefficient of 0.784, indicating a significant interdependence between drought risk management and the availability of equipment and services. Components C1 and C3 show weaker correlations with the other components. Specifically, C1 is correlated with C2 (0.552), C3 (0.416) and C4 (0.560), while C3 correlates with C2 (0.542) and C4 (0.565). These coefficients suggest that C1 and C3 contribute more autonomously to the RCI, with weaker links to the other components. These relationships support the internal validity of the index by demonstrating a logical articulation between its components, while maintaining a certain degree of functional diversity.

3.1.7 Spatial analysis of the agro-pastoralists' response capacity index (RCI) to drought

The spatial analysis highlights a clear distinction between the beneficiaries and non-beneficiaries of water reservoirs. In all communes, beneficiaries exhibit moderate to high RCI levels (ranging from 0.47 to 0.62), while non-beneficiaries show much lower levels (between 0.21 and 0.25) (Table 6; Figures 4a and 4b). These differences confirm previous results regarding the structuring effect of water access on resilience. However, territorial analysis reveals significant internal disparities.

The communes of Bassila and Ouesse show the highest average scores among beneficiaries, yet some components still exhibit room for improvement. In Bassila, for instance, access to infrastructure (C4) still shows potential for enhancement. In Ouesse, components C3 (material resources) and C4 only reach an intermediate (moderate) level. These weaknesses call for targeted actions to strengthen operational tools and equipment (Table 6; Fig. 4a).

In the commune of Tchaourou, the beneficiaries of the Mala-Boro reservoir are characterised by a low prevention capacity (C1), revealing organisational shortcomings that need to be addressed (Table 6; Fig. 4b). Finally, around the reservoirs of Odo-Otchere, Gnanhoun, Botti-Houegbo and Mala-Boro, the moderate scores observed for component C3 seem to reflect the existence of community-based mechanisms (fodder plots, management committees, indigenous early warning systems, small-scale irrigation devices, etc.) that are still weakly structured or insufficiently deployed. These results suggest that, beyond the construction of infrastructure, institutional and community organisation remain key factors in maximising the impact of water reservoirs on agro-pastoralists' response capacity. Overall, the RCI is moderate, regardless of the components and the municipalities (Table 6; Figure 4c).

Table 6: RCI by component, by commune, by status and by water reservoir

Communes	Water reservoirs	RCI components	RCI by component		Average RCI per commune		Commune-level RCI
			Beneficiaries	Non-beneficiaries	Beneficiaries	Non-beneficiaries	
Bassila	Akarade	C1	0.65	0.18	0.62	0.25	0.43
		C2	0.7	0.3			
		C3	0.6	0.35			
		C4	0.54	0.15			
Dassa-Zoume	Odo-Otchere	C1	0.6	0.22	0.57	0.21	0.39
		C2	0.61	0.21			
		C3	0.54	0.28			
		C4	0.54	0.12			
Nikki	Gnanhoun	C1	0.37	0.25	0.58	0.25	0.42
		C2	0.73	0.17			
		C3	0.56	0.38			
		C4	0.66	0.21			
Nikki	Gah-Maro	C1	0.47	0.23	0.58	0.22	0.4
		C2	0.69	0.24			
		C3	0.59	0.25			
		C4	0.57	0.15			
Ouesse	Botti-Houegbo	C1	0.67	0.19	0.62	0.24	0.43
		C2	0.68	0.21			
		C3	0.54	0.38			
		C4	0.58	0.18			
Tchaourou	Mala-Boro	C1	0.24	0.2	0.47	0.23	0.35
		C2	0.59	0.23			
		C3	0.52	0.4			
		C4	0.51	0.08			

Notes: Green colour: High RCI; Yellow colour: Moderate RCI; Red colour: Low RCI.
C1: Risk prevention related to drought events and organisational aspects.
C2: Level of knowledge for managing drought-related risks.
C3: Resources and tools available to cope with drought.
C4: Services, infrastructure and equipment that can be mobilised in the event of a water emergency.

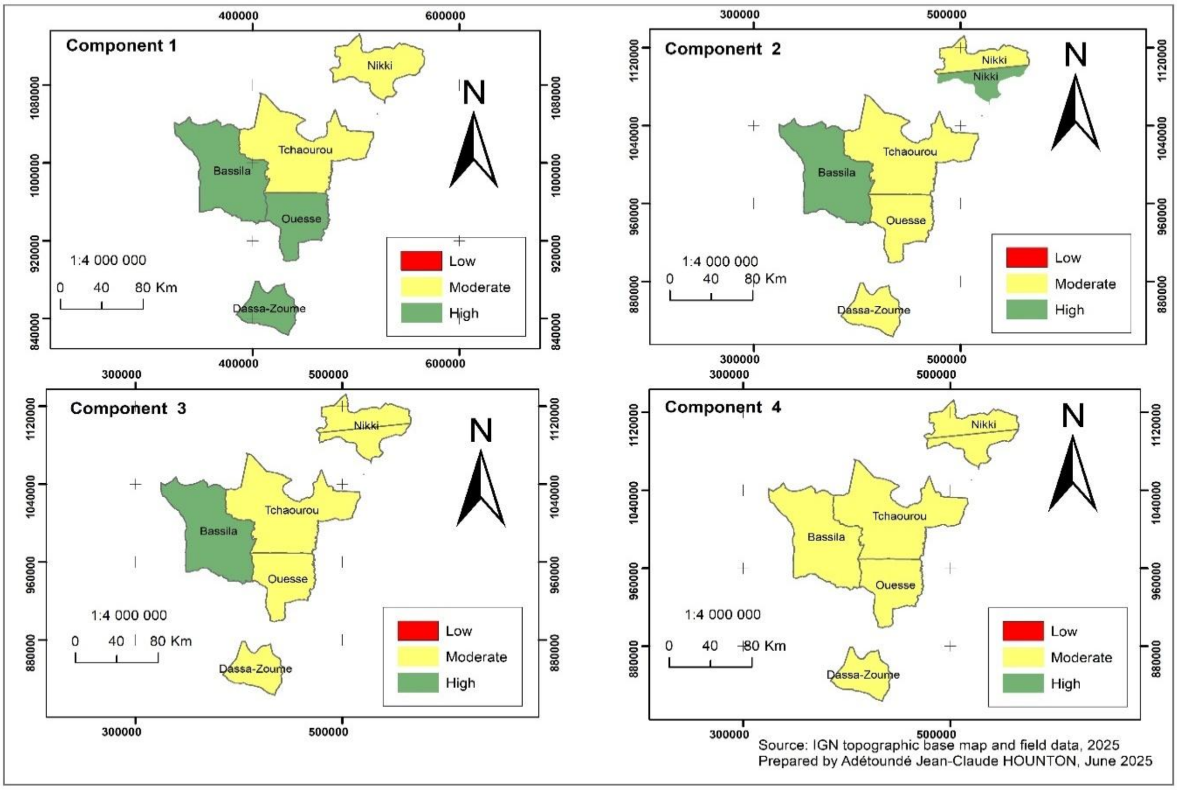

Figure 4a: **Components of the RCI of beneficiaries by municipality**

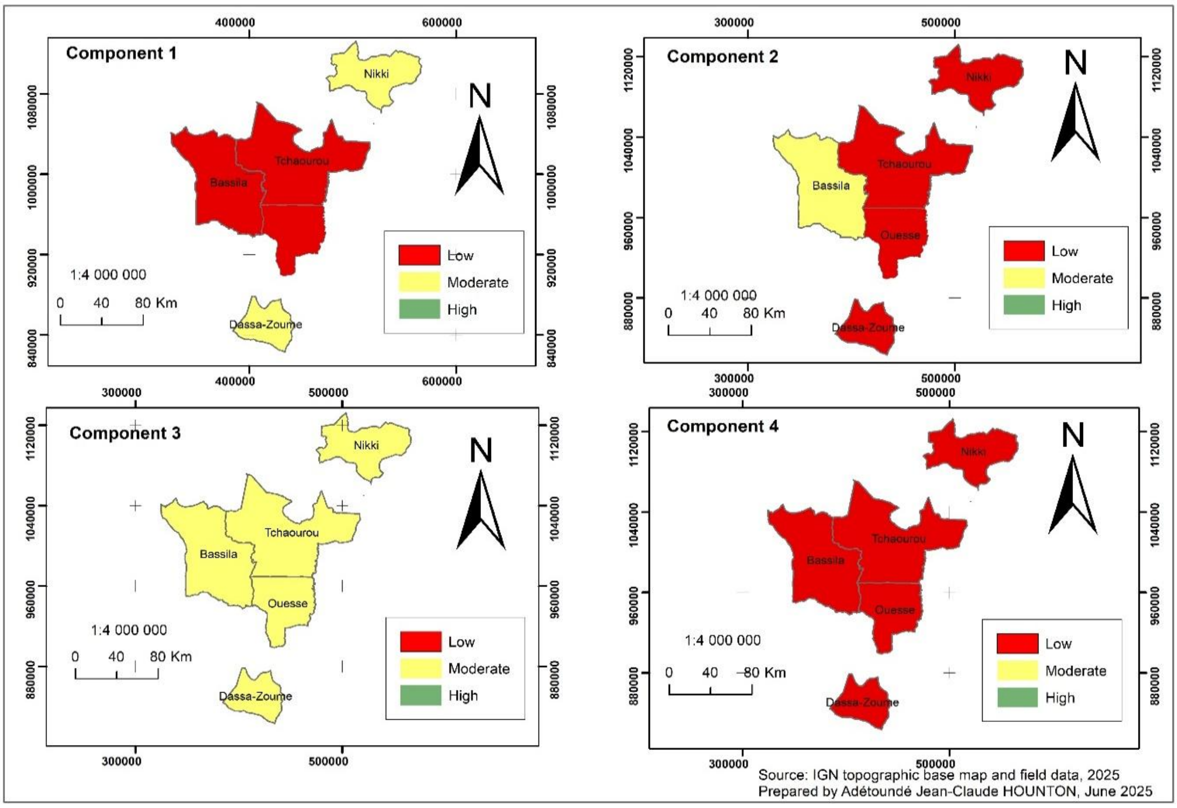

Figure 4b: **Components of the RCI of non-beneficiaries by municipality**

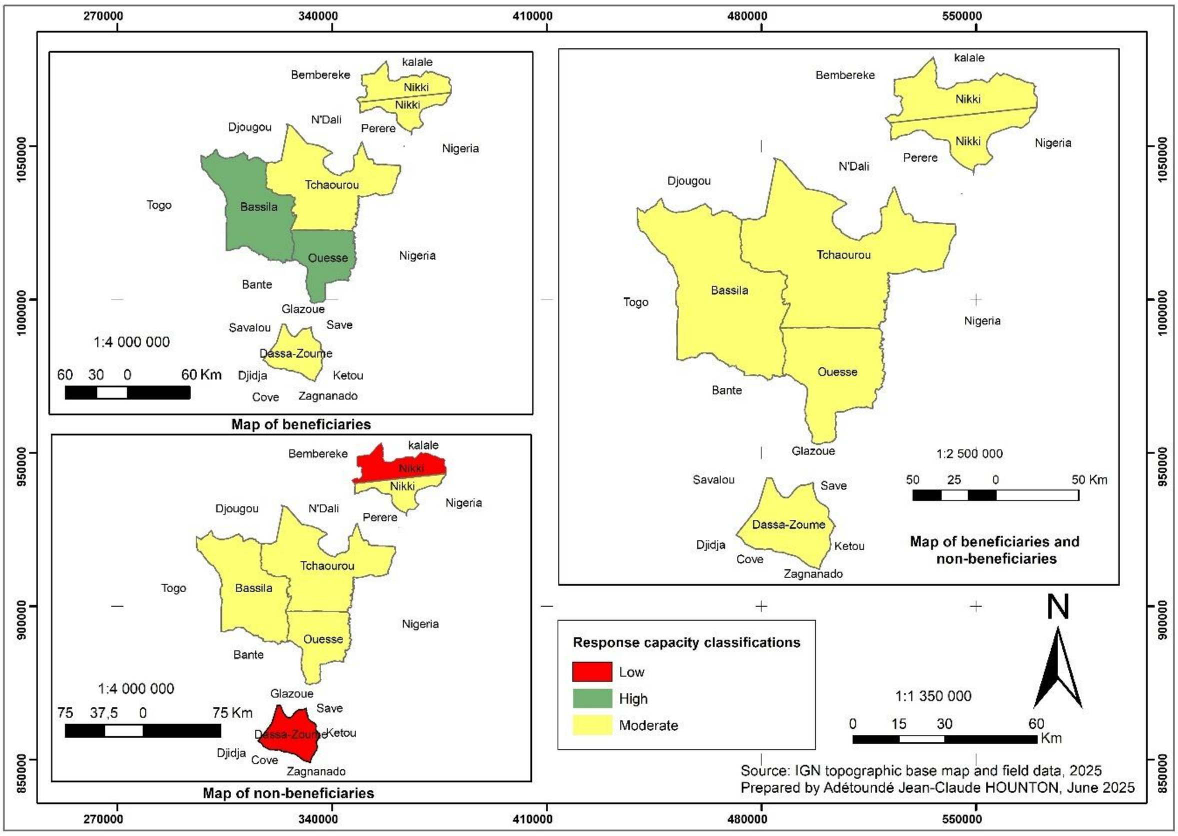

Figure 4c: Map of agro-pastoralists' response capacity indices by municipality

3.1.8 Analysis of the relationship between reservoir utilisation and agro-pastoralists' response capacity

The Shapiro-Wilk test (Table 7) confirms non-normality for both indices (RCI: $W = 0.9859$; $p < 0.01$; VRI: $W = 0.9529$; $p < 0.01$), justifying the use of Spearman's rank correlation. The results show a moderate but significant positive correlation between RCI and VRI ($\rho = 0.672$; $p < 0.01$), indicating that better reservoir utilisation is generally associated with a stronger response capacity. However, variations exist across activities and statuses (see Figure 5): in agriculture, the correlation is positive for all groups, and stronger among beneficiaries; in livestock, the trend is upward but more dispersed; in fish farming, the correlation is weak or even negative, especially among beneficiaries. Finally, collinearity tests confirm no problematic multicollinearity among explanatory variables (VIF < 5) (Figure 5).

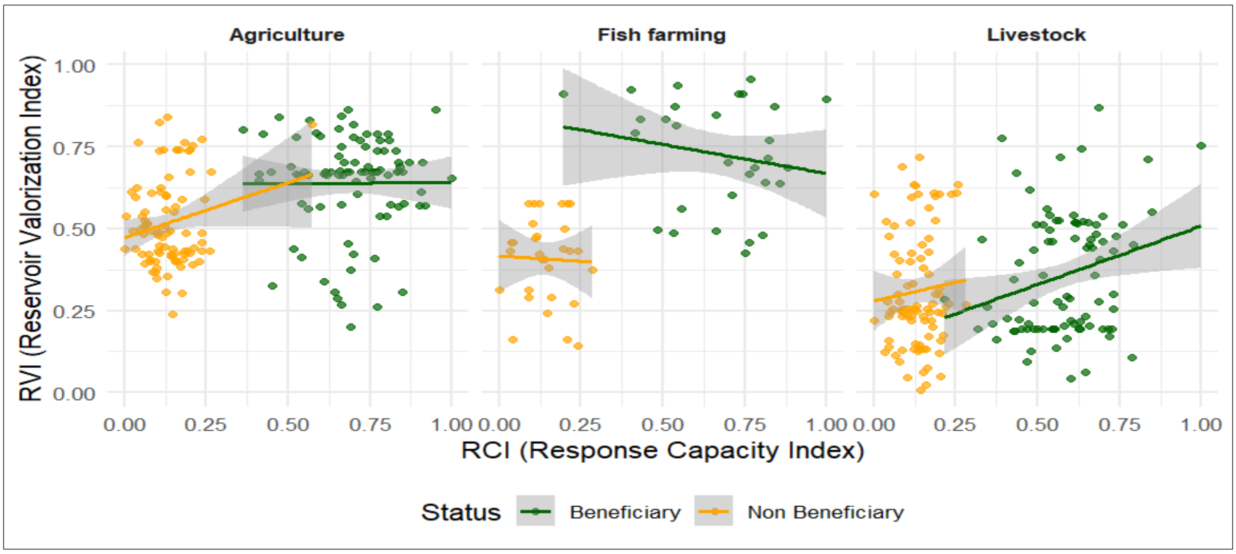

Figure 5: Relationship between water reservoir utilisation index and agro-pastoralists' response capacity index

Table 7: Results of normality, correlation, and multicollinearity tests

Analysis	Variables	Statistic
Normality test (Shapiro-Wilk)	RCI	W = 0.9859***
	RVI	W = 0.9529***
Correlation (Spearman's rho)	RCI ~ RVI	ρ = 0.672***
VIF	TYPACT	1.2
	SEX	1.07
	RVI	1.34
	ZAE	1.04
	EFMOF	1.19
	EXPACT	1.21
	APCOOP	1.15
	ALPHABET	1.04

Notes: *** = Significant at 1%. VIF = Variance inflation factor

3.2 Modelling the interactions between water reservoir enhancement and agro-pastoralists' drought response capacities

The robust MM-type regression model (Table 8) shows a good fit (robust $R^2 = 0.645$), with 64.5% of the variance in the response capacity index (RCI) explained, and a significant pseudo-F statistic (37.077; $p < 0.01$). The reservoir valorisation index (RVI) exerts the strongest positive effect on RCI ($\beta = 0.714$; $p < 0.01$), confirming its central role in enhancing drought response, consistent with the Spearman correlations. Activity type is a key factor: livestock farmers record a significantly lower RCI, by 0.053 units ($p < 0.05$), compared to crop farmers, whereas fishing/aquaculture shows no significant effect. Among socio-economic factors, only experience in the main activity (EXPACT) has a positive, though modest, influence ($\beta = 0.002$; $p < 0.05$). Gender, household labour, literacy, cooperative membership and agroecological zone are not significant predictors.

Table 8: Estimation results of the robust MM-type regression model

Variables	Coefficients	Standard error
Constant	0.175***	0.030
RVI (Reservoir valorisation index)	0.714 ***	0.054
TYPACT (Livestock)	-0.053**	0.019
TYPACT (Fishing/aquaculture)	-0.054	0.076
SEX (Male)	0.015	0.019
EXPACT (Experience in the activity)	0.002 **	0.001
EFMOF (Family labour force size)	-0.003	0.005
APCOOP (Cooperative membership = Yes)	-0.018	0.015
ALPHABET (Literate = Yes)	-0.017	0.022
ZAE 4 (Agro-ecological zone 4)	-0.025	0.022
ZAE 5 (Agro-ecological zone 5)	0.001	0.017
Robust R^2	0.645	-
Residual error	0.123	-
Pseudo F-statistic	37.077***	-

Note: ** = Significant at 5%; *** = Significant at 1%

4. Discussion

This study demonstrates that enhancing water reservoirs significantly strengthens agro-pastoralists' drought response capacity. Beneficiaries record higher scores in both the response capacity index (RCI) and the reservoir valorisation index (RVI) than non-beneficiaries, confirming the structural role of reservoirs in resilience building. These findings echo those of Speranza *et al*. (2014) and Zarafshani *et al*. (2016), who emphasise unequal access to adaptation resources, particularly water. The performance gap highlights under-utilisation among livestock keepers, likely due to organisational or accessibility constraints. The study also reveals disparities across activity types, showing that adaptation responses are shaped by livelihood systems and resource appropriation modes. The RCI developed here aligns with Amer *et al*. (2022), serving as a composite tool to capture heterogeneity and identify key drivers. Component analysis points to C2 (drought risk management knowledge) and C4 (services and infrastructure in water emergencies) as priority levers, with improvements of 96.97% and 63.16%, together explaining over 55% of the effect (Pareto) and showing strong correlation ($r = 0.784$). However, as Fisher (2010), Eriksen *et al*. (2011) and Susskind and Kim (2022) argue, technical levers alone are insufficient: the effectiveness of C2 and C4 depends on C1 (organisational systems) and C3 (material resources).

Weaknesses in governance and equipment functionality, particularly in Tchaourou (Mala Boro reservoir) and municipalities such as Dassa-Zoumé, Ouesse and Nikki, illustrate how community-based mechanisms may fail to function effectively, limiting the leverage of technical investments. These findings highlight the need to reinforce local governance, professionalise management and align infrastructure development with institutional strengthening. Spatial disparities further underline the unevenness of adaptation capacities. Beyond descriptive analysis, robust regression confirms RVI as the main determinant of RCI, validating the role of infrastructure use and management in building resilience. Yet activity type remains discriminating: livestock keepers show a significantly lower RCI than crop farmers, reflecting vulnerabilities linked to pastoral mobility, weaker integration into support systems, and less regular water access. This calls for adaptation policies tailored to pastoral contexts, rather than uniform models. These results underline the need to jointly consider technical investments, organisational arrangements and patterns of resource access when designing drought-response strategies.

5. Conclusion and recommendations

The results show that the valorisation of water reservoirs significantly strengthens agro-pastoralists' drought response capacity. Strengthening knowledge systems and improving access to infrastructure constitute key levers, although their effectiveness depends on coherent integration with organisational dynamics and resource availability. However, farmers – despite exhibiting a high level of reservoir valorisation – display only a moderate response capacity. To more effectively translate water access into resilience, they should: (i) improve their technical practices in water use; (ii) enhance their knowledge of climate risk management through participation in training programmes; (iii) engage more actively in support mechanisms and local governance structures; (iv) join water-user cooperatives to strengthen collective management; and (v) diversify production systems to reduce vulnerability. The disparities observed across activity types and territories confirm that hydraulic infrastructure alone is insufficient; context-specific approaches combining training, organisational support and improved access to services and equipment are necessary to ensure durable and inclusive outcomes.

This study presents certain limitations: the use of cross-sectional data limits causal inference; the construction of composite indices involves potentially subjective weighting choices; institutional and sociocultural dimensions of resilience are only partially captured; and the analysis does not fully account for temporal dynamics or long-term ecological impacts. Nevertheless, these limitations do not undermine the credibility of the results but rather indicate that they should be interpreted as a robust analytical basis, calling for further methodological and empirical refinement in future work.

Future research should: (i) analyse the temporal evolution of resilience using longitudinal approaches; (ii) examine the mechanisms through which water-management practices translate – or fail to translate – into response capacity; (iii) develop differentiated intervention frameworks for agriculture, livestock and aquaculture; (iv) assess the ecological and socio-territorial sustainability of water reservoirs at the watershed scale; (v) test alternative index-construction methodologies – including confirmatory factor analysis, multiple correspondence analysis, entropy- or AHP-based weighting, and Bayesian or machine-learning approaches – to refine measurement tools; and (vi) compare institutional and territorial contexts to identify best governance practices.

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Supplementary material

Results of the principal component analysis (PCA) for the construction of the reservoir valorisation index (RVI)

Activity sector	Variable	PC1 loading	Explained variance (%)
Agriculture	Irrigated agricultural area (ha) using the water source	0.607	54.32
Agriculture	Changes in yields / income from agricultural activities	0.508	54.32
Agriculture	Number of cropping cycles carried out per year	0.611	54.32
Livestock	Number of seasonal livestock movements per year	0.707	64.37
Livestock	Frequency of animal watering per day during the dry season	0.707	64.37
Fish farming	Annual quantity of fish produced (kg/year)	0.707	51.63
Fish farming	Type of fish farming infrastructure used (pond, floating cage, tank, etc.)	0.707	51.63