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THEME : ÉTUDE DES PRATIQUES DE GESTION AGRICOLE EN RELATION AVEC LE CHANGEMENT CLIMATIQUE AU NIGER

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ECOLE DOCTORALE SCIENCES JURIDIQUES, POLITIQUES, ECONOMIQUES ET DE GESTION

FACULTY OF ECONOMICS AND MANAGEMENT SCIENCES (FASEG)

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PHD THESIS

TOPIC: INVESTIGATING AGRICULTURAL MANAGEMENT PRACTICIES IN RELATION TO CLIMATE CHANGE IN NIGER

YEAR: 2025

BY:

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Dedication

This thesis is dedicated to my parents and all family members; may Allah grant them long life in piety.

Acknowledgement

I would like to express my deepest gratitude to my family, whose constant love and support have sustained me throughout this journey. I am particularly grateful to my beloved sister for her unwavering encouragement at every stage of this work.

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Acronyms

AC	Adaptive Capacity
ACI	Adaptive Capacity Index
AHP	Analytic Hierarchy Process
ANOVA	Analysis of Variance
CC	Climate Change
CGE	Computable General Equilibrium
CI	Consistency Index
CR	Consistency Ratio
CSA	Climate-Smart Agriculture
DEMETRA	Dynamic Equilibrium Model for Economic Development Resources and Agriculture
ECVMA	Enquête sur les Condition de Vie des Ménages Agricoles
FA	Factor Analysis
FC	Financial Capital
GAMS	General Algebraic Modeling System
GDP	Gross Domestic Product
HC	Human Capital
HH	Household
INRAN	Institut National de la Recherche Agronomique du Niger
NC	Natural Capital
NDC	Nationally Determined Contribution
NGO	Non-Governmental Organization
PC	Physical Capital
PCA	Principal Component Analysis
PDES	Plan de Développement Economique et Social
RECA	Réseau national des Chambres d'Agriculture du Niger
RI	Random Index
RSD	Relative Standard Deviation
RTFG	Réserve Total de Faune de Gadabédji
SA	Sensitivity Analysis
SC	Social Capital
SDDCI-2035	Stratégie de Développement Durable et de Croissance Inclusive 2035
SPN2A	Stratégie et Plan National d'Adaptation face aux changements climatiques dans le secteur Agricole
UA	Uncertainty Analysis

Résumé

Au Niger, les évènements climatiques ont structurellement exacerbé les défis existants de pauvreté, d'insécurité alimentaires et de stratégie limités de moyens de subsistances pour les ménages agricoles pauvres. Dans ces conditions, il est urgent de soutenir de manière adéquate les pratiques de gestion agricoles afin d'éviter que les options d'adaptation autonomes prises par ces ménages ne crée plus de vulnérabilité. L'objectif principal de ce travail est de contribuer à la production de connaissances fiables permettant la mise en œuvre d'options d'adaptation efficaces et adaptées au Niger. De manière spécifique, ce travail étudie la capacité des ménages agricoles des localités de Tillabéri et de Maradi à s'adapter au changement climatique, ainsi que les implications macroéconomiques de la diversification de la main-d'œuvre agricole au Niger dans un contexte de chocs de productivité induits par le climat. A travers l'utilisation de méthodologies de calcul d'indice, d'analyse combinés d'incertitude et sensibilité et de modèle statique d'équilibre générale calculable DEMETRA sur un pays unique calibré sur la Matrice de Comptabilité Sociale de 2019, cette étude repose sur un cadre théorique d'analyse rigoureuse, adéquat et adapté aux réalités locales des ménages nigériens afin de proposer des implications de politiques conséquentes. Les résultats de l'analyse de la capacité d'adaptation ménages nigériens a révélé d'importantes disparités dans les portefeuilles d'actifs des ménages, nombre d'entre eux ne disposant pas d'actifs essentiels, notamment en termes d'éducation et des compétences nécessaires pour accéder à l'information, aux technologies et aux sources de revenus non agricoles. L'examen du comportement de l'offre de main d'œuvre des ménages agricoles nigériens a fait ressortir que la main d'œuvre agricole nigérienne est sensible aux incitations économiques de productivité agricole et est systématiquement réaffectée en direction des secteurs agricoles et de transformations alimentaires des régions voisines affichant un meilleur résultat en termes de productivité agricoles. Ce faisant, les résultats de ce travail fournissent une base pour l'élaboration de politiques globales, intégrées et adaptées au contexte, qui permettent de renforcer, d'une part la capacité d'adaptation et le bien-être des ménages agricoles au Niger, et d'autre part, d'amorcer un développement économique local pour une éventuelle transformation structurelle qui peine à s'enclencher au Niger.

Mots-clés : Adaptation, ménages agricoles, changement climatique, main-d'œuvre, capacité d'adaptation, Niger, Tillabéri, Maradi.

Abstract

In Niger, climate-related shocks have structurally intensified persistent challenges of poverty, food insecurity, and limited livelihood opportunities among poor farming households. In this context, there is an urgent need to support appropriate agricultural management practices to ensure that autonomous adaptation strategies do not further exacerbate household vulnerability. The primary objective of this study is to contribute to the generation of robust evidence to inform the design and implementation of effective and context-appropriate climate change adaptation policies in Niger. Specifically, the study examines the adaptive capacity of farming households in the Tillabéri and Maradi regions and assesses the macroeconomic implications of agricultural labor diversification in the presence of climate-induced productivity shocks. The analysis combines index-based methodologies with uncertainty and sensitivity analyses and employs a single-country static computable general equilibrium (CGE) model (DEMETRA) calibrated using the 2019 Social Accounting Matrix. This integrated and rigorous analytical framework is tailored to the socio-economic realities of Nigerien households and supports the formulation of meaningful policy insights. The results reveal substantial disparities in household asset endowments, with many households lacking critical assets—particularly education and skills required to access information, technology, and non-agricultural income opportunities. Furthermore, the analysis of labor supply behavior indicates that agricultural labor in Niger is responsive to productivity-related economic incentives and is systematically reallocated toward agricultural and food processing activities in neighboring regions exhibiting higher agricultural productivity. Overall, the findings provide a solid foundation for the development of comprehensive, integrated, and locally grounded policy interventions aimed at enhancing the adaptive capacity and well-being of farming households while simultaneously fostering local economic development and facilitating the structural transformation that has thus far progressed slowly in Niger.

Keywords: Adaptation; agricultural households; climate change; labor force; adaptive capacity, Niger, Tillabéri, Maradi.

GENERAL INTRODUCTION

Climate change (CC) has emerged in recent decades as a threat with cross-cutting consequences, altering governments' efforts to improve the well-being of their populations in terms of health, education, income and the provision of basic social services. It is a phenomenon that significantly challenges governments' efforts to achieve the Sustainable Development Goals (SDGs) (FAO, 2021).

Most studies on CC point to a change in several climate parameters, including rainfall and temperature variability. These changes will probably lead to an increase in the incidence of environmental disasters (IPCC, 2014, 2019, 2022). Various consequences are already being felt around the world: record-breaking, multi-year droughts, unprecedented floods, intense summer heat, to name but a few (UNEP, 2022). Poverty and inequality are increasing and will increase further for many populations as global temperatures rise from 1□C to 1.5□C (IPCC, 2018). This could result in an additional 122 million people falling into extreme global poverty by 2030, mainly due to rising food prices and deteriorating health (IPCC, 2021). The consequences would be particularly acute for poor rural populations in developing countries, especially in terms of their livelihoods (IPCC, 2018).

Livelihoods in agriculture-dependent economies are particularly vulnerable to climate risks. In this respect, Africa, particularly the Sahel, is often cited as the most affected region by the effects of climate change, with record temperature rises above the global average (Baroudy et al., 2022). It is one of the world's most vulnerable regions, already plagued by food insecurity, high population growth rates, low incomes, minimal education, epidemics, violent conflict, undernourishment, chronic humanitarian crises due to recurrent droughts and floods, a lack of technical knowledge and inadequate or insufficient policy responses and social safety nets (Leary et al., 2007; FAO, 2013; Wreford et al., 2017; Lalou et al., 2019; USAID, 2021; Earth et al., 2022). Climate shocks exacerbate these crises leading to losses in production and human capital as well as serious economic damages, particularly for poor rural populations whose livelihoods and income heavily depend on natural resources (Thornton et al., 2018; Wiederkehr et al., 2018; Baroudy et al., 2022). In terms of production losses, for example, it is estimated that temperature rises in Africa have contributed to reducing agricultural productivity growth by almost 34% since 1961, and that an increase of 1.5□C is equated with considerable declines in cereal yields in West Africa (WMO, 2022). It is also a region particularly prone to land degradation and desertification (Jones and Thornton, 2009; Zougmoré et al., 2016). Under these conditions, warming and drying could reduce crop yields by 10% to 25% by 2050 (FAO, 2018a). Yet, given its high population growth rate, an increase in agricultural production of at least 70% is expected to meet demand and improve nutrition by 2050 (Lalou et al., 2019; Wijk et al., 2020).

This picture strongly legitimizes the frequent calls for urgent action from international and scientific communities. Gradual change is now an option that must be urgently replaced by a rapid and structural transformation involving the implementation of ambitious adaptation and mitigation policies, in order to avoid *"closing the window of opportunity to limit global warming to well below 2°C, preferably 1.5°C"* (UNEP, 2022). It has been shown that inaction in this area would result in very high peak costs that would be reached earlier if mitigation efforts began later, and discounted damages that will be increased by $0.6 trillion per year in 2020 (Sanderson and O'Neill, 2020). Clearly, the much-needed structural transformation is far more relevant to the agricultural sector in vulnerable countries, where farm management practices must be sufficiently informed to effectively adapt to the effects of increasing and uncertain climate change in order to ensure food security.

Farm management practices can be defined as a broad set of techniques and decisions used by farmers to organize and carry out their agricultural production. In the climate change literature, they occupy a central place in adaptation, as they influence how farmers cope with climate risks, adapt their production systems, and manage their livelihood strategies in the context of environmental stress (Campbell et al., 2014; Wreford et al., 2017; FAO, 2018b; Rosenstock et al., 2019). In the agricultural sector, adaptation can be autonomous or planned (Adger and Vincent, 2005; Smit and Wandel, 2006; Wreford et al., 2017; Vanschoenwinkel et al., 2020). Autonomous adaptation is a process undertaken by farmers, without explicit planning or guidance, in response to observed climate change. This type of adaptation can take the form of changes in livestock or farm management practices, diversification of varieties and species, or modification of cropping schedules, adoption of mixed crop and livestock systems, and many other key activities (Agrawal, 2010; Campbell et al., 2014; FAO, 2018b; Rosenstock et al., 2019; Berrang-Ford et al., 2021). Conversely, planned adaptation results from an intentional decision-making process, most often undertaken by groups of actors or public entities in anticipation of or in response to climate change. Given that farmers make their decisions within a context of socio-economic institutions that either limit or facilitate their adaptive capacity, public policies have a crucial role to play in creating an enabling environment (OECD, 2023). Among the adaptation actions that justify public intervention from an economic perspective are those that generate or transfer knowledge, correct externalities, enable the sharing of extreme risks, and remove institutional, regulatory, or financial barriers to adaptation (Wreford et al., 2017).

Several case studies in Africa show that successful adaptation options yield significant improvements in agricultural yields and productivity, reduced climate risks, and mitigated risks to the livelihoods of poor farmers (Neate, 2013; Nyasimi et al., 2014; Campbell, 2017). The question of the success and effectiveness of the adaptation process is consistently raised in light of the inherent uncertainty of climate change (IPCC, 2022), as well as the highly contextual nature of adaptation, which must necessarily consider the variety of social, economic, and environmental factors influencing farmers' decisions to adopt appropriate options (Thornton et al., 2018; Lalou et al., 2019; Wijk et al., 2020). Adaptation strategy planning can therefore fail, or even lead to maladaptation (Owen, 2020; Singh et al., 2022), defined as "an action ostensibly taken to avoid or reduce vulnerability to climate change that negatively impacts other systems, sectors, or social groups, or increases their vulnerability" (Barnett and O'Neill, 2010). Consequently, it is difficult for policymakers to determine which adaptation options are best suited to local conditions.

But for Africa, particularly the Sahel, since productivity is a priority in the countries of this region that depend on agriculture for their livelihoods, interventions will need to focus on practices that offer immediate benefits in terms of productivity and adaptive capacity. Thus, an approach with the aim of assessing farmers' adaptive capacities can be very useful in identifying and prioritizing adaptation strategies based on what is feasible and in what context (Shikuku et al., 2017). This is all the more important as the resources that underpin the livelihoods of vulnerable populations - such as labor and crop diversification within economic portfolios - can play a key role in meeting current and future climate challenges (Vincent, 2007; Chepkoech et al., 2020). Consequently, assessing the adaptive capacity of agricultural producers, particularly in vulnerable countries, has become increasingly urgent (UNEP, 2022). Reliable information is essential for developing and implementing effective adaptation policies, hence the need for robust assessments to guide decision-making. This approach is supported by the literature, as it aligns with the principles of effective adaptation identified and explained by (Singh et al., 2022)[1].

Adaptive capacity is an important attribute as it describes the ability of a system to mobilize resources to respond, recover and/or maintain its functions in response to stresses and shocks (Vincent, 2007). It identifies the positive features of a system that can reduce the biophysical and/or socio-economic vulnerability associated with climate change (Engle, 2011). In fact, it simply identifies strategic factors that can serve as important levers for identifying and implementing effective adaptation options, particularly in a context of resource scarcity. However, according to Choden et al. (2020), the literature on assessing adaptive capacity suffers from a lack of consideration of contextual variability between communities and within households, and this work will need to focus on addressing this limitation. Therefore, this work carries multiple contributions to the literature as well as to the decision-making process by assessing the adaptive capacity of Niger farmers. More specifically, the aim is to contribute to a better understanding of contextual vulnerability factors in order to reduce the risks of maladaptation and to enable national planning leading to an efficient, effective and equitable allocation of limited resources for the benefit of well-targeted and most vulnerable groups and systems (Below et al., 2012; Vermeulen and Dinesh, 2016; Christiansen et al., 2018; Thornton et al., 2018; Leiter et al., 2019).

From the first vulnerability assessments (i.e. Adger and Vincent (2005)) to the present day (ND-GAIN index 2020[2]), Niger is considered one of the most vulnerable and least prepared countries in the world to cope with the effects of climate change. According to Smit and Wandel (2006), any country whose economy and communities are highly exposed to the adverse effects of CC, with limited economic resources, low levels of technology, insufficient information and skills, poor infrastructure, unstable or weak institutions and inequitable access to resources, generally has low

[1] For more details on the 11 principles of effective adaptation, follow the link below: https://doi.org/10.1080/17565529.2021.1964937.
[2] Vulnerability rankings | ND-GAIN Index

adaptive capacity and is highly vulnerable. In this context, the case of Niger is relatively alarming. 2/3 of the country lies in the Sahelian zone, leaving a limited area suitable for agricultural production (INS, 2017; Röhrig et al., 2022). Agriculture is essentially rain-fed, and highly dependent on the vagaries of the climate. With around 80% of the population employed in the agricultural sector, which contributes 40% of the country's GDP, poverty reduction and the improvement of community well-being in Niger largely depend on the performance of this sector (WB, 2017; ME/LCD, 2021; CNEDD, 2022). Among various challenges facing the country, increasing the income of producers remains critical as 63% of them live below the poverty line and 34% are extremely poor (Agbegnido and ADAMOU, 2018).

Yet agricultural production is characterized by remarkably low levels of productivity, frequently threatened by rainfall deficits, inter- and intra-annual variability of rainfall and high temperatures of up to 45ºC. The most well-known adverse consequences are recurrent droughts[3] and floods, as well as ongoing degradation of natural resources and land, resulting in enormous economic and ecological losses. The negative effects of CC have led to a considerable increase in food and nutritional insecurity (affecting over 40% of the population), loss of herds (over 17 million cattle perished between 2001 and 2014), loss of housing (176,000 homeless people in 2012 due to violent winds) and land (Niger lost 310,000 ha between 1974 and 2004), regular migration and rural exodus of populations, conflicts between producers over the management of and access to natural resources, disruptions to river regimes and the availability of water resources, the accentuation of climate-sensitive diseases, and of course a reduction in crop yields, to name but a few of the effects that future changes are likely to increase if no action is taken (INS, 2017; WB, 2017; CNEDD, 2022; DTDA, 2022). Drought is also the main trigger for soaring food prices and conflicts over pasture and water (BM, 2013).

Estimates predict increased and uncertain rainfall variability, coupled with a significant rise in temperatures to 2.1ºC in 2030, between 2.5ºC and 2.7ºC in 2050 and between 2.6ºC and 3.7ºC in 2080, depending on low and high emission scenarios (GIZ, 2020). This situation will lead to a 10-20% drop in yields for most rainfed crops by 2050, compared with 2020 (ME/LCD et al., 2020). In particular, the most recent simulations show that climate change is expected to lead to a 9-15% decrease in non-photoperiodic millet grain yields by 2050, and an 18-23% decrease in sorghum grain yields (Lona et al., 2019), which are among the population's staple foods. These current and future effects of climate come on top of multiple challenges of insecurity and health crises, high prevalence of extensive rainfed subsistence farming, low education rates, insufficient infrastructure, and limited capacity of producers characterized by low levels of livelihood diversification, limited access to technical guidance and policy support (particularly in terms of high-yield inputs adapted to a changing climate) (Agbegnido and ADAMOU, 2018; Asfaw et al., 2018; M/P, 2022). These constraints explain the low adoption of adaptation options in the face of

[3] Between 1980 and 2010, the country experienced seven waves of drought (WB, 2013).

CC by farmers whose decisions mostly boil down to survival strategies with a tendency to choose low-yield, but less risky inputs (WB, 2017; Asfaw et al., 2018; Lalou et al., 2019).

As a result of the health, climate and security crises, the growth rate has fallen from 5.9% in 2019 to 3.6% in 2020 and 1.3% in 2021 (CNEDD, 2022). This situation of crises combined with extreme climatic events is an obstacle to achieving the objectives of the fight against poverty and for economic and social development as set out in national policies and strategies (SDDCI-2035[4], PDES[5], SPN2A[6], etc.). It also hinders the objectives of reducing carbon emissions by 35% by 2030 in accordance with Niger's Nationally Determined Contribution (NDC) (ME/LCD et al., 2020). Despite the investment efforts and objectives consistent with the needs of the agricultural sector, these national policy and strategy documents recognize the lack of reliable information on the agricultural sector as a major constraint to achieving their objectives. Indeed, among the various studies that have analyzed the impact of climate change on adaptation strategies in the Sub-Saharan African region, Niger has received surprisingly little attention[7].

Existing studies on adaptation to climate change in Niger have primarily examined factors influencing farm households' adoption of adaptation practices and their effects on productivity and food security (Asfaw et al., 2016; Djibo and Maman, 2019; Röhrig et al., 2022; Zakari et al., 2022). While these works have identified contextual determinants relevant to adaptive capacity, they did not explicitly assess AC. Other research has focused on crop and labor diversification as key strategies, demonstrating significant positive impacts on household well-being when used as both medium-term adaptation to climate change (CC) and short-term responses to market shocks (Asfaw et al., 2018). Such findings underscore that AC in Niger extends beyond economic resource endowments, reflecting a more complex set of determinants (Adger et al., 2007; Juhola and Kruse, 2013).

A smaller body of work has directly explored farmers' AC as a mean to reduce vulnerability and strengthen resilience to CC across different scales (Vincent, 2007; Gambo Boukary et al., 2016; Epule et al., 2023). At household level resilience study, AC was proxied by economic wealth, technology, information and skills, infrastructure, institutions and equity (Gambo et al., 2016). Surprisingly, findings reported a negative relationship between AC and resilience, contrary to the broader literature. This result was attributed to households' poor access to credit and limited income sources, though it may reflect methodological limitations in capturing the full complexity of AC determinants.

[4] Stratégie de Développement Durable et de Croissance Inclusive, Niger 2035 (M/P, 2017).
[5] Plan de Développement Economique et Social 2022-2026 (M/P, 2022).
[6] Stratégie et Plan National d'Adaptation face aux changements climatiques dans le secteur Agricole 2020-2035 (MESUDD, 2020).
[7] To date and to our knowledge, the only studies that assess the impact of climate change on adaptation in Niger are the following: Boukary et al (2016a, 2016b), Baidu-Forson (1999, 2011), Zakari et al (2022), Asfaw et al (2016), Asfaw et al (2018), Djibo and Malam Maman (2019), Epule et al (2023).

At national level, comparative studies positioned Niger as having the lowest AC in Africa (Vincent, 2007; Epule et al., 2023). These analyses, however, faced the common limitation of national indices: they fail to capture sub-national variations in vulnerability and cannot be easily downscaled, as the processes shaping vulnerability differ across scales (Adger et al., 2004; Clay, 2017). This is especially problematic in African contexts, where rural households rely on diverse livelihood strategies and local environmental conditions to manage risks (Gbetibouo et al., 2010). Moreover, theory-driven approaches to indicator selection often overlook local constraints and opportunities, limiting their usefulness for strengthening AC in practice (Brown et al., 2010; Leith et al., 2012).

To address these gaps, the present study adopts a mixed approach that combines theory with expert validation, thereby tailoring AC assessment to the unique characteristics of the study sites (Below et al., 2012; Abdul-Razak and Kruse, 2017; Azam et al., 2019; Choden et al., 2020). Given the highly context-specific and dynamic nature of AC, the household level was chosen as the appropriate scale of analysis, since households are primary locus of decision-making and directly experience the impacts of CC, including extreme events (Brooks et al., 2005; Smit and Wandel, 2006; Antwi-Agyei et al., 2013; Clay, 2017).

Furthermore, much of the literature has neglected intra- and inter-community variability in AC (Choden et al., 2020). By applying a consistent methodological and analytical framework adapted to local realities, this study contributes to filling this gap while generating policy-relevant insights for Niger. Specifically, it addresses three key questions: To what extent do Nigerien farmers have the capacity to adapt to current and future climatic changes? Why do farmers differ in their adaptive capacities? And which contextual factors serve as strategic levers for strengthening adaptation?

It is noteworthy that this study also contributes to the literature on AC assessments using the Sustainable Livelihood Framework (SLF) by demonstrating the explanatory power of livelihood capitals for farming households' AC (Antwi-Agyei et al., 2013; Ng'ang'a et al., 2016; Abdul-Razak and Kruse, 2017; Shikuku et al., 2017; Chepkoech et al., 2020; Jamshidi et al., 2020; Datta and Behera, 2022). Unlike earlier studies that overlooked or downplayed the role of capitals in shaping overall AC, this work explicitly incorporates their relative importance through expert-derived weights, consistent with the treatment of individual indicators. This approach aligns with evidence that poor households often face trade-off in their livelihood strategies (Serrat, 2017), and with the assumption that a diversified asset portfolio enhances sustainability by enabling substitution between shrinking and emerging opportunities (Ellis, 1999; Clay, 2017). Accordingly, any SLF-based assessment must account for asset weights and provide a detailed analysis of their substitutability. This methodology not only avoids the limitations of direct aggregates of indicators into an adaptive capacity index – which can lead to inappropriate policy recommendations(Zanmassou et al., 2020) – but also enables a more nuanced analysis of adaptive capacity.

However, the approach of calculating AC indices has proved to be fraught with uncertainties and subjectivities that can negatively impact the validity of the indices and, consequently, lead to non-robust, erroneous or inappropriate policy outcomes when they are poorly constructed or misinterpreted (Nardo et al., 2005; OECD, 2008). In the index construction procedure, a number of subjective choices and judgements will have to be made: the selection of indicators, the normalization method of indicators, the weighting system for indicators and components, and the respective aggregation methods, etc. All these successive choices converge to calculate the value of the index and shape the message communicated by the composite index. In other words, all sources of subjective judgements and choices will affect the message conveyed by the composite index (Nardo et al., 2005) and constitute an uncertainty factor that must be rigorously taken into account. Uncertainty studies carried out on other composite indices confirm that uncertainty is an unavoidable factor in the construction of composite indices (Saisana et al., 2005).

In this context, it seems important to ask the question: How can we judge of the robustness and transparency in the construction procedure of the adaptive capacity index? This issue is addressed in this work by a combined analysis of the uncertainty and sensitivity of the computed adaptive capacity index. The second objective of this work is to analyze the uncertainty and sensitivity of the ACI. While the uncertainty analysis (UA) focuses on how different choices of input factors (i.e. the normalization method, the weighting method and the aggregation method) affect the value of the composite index, the sensitivity analysis (SA) analyses how the observed changes can be qualitatively or quantitatively attributed to different sources of variation in the input factors, and how the composite indicator depends on the information provided to it (Saisana et al., 2005; OECD, 2008). Simply put, the iterative use of the UA and the SA makes it possible to assess how changes in the steps involved in constructing the composite index affect its final value, and which input factors have the greatest influence on the composite index. In this way, the combined use of these tools guarantees the robustness and transparency of the calculated ACI, and greatly reduces the possibility of communicating the wrong message (Saisana et al., 2005). However, it is often the case that these two types of analysis are treated separately, with UA being the tool most frequently used (Dobbie and Dail, 2013). It is important to note that uncertainty and sensitivity analyses, while necessary in the construction of the composite index, cannot on their own guarantee the robustness of the index. The methodological and analytical framework is considered to be the "main ingredient" and must be sufficiently robust and informed to produce adequate results to better inform decision-making processes (OECD, 2008).

Analysis of previous studies on climate change and livelihoods, particularly in Africa, provides useful additional information for this work. Labor diversification is often identified as a suitable livelihood strategy to combat the negative effects of CC. For example, in Ghana, Antwi-Agyei et al. (2013) found that households that engaged in other activities outside agriculture tended to be less vulnerable to CC. Although the proportion of households in this category was low, they had diversified livelihoods and were thus better able to cope with climate shocks. Also in Ghana, Antwi-Agyei et al. (2018) illustrated that the diversification of non-agricultural livelihoods provided employment opportunities, thus accumulating additional resources to support agricultural incomes. Similarly, the findings of Mogomotsi et al. (2020) showed that low-income returnees were less likely to adopt climate change adaptation strategies to improve their agricultural productivity.

In the specific case of Niger, the diversification of livelihoods, in particular through the diversification of the workforce (agricultural, non-agricultural and other), has been identified as an important adaptation strategy in Niger's national policies and strategies. For example, SPN2A intends to support the development of income-generating activities for the most vulnerable producers while reducing obstacles and constraints to seasonal and temporary mobility, an action considered to be a key adaptation option in the face of the climate. In fact, and in general, the accompanied diversification of the workforce, and therefore of sources of income (especially in rural areas), has been identified as an important avenue for the structural transformation of African economies and poverty reduction, particularly for young people (Mueller et al., 2020). This assertion is supported by the study of Dedehouanou et al. (2018), whose main findings suggest that promoting the development of the non-agricultural rural economy is an important way for young people in Niger to escape poverty. These results can also be supported by World Bank statistics which add that over 90% of young people aspire to non-agricultural jobs (WB, 2017).

In the context of climate change that is of particular interest to this work, Asfaw et al. (2018) find that crop and labor diversification positively and significantly affect well-being when used by the most vulnerable households as a coping strategy to medium-term climate variability and as a coping strategy to short-term market shocks. Although the main objective of their work is to analyze the impact of work diversification on well-being, thus considering work reallocation as a simple result of climate shocks, it is a coping/an adaptation strategy that is attracting growing interest among researchers. In other words, it is not well understood how changes in climate and its uncertain effects will modify labor responses and their impacts on the national economy, particularly on the agricultural sector, and, as Hill et al. (2021) eloquently put it, "they should be at the forefront of the concerns of researchers and decision-makers". Thus, a third objective of this work is to analyze the supply behavior of agricultural labor in a CC context in Niger.

Finally, the framework of our research (summarized in Figure 1) structures the present work in 3 sections: (i) the evaluation of the adaptive capacity of producers faced with CC in Niger, particularly those located in the Maradi and Tillabéri zones; (ii) the uncertainty and sensitivity analyses of the composite index calculated; and (iii) the analysis of the agricultural labor supply behavior of Niger households in a CC context.

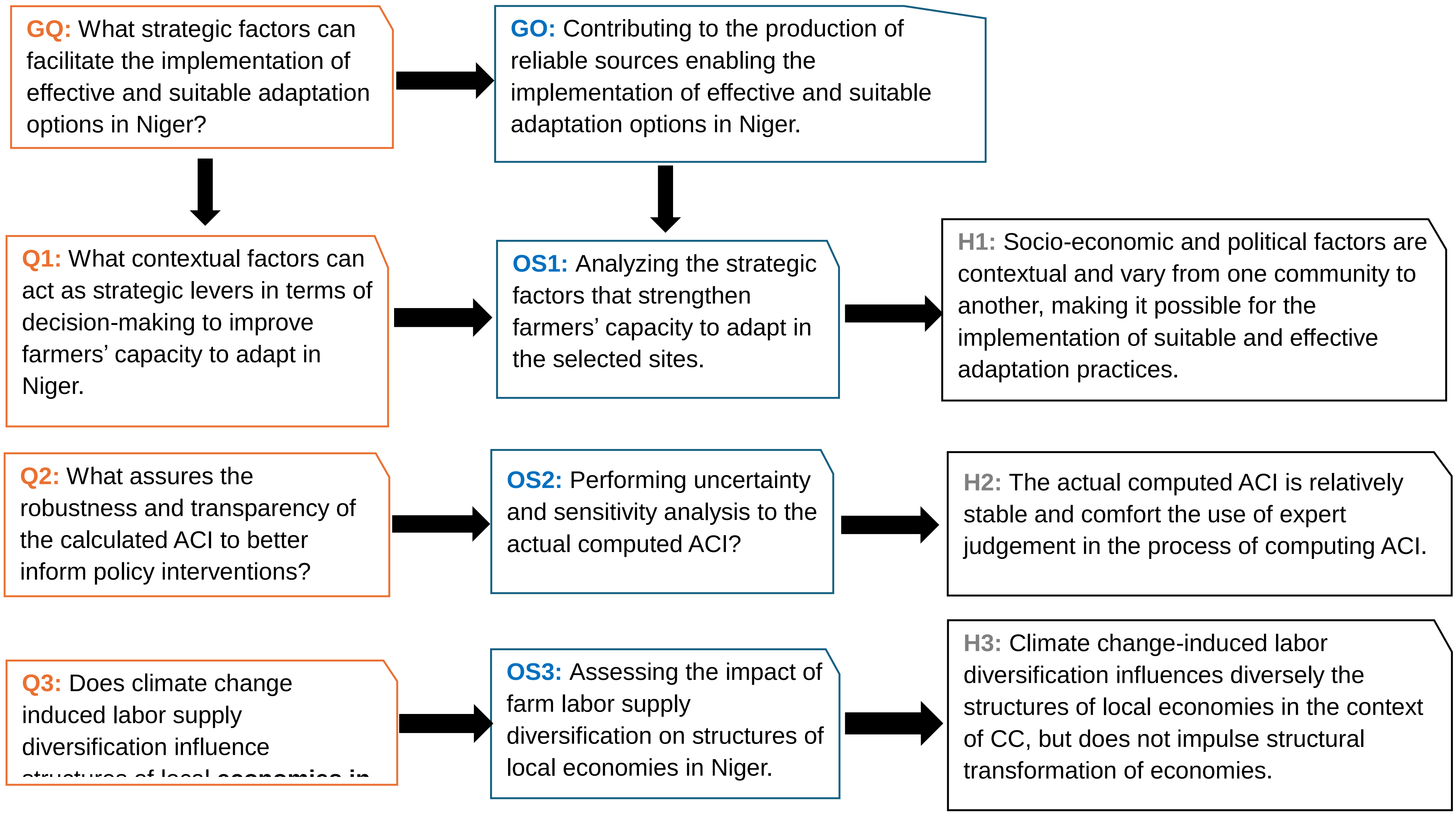

Figure 1: General research framework

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ESSAY 1: ANALYSIS OF THE CAPACITY OF HOUSEHOLDS IN TILLABERI AND MARADI TO ADAPT TO CLIMATE CHANGE: AN INDEX-BASED APPROACH

Abstract:

In Niger, a Sahelian country characterized by resource scarcity, even minor climatic variations can severely impact agricultural households. This study develops an adaptive capacity index using a robust framework that integrates an in-depth literature review with site-specific parameters. Primary data from 343 households in highly vulnerable agricultural regions, in Tillabéri and Maradi, were complemented by qualitative insights from expert interviews and workshop. The analysis revealed significant disparities in household asset portfolios, with many households lacking critical elements, particularly education and skills for accessing information, technologies, and off-farm income opportunities. Households with moderate adaptive capacity were more likely to engage in diversified off-farm activities, which significantly enhanced their ability to adapt to climate change. Insights from this analysis, combined with comparative analysis of factors that can serve as policy levers, provide a foundation for evidence-based interventions. The proposed index-based approach offers valuable insights for addressing climate vulnerabilities and strengthening resilience in Niger's agricultural sector.

Key-words: Adaptive capacity, Tillabéri, Maradi, households, index-based approach

Introduction

The previous section illustrates the high vulnerability of Niger's agricultural systems. Even minor changes in climatic parameters can have significant negative impacts on producers, particularly those with limited adaptive capacity.

Yet, livelihoods in agriculture-dependent economies like Niger are particularly vulnerable to climate risks (Adger, 2006; Adger et al., 2007; Zougmoré et al., 2016; UNEP, 2021; Röhrig et al., 2022). Recent studies have shown that climate change not only have a considerable negative impact on agricultural yields of vulnerable populations (FAO, 2018; WMO, 2022), but also hinders the use of the range of socio-economic, natural, physical and human resources available to farming households that are combined in the pursuit of their livelihood strategies, therefore their capacity to adapt (Zougmoré et al., 2016; Christiansen et al., 2018; Thornton et al., 2018; Lalou et al., 2019; Wijk et al., 2020). Yet, it is well documented that enhanced adaptive capacity reduces farmers' vulnerability to current and future climate events (Gallopín, 2006; Smit and Wandel, 2006).

Adaptive capacity is a critical attribute of the adaptation process as it refers to the resource base from which adaptation actions and investments are feasible (Adger et al., 2007). It identifies key strategic factors that can act as levers for developing and implementing effective adaptation measures, particularly in contexts of resource scarcity. Consequently, effective policies to reduce local producers’ vulnerability to climate change require robust assessments of their adaptive capacities to provide the reliable evidence needed for sound decision-making (Adger et al., 2007; Juhola and Kruse, 2013). Despite its acknowledged importance in literature, AC remains one of the least studied topics in the science of adaptation to climate change (Vincent, 2007; Engle, 2011; Choden et al., 2020).

The present study adopts a mixed approach that combines theory with expert validation, thereby tailoring AC assessment to the unique characteristics of the study sites. Given the highly context-specific and dynamic nature of AC, the household level was chosen as the appropriate scale of analysis, since households are primary locus of decision-making and directly experience the impacts of CC, including extreme events. By applying a consistent methodological and analytical framework adapted to local realities, this study contributes to generating policy-relevant insights for Niger. Specifically, it addresses three key questions: To what extent do Nigerien farmers have the capacity to adapt to current and future climatic changes? Why do farmers differ in their adaptive capacities? And which contextual factors serve as strategic levers for strengthening adaptation?

To this end, this study aims to provide reliable information by analyzing the processes determining adaptation through the calculation of an adaptive capacity index for producers in the Kollo and N'Dounga localities in the Tillabéri region, and Guidan Roumdji and Gadabedji localities in the Maradi region. These localities, frequently identified as highly vulnerable to climate change, are situated within two agroecological zones with significant agricultural activity: the Sudan-Sahel and Sahel-Sahara zones, which are the focus of this study.

This essay is structured into three main sections. *Section I* reviews the literature on adaptive capacity and the livelihoods framework. *Section II* presents the methodological and analytical framework used to compute the Adaptive Capacity Index of agricultural households in the selected study sites. *Section III* reports and discusses the empirical results.

I. Literature review on adaptive capacity and the livelihood framework

Rather than reviewing the evolution of adaptive capacity (AC) in climate change adaptation science, this review aims to highlight the importance attributed to this concept. It also discusses the controversies surrounding AC, which reflect the complexity of its assessment. In addition, this review highlights the need for a robust methodological framework adapted to local contexts. Such a framework would enable the extraction of relevant information and the use of tools adapted to the local contexts of farmers in Niger. This is essential for effective adaptation and for informed decision-making in Niger.

1.1. Definition and determinants of adaptive capacity

1.1.1. Vulnerability vs. adaptive capacity

It is important to note that this essay gains its full significance by opting to strengthen adaptive capacity (AC) as a framework for assessing the effectiveness of the adaptation process. The emerging literature's interest in this framework is not coincidental. It is justified by the assumption that improving AC will reduce vulnerabilities while promoting sustainable development (Adger and Vincent, 2005; Adger, 2006; Gallopín, 2006; Smit and Wandel, 2006; Singh et al., 2022).

Thus, AC is closely linked to the concept of vulnerability as it is a component of vulnerability, in addition to exposure and sensitivity (McCarthy et al., 2001; Adger and Vincent, 2005; Smit and Wandel, 2006). Exposure refers to the susceptibility of a human and/or environmental system to be affected by nature, magnitude and rates of change and variability of climate parameters. Sensitivity refers to the degree to which the system is positively or negatively affected by variability or CC, while adaptive capacity is often defined as the ability of a system to adapt to CC (including climate variability and extremes), moderate potential damages, take advantage of opportunities and cope with consequences (Adger et al., 2007; IPCC, 2014). Vulnerability, on the other hand, is generally portrayed in negative terms as the propensity or predisposition to be damaged (IPCC, 2014). Generally, the first two determinants (exposure and sensitivity) are considered positively linked to vulnerability because they dictate the potential for negative consequences to occur, while the third (adaptive capacity) is negatively linked to it because it refers to the system's ability to manage, and therefore reduce vulnerability.

AC is a positive component of vulnerability, and adaptation planning processes have switched from country vulnerability assessments to the need for a better understanding of farmers' capacities to adapt at local level for diverse reasons. Much of the understanding of AC comes from vulnerability assessments based on the calculation of indices and indicators at different scales (local, national and regional) (Adger et al., 2007). These assessments often provide important insights into the factors, processes and structures that promote or limit farmers' AC. However, Eriksen and Kelly (2007) explain that these vulnerability indices have failed to explicitly include the determinants of AC. One explanation given by these authors is that these vulnerability indices fail to capture the complexity of the processes and contextual factors that influence AC. For example, some criticize vulnerability perspectives for having long focused on biophysical and/or technological mechanisms, while often neglecting the political, economic, social and ecological characteristics that could enable more appropriate and transformative adaptation policies (Preston and Stafford-Smith, 2009; Clay, 2017). These characteristics are undeniably crucial in the adaptation process for the simple reason that before agricultural systems can adapt effectively and efficiently, they must meet the necessary mix of natural, financial, institutional and human resources, as well as the necessary capacity, expertise and knowledge (Brooks et al., 2005). These factors and their combination determine AC and vary considerably from one farm to another, from one community to another. Thus, although vulnerability assessments have contributed to our understanding of the causes of large-scale vulnerability, they generally fail to capture the variability that exists at the local scale (Antwi-Agyei et al., 2013). Other authors add that the key vulnerability components of exposure and sensitivity may be difficult to separate at the local household level, may be modulated by AC (Smit and Wandel, 2006; Adger et al., 2007), and can only be predicted with great uncertainty (Vincent, 2007). As an illustration, in calculating the Livelihood Vulnerability Index for communities in the Char Land of Bangladesh, Azam et al. (2019) found that the adaptive capacity index is a more important component than those of sensitivity and exposure, thus recommending the implementation of adequate programs aimed at strengthening adaptive capacity as the main determinant of vulnerability. Similarly, Mandal et al. (2017) found that higher AC is associated with lower levels of vulnerability, and that there is therefore a need to strengthen the AC of farmers in Sagar Island (India). Defiesta and Rapera (2014) found that farm households in the Philippines with higher adaptive capacity use more adaptation strategies.

These shortcomings related to vulnerability assessment make the concept an inadequate tool for mainstreaming adaptation in development (Lemos et al., 2013). This has led to the emergence of a generation of researchers and practitioners dedicated to the conceptualization, as well as the development of frameworks, methods and tools for the assessment of AC (Yohe and Tol, 2002; Adger and Vincent, 2005; Brooks et al., 2005; Smit and Wandel, 2006; Hinkel, 2011; Hogan et al., 2011). AC is an important attribute of the adaptation process as it refers to the asset base from which adaptive actions and investments are feasible (Adger and Vincent, 2005). Adaptation is therefore highly dependent on the capacity of a system, region or community to adapt to the effects and risks of CC (Smit and Wandel, 2006). Consequently, understanding the factors that determine the AC of farming communities or households means having the means to develop an appropriate adaptation policy, since the factors that underpin and enable the management of adaptation activities are analyzed (Adger et al., 2007; Juhola and Kruse, 2013). In other words, adaptation is highly dependent on the adaptive capacity of farmers, and the assessment of AC will make it possible to identify not only who is vulnerable and who has the capacity to adapt, but also why producers are vulnerable and why they have different adaptive capacities (Singh et al., 2022). This is therefore a prerequisite for effective adaptation. Despite its acknowledged importance in literature, AC remains one of the least studied topics in the science of adaptation to CC (Vincent, 2007; Engle, 2011; Choden et al., 2020).

However, it has been recognized that AC is a potential rather than an actual response to climate stimuli and does not systematically translate into adaptive actions and reduced vulnerability (Adger et al., 2004; Adger and Vincent, 2005). Mortreux and Barnett (2017) consider this to be the most important limitation of AC assessments due to the lack of sufficient empirical studies that prove otherwise. Adger et al. (2007), for their part, put this inadequacy down to major obstacles to the implementation of adaptation, including the inability of natural systems to adapt to the pace and scale of climate change, as well as technological, financial, cognitive and behavioral, social and cultural constraints. For example, in a study conducted in northern Burkina Faso, Nielsen and Reenberg (2010) found that households from the traditionally disadvantaged 'Rimaaibe' ethnic group adopted multiple livelihood strategies that enabled them to better adapt, whereas the cultural values of the 'Fulbe' group, such as valuing isolated life in the bush rather than in the village, limited their adaptation despite their traditionally higher social status and wealth. Similarly, Hogan et al. (2011) found that levels of adaptive capacity of farm households are not determinant of adaptation options. Therefore, while those with apparently low adaptive capacity adapt and those with high adaptive capacity do not, the relationship between adaptive capacity and adaptation is far from straightforward, and theories and evidence are needed to better explain this association (Mortreux and Barnett, 2017). Nevertheless, even though AC is latent in nature, meaning that it can only be identified after being subjected to extreme weather events or long-term climate stress conditions (Engle and Lemos, 2010), its assessment remains vital from both a research and policy perspective due to its non-static nature: it can be improved over time (Lemos et al., 2013).

Thus, assessing the adaptive capacity (AC) of rural farmers in Niger is both relevant and necessary. The focus on households is justified because climate change effects are often most acutely experienced at this scale. Additionally, households are critical sites for decision-making regarding adaptation strategies.

1.1.2. Determinants of adaptive capacity

The determinants of a system's AC are the forces or drivers that influence it (Adger et al., 2003). Several of these determinants derive from vulnerability assessments and others from normative and theoretical analyses of the concept itself. It is important to recall that this concept has its origins in Sen (1981) theory of capabilities Sen's theory posited that, contrary to traditional analyses of famine which focus on food availability, a more comprehensive understanding is achieved by examining people's capabilities to access and utilize food through the available legal means within society. This approach better explains certain famine situations where food availability did not significantly decline, such as the Bengal famine of 1943, the Ethiopian famine of 1973, and the Bangladesh famine of 1974. This framework is known as Sen's "theory of entitlement." He sees capabilities as "what people can do or be with their rights", a concept that encompasses much more than just the material concerns of food availability or income. Applied to CC, this theory sees AC as a function of entitlement (access and use) to material goods and social opportunities, where more entitlement is equated with greater ability to adapt to CC, and less entitlement is interpreted as greater vulnerability (Lemos et al., 2013; Mortreux and Barnett, 2017).

It is therefore clear that AC is closely linked to the socio-economic characteristics of communities (Adger and Vincent, 2005). Several studies have been based on the IPCC report (McCarthy et al., 2001; Smit and Pilifosova, 2003) which introduces for the first time a series of six (6) characteristics that determine the AC of communities or regions. These are economic resources, technology, information and skills, infrastructure, institutions and equity. This initial list has been improved and redefined by several other researchers. Some suggest that AC of communities is determined by the ability to act collectively. In this context, social capital, trust and organizations greatly influence this capacity (Adger et al., 2003; Pelling and High, 2005). Others focus on institutions, governance and management as critical determinants of the ability of a system or individuals to adapt to CC (Yohe and Tol, 2002; Brooks et al., 2005; Eakin and Lemos, 2006; Agrawal, 2010). Several others highlight characteristics internal to individuals as fundamental to high AC and facilitating the translation of this capacity into action. These include risk perception, self-efficacy beliefs and perceived adaptation costs, personal experience, household composition and dynamics, perceived importance of assets (resources) mobilized for adaptation actions, and trust in and expectations of authorities (Grothmann and Patt, 2005; Mortreux and Barnett, 2017; Zanmassou et al., 2020).

Adger et al. (2004) group these different determinants of AC into two (2) dimensions representing generic and specific adaptive capacity. The generic dimension refers to the determinants that enable systems, individuals or communities to adapt or to be vulnerable to a wide range of risks that threaten the functioning of systems. These generic factors may include income, education, technology, institutions or social capital (Adger and Vincent, 2005; Adger et al., 2007). For example, Adger et al. (2004) explain that poverty or high levels of inequality can be very restrictive to investment in the agricultural inputs needed for diversification, or can lead to the formation of very vulnerable, financially and socially marginalized groups unable to adapt to the effects of CC. The specific dimension of AC refers to the mobilization of factors to deal with a particular threat or risk and only with that threat or risk, such as drought or flooding. These factors may relate to knowledge, technology, management capacity or the institutional environment in which adaptations take place (Smit and Wandel, 2006).

In the specific case of Niger, there is little work on adaptation to CC and an almost total absence of works explicitly assessing the AC of Nigerien farmers. These studies do, however, make it possible to identify certain factors likely to influence the AC of farming households. For the most part, these studies aim to analyze the factors that facilitate or constrain farm households' decision to adopt adaptive farming practices and their impact on productivity or food security. These factors are then likely to influence the AC of farming households in Niger. The main factors to emerge from these works are access to resources, knowledge and information. In a study based on socio-economic data (ECVMA) collected from farming households in Niger in 2011 and 2014, Asfaw et al. (2016) and Djibo and Maman (2019), respectively, found that the adoption of practices such as the use of modern inputs or improved seeds was determined by household wealth, with wealthier households being more likely to adopt CC adaptation practices than poorer ones. Similarly, Zakari et al. (2022) found that access to credit and market, as well as asset ownership, enabled farming households in four (4) major agricultural regions of Niger (Dosso, Tillabéri, Maradi and Zinder) to carry out adaptation activities such as adopting climate-resistant crop varieties, using irrigation and water conservation practices, or diversifying crops and income. In addition, a larger number of household members as well as larger land holdings, which may indicate greater human and financial resources, had positive and significant effects on CC adaptation actions (Röhrig et al., 2022). Asfaw et al. (2016) add land ownership as a factor determining the likelihood of adopting long-term adaptation strategies.

In addition to access to resources, agricultural extension services have traditionally played an important role in communicating effectively about climate risks to increase farmers' awareness and understanding (Röhrig et al., 2022). However, access to these services is often poor in Niger. In this context, Assoumana et al. (2016) conducted a study in two (2) rural communes in Niger and found that 32% of respondents had never been visited and 55% had rarely been visited by extension agents. They also explained that extension services in Niger have been in gradual decline since around 1998. They conclude that a lack of pedagogical knowledge, external support and access to information are major constraints to effective adaptation and therefore to improved productivity. The results of a study conducted in fifteen (15) villages around the capital Niamey by Roudier et al. (2016) corroborate these conclusions. They found that a ten-day forecast led to positive changes in income in more than 75% of cases, the most significant being for farmers who had access to fertilizers and more arable land.

Other socio-demographic and economic factors, such as the age, gender and/or level of education of the head of household, his or her farming experience, or his or her membership of a social group, have been identified in the above-mentioned studies as factors determining adaptation actions in the face of CC. These factors include also the characteristics and quality of the soil on the farms, as well as the existence of infrastructure or, more generally, the presence of local institutions.

Very few studies have analyzed the importance of AC for farmers in Niger as a mean of reducing their vulnerability and improving their resilience to CC. Gambo Boukary et al. (2016) studied factors affecting the resilience of rural households using principal component analysis, then applying structural equation modelling to identify its determinants, including AC. The latter was approximated by economic wealth, technology, information and skills, infrastructure, institutions and equity, parameters considered to be the main determinants of the AC of a household in a community or region. The results showed a significant and negative relationship between AC and household resilience, whereas the literature admits that greater adaptive capacity improves resilience. They explain this result by the presence of poor access to credit and a limited number of income sources, which are characteristic of rural households in Niger and constitute their main determinants of AC. However, one explanation for this contradictory relationship may be that the analysis does not consider the full complexity of AC determinants, as demonstrated above, thus neglecting several other fundamental AC determinants, especially when the scale is the household level. This is indeed a recognized limitation of vulnerability and resilience assessments (Clay, 2017), particularly in Africa where rural populations have traditionally used strategies related to their livelihood assets as a whole (asset portfolio), as well as to the environmental and local characteristics that are accessible to them both to reduce risks and to adapt to shocks (Gbetibouo et al., 2010). In addition, we will demonstrate in the section methodology (*Section II*) how an approach based solely on theory can lead to erroneous results.

Asfaw et al. (2018) focused on two (2) livelihood strategies, crop diversification and work diversification, to analyze the main drivers and their impacts on the well-being of rural communities in Niger, and hence on their capacity to reduce vulnerability to CC. Their estimates showed a significant positive impact of the two (2) strategies on the well-being of vulnerable households when used as a medium-term CC adaptation strategy and as a short-term market shock adaptation strategy. These results are likely to promote a better understanding of farmers' AC in Niger, whose determinants go well beyond their endowment of economic resources and labor, as we highlight in this section.

However, as mentioned earlier, these different factors that determine AC are not isolated. AC is the result of a series of factors that are neither independent nor mutually exclusive, but rather a combination of these factors (McCarthy et al., 2001). It also varies considerably according to scale, time and specificity (Vanschoenwinkel et al., 2020), which makes its assessment a difficult task requiring a robust methodological framework that is sufficiently context specific. Although there is no single method for its assessment, the livelihoods framework is often used (Singh et al., 2022). To overcome the shortcomings still present in AC assessments using this framework, we will put in place a mixed methodological framework based on the literature and emphasizing the uniqueness of the identified sites (cf. *Section II*).

1.2. The livelihoods framework as an approach to assessing adaptive capacity

It has been explored that in the face of a current or future shocks such as CC, communities, households or individuals draw on the range of resources or assets directly available to them, which they combine in the search for short- or long-term adaptation strategies. These resources or assets have very often been analyzed in the literature, both theoretical and empirical, in the context of the livelihood framework. Hence, we characterize the AC of farming households in Niger as dependent on livelihoods.

As introduced above, livelihoods research is based on Sen's (1981) theory of rights. Its origins can be traced back to the work of Chambers (1987) who developed the concept of capital assets. He later (Chambers, 1989) built his theory of vulnerability and adaptation on several case studies of poor smallholders and concluded that the poor often seek to reduce their vulnerability by developing and diversifying their portfolio of assets or capital, rather than by maximizing any income. This concept was extended and further elaborated by (Scoones, 1998) in the Sustainable Livelihoods Framework (SLF), and then used and improved by various researchers such as Ellis (1999), Lemos et al. (2013) or Serrat (2017) and some international agencies such as the UK

Department for International Development (DFID, 1999), to guide policies and programs for poverty reduction and adaptation to shocks.

In its simplest form (summarized in *Figure 2* below[8]), the framework sets out the main factors affecting livelihoods and their relationships and shows how, in different contexts of vulnerabilities and institutional settings that affect entitlements and access to the household resource base, sustainable livelihoods are achieved by combining these resources in pursuit of different livelihood strategies, well-being or what are commonly referred to as outcomes or responses (Scoones, 1998). Here, the resource base is often categorized into five (5) assets/capitals, also referred to as the asset pentagon (in reference to their schematic representation), which interact and lead to short- or long-term adaptation strategies. They thus constitute the means of subsistence for which the poor often must make compromises and choices in pursuing their strategies (Serrat, 2010). According to Chambers and Conway (1992), livelihoods comprise the capabilities, assets and activities needed to live. They are sustainable when they can adapt to and recover from stresses and shocks, maintain or enhance their capabilities, without damaging the natural resource base (Scoones, 1998). According to Ellish (2000), a diversified portfolio of activities or assets generally contributes to this sustainability of livelihoods because it offers more opportunities for substitution between declining and expanding opportunities. Substitutability between assets is thus a fundamental element of the livelihood framework as it makes them more resilient, better able to adapt to unforeseen trends and hazards. DFID (1999) defines assets (or the 5 capitals categorized above) as stocks of different types of capital that can be used directly or indirectly to generate livelihoods. They may give rise to production flows, eventually being depleted as a result, or they may be accumulated as a surplus to be invested in future productive activities. They are considered to vary over time and space, between households and within households, and any decision by some actors to use their assets in pursuit of a livelihood strategy can lead to fluctuations in the assets and rights of others (Ellis, 1999). These are therefore fundamental to both household livelihood strategies and the decision-making process.

The analysis of entitlements is also useful in explaining how individuals' access to different capital goods shapes social vulnerability under changing climatic and socio-economic conditions. Rights are seen as all the possible combinations of goods and services that a person can legally obtain using the resources at their disposal (Choden et al., 2020). They strengthen the ability of individuals or households to benefit from their resources. Policies and institutions transform the environment of structures (public and private sector organizations) and processes (laws, regulations, policies, agreements, societal norms and practices, etc.) (Serrat, 2017). The structures that determine policies cannot be effective in the absence of appropriate institutions and processes to implement them. Processes provide incentives that encourage people to make better choices. They grant or deny access to assets. They allow people to transform one type of asset into another through markets and influence interpersonal relationships.

[8] See for example Serrat (2010) for a broader understanding of the livelihood framework and its components

The different elements explained so far combine to produce livelihood outcomes. Potential livelihood outcomes can include increased income, increased well-being, reduced vulnerability, improved food security, more sustainable use of natural resources, etc.

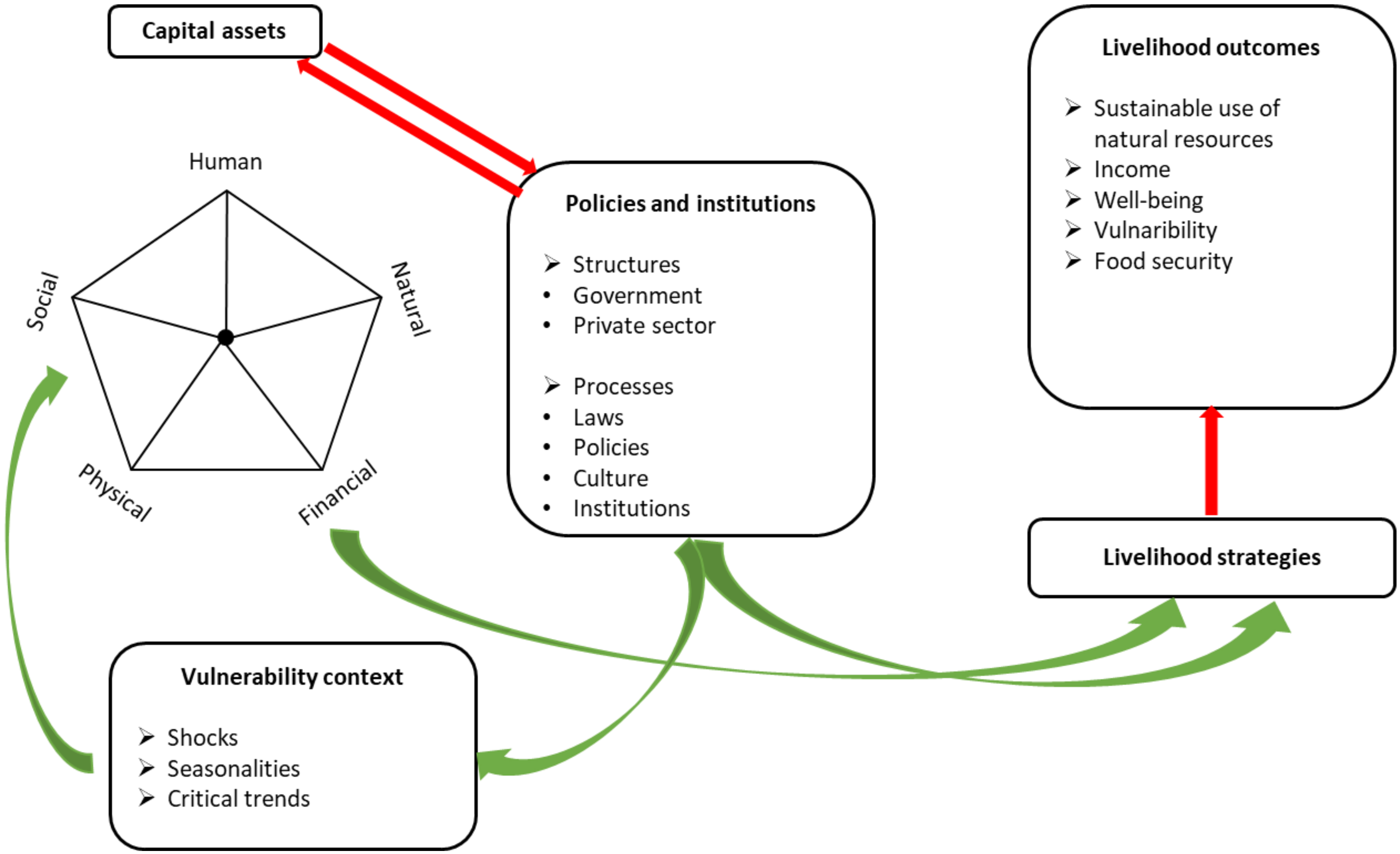

Figure 2 : The livelihoods approach, based on literature

It follows from the above that the livelihoods framework provides an interdisciplinary theoretical platform for visualizing complex adaptation pathways, shedding light on how households and individuals come to differ in their capacities to adapt to CC (Clay, 2017). It is indeed people-centered, responsive and participatory, dynamic and sustainable, promoting and facilitating the identification of practical priorities for adaptation actions as the factors that constrain or promote household AC are analyzed (Reed et al., 2013). These clear advantages justify the choice of this approach as the framework for analysis in this work. However, in view of the need to adapt this framework to local realities, the remainder of this work uses a mixed approach based on theory and the uniqueness of the sites selected, to identify indicators of the AC of producers in Niger.

II. Methodological framework

This section presents the characteristics of the study area, the sampling and data collection method, and the data analysis framework.

2.1. Study area

The study area consists of two agroecological zones purposely selected in Niger. These are the communes of Kollo and N'Dounga (Sahelian zone) in the Tillaberi region and those of Gadabedji and Guidan Roumdji (Sahelo-Saharan zone) in the Maradi region. Given the lack of data at commune level, this section focuses on describing the socio-economic and climatic characteristics at regional level. This information is drawn and summarized from the following literature: Tougiani et al. (2020), Favreau and Nazoumou (2010), INS (2022), LeMarois et al. (2021), MAG (2019), OCHA (2021), Tarchiani et al. (2016) and WB (2017).

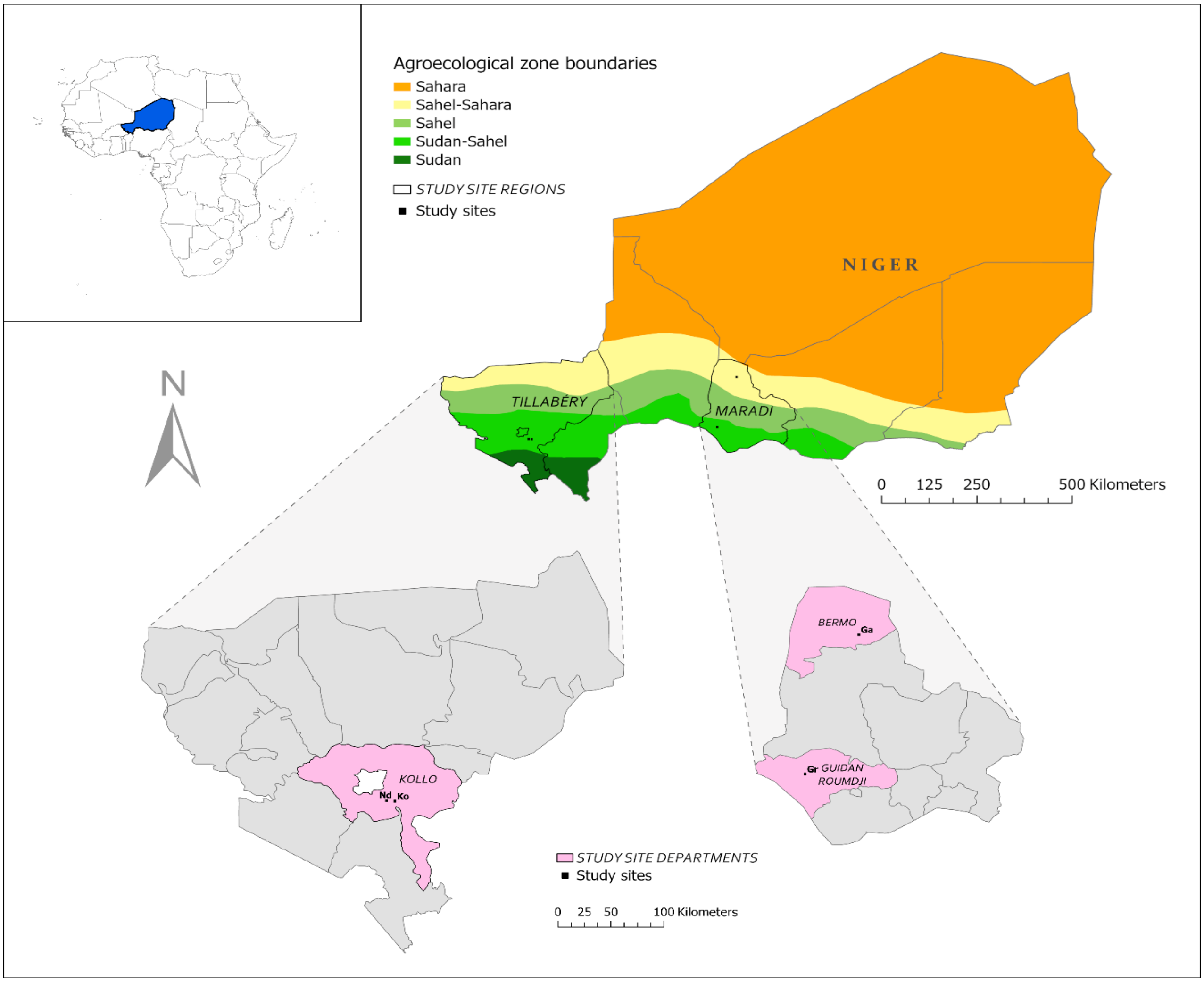

Figure 3 : Study area overview

*The top left corner highlights Niger's location in Africa. The main map displays Niger, including its agroecological zones and administrative boundaries (regions), with the study regions Tillabéri and Maradi and the respective study sites indicated. Enlarged views of the Tillabéri and Maradi regions show the study departments and precise locations of the study sites: Kollo (**Ko**) and N'Dounga (**Nd**) in the Kollo department, Guidan Roumdji (**Gr**) in the Guidan Roumdji department, and Gadabedji (**Ga**) in the Bermo department. Agroecological zones are based on previous work(Kamara et al., 2023), and administrative boundaries, including country, region, and department levels, are sourced from publicly available data sources (GADM maps and data and Humanitarian Data Exchange (HDX), OCHA services, Niger Data Grid).*

2.1.1. The region of Tillabéri

The Tillaberi region is in the west of Niger and is one of the largest of the country's eight regions, with a surface area of 97,251 km^2, or around 7.68% of the country's total surface area. It is bordered to the north by Mali, to the north-east by the Tahoua region, to the east by the Dosso region, to the west by Burkina Faso and to the south by Benin. It is laid out in a ring around the city of Niamey, the country's capital, which lies in the middle of the region. Administratively, the region is divided into 13 departments, 32 rural communes and 13 urban ones. The population is estimated at 3,903,596 in 2022, giving an average density of 43 inhabitants/km^2 (INS, 2022), although this can vary, from 50 to 150 inhabitants in the valleys. The population growth rate (3.2% according to INS estimates for 2022) puts the region in third place among the lowest in the country.

The climate of the Tillaberi region is Sudano-Sahelian in the south and Sahelo-Sahelian in the north. Average annual rainfall varies from around 250mm in the north of Filingue to over 700mm in the extreme south of Say. Temperatures range from 42°C in April-May to 18°C in December-January (average daily maximum and minimum temperatures respectively).

The main economic activities are agriculture, livestock, fishing, and forestry. Agriculture is by far the main branch of household activity, contributing more than 50% to the region's primary sector GDP (CNEDD (2004) cited by Favreau and Nazoumou (2010)). Agriculture employs 90% of the population and its crop production component is subdivided into rain-fed agriculture (millet, sorghum, cowpeas, and groundnuts) and irrigated agriculture (rice all along the river) and market gardening (off-season). In this context, the department of Kollo, where the communes selected for this study are located, is recognized as a major producer with the highest average production of millet.

The region also has significant natural resource potential. It drains most of the country's surface water resources through the Niger River, the only permanent watercourse, which crosses the region from north-west to south-east for around 420 km. The river is fed by seven main affluents, namely (from north to south) the Gorouol, the Dargol, the Sirba, the Goroubi, the Diamangou, the Tapoa and the Mékrou. In terms of groundwater resources, the region has significant shallow alluvial aquifers (0 to 20 m) located in the fossil valleys of the Dallols ("*Dallol*": wide valley), and Koris ("*Kori*": valley with temporary, localized and/or discontinuous surface water), a generalized water table over most of the area to the east of the river, and several aquifers of regional extent. There are also 145 ponds in the region, 51 of them permanent and 84 semi-permanent. The region thus offers great potential for the development of irrigated agriculture. Most of the region's soils (sandy valleys and plateau), however, are shallow and poor in organic matter. These low-fertility soils are hardly suitable for agriculture but often used for grazing or forestry. They are also highly vulnerable to erosion due to the climate, human pressure, and overgrazing unlike soils of the Niger River valley, which are rich in organic matter and fertilizing elements and offer one of the best opportunities for agricultural intensification. In terms of forest resources, the Tillaberi region used to have enormous forest resources, dominated by tiger bush. Today, these resources consist only of the National Park W, the Tamou Total Faunal Reserve, the galleries, and other forest formations in the Sirba and Diamangou areas. The Parc W and adjacent reserves contain almost 80% of the country's biodiversity (CNEDD (1997) cited by Tarchiani et al. (2016).

Despite its many potential assets, the region is classified as one of the poorest in the country, with an incidence of poverty of 40% (WB, 2017). The performance of the agricultural sector remains mitigated, and for several years the region has been experiencing difficulties in meeting its cereal needs, with a chronic deficit cycle and a food deficit situation every three years on average. The main constraints on production are the poor distribution of rainfall in time and space, resulting in droughts and floods that often recur over several years, locust invasions, crop pests and diseases, windstorms and bush fires, the use of unrestricted and unconservative exploitation techniques for natural resources, and the shortage of improved seeds for the main plant species. As a result, the enormous potential of the region's natural resources continues to deteriorate, with the formation of glacis, the silting up of ponds, shallows and the river, and soils regularly subjected to all forms of erosion. Yet, analysis predict an increase in minimum and maximum temperatures by 2025 and 2049 that exceeds the increase recommended by the IPCC for 2100 (2ºC), an increase in extreme temperatures, and high inter- and intra-annual and spatial variability in rainfall, with a global trend towards increased precipitation (Tarchiani et al., 2016), tending to increase the risk of drought and flooding events.

2.1.2. The region of Maradi

The Maradi region, where the other two selected sites are located, is situated in the center south of the country, bordered to the east by the Zinder region, to the west by the Tahoua region, to the north by the Tahoua and Agadez regions and to the south by the Federal Republic of Nigeria, with which it shares a border of around 150 km. It has a surface area of 41,796 km², or 3% of the national territory, divided as follows: 71.5% agricultural land, 25% pastoral land and 3.5% forest land. The region has 47 communes spread across 9 departments, with an estimated population of 3,766,520 in 2019 (INS, 2020).

Also known as the country's economic capital because of the importance of trade transactions between Nigeria and other neighboring regions, Maradi is best known for its agropastoral activities. In addition to commercial activities, the population's main economic activities are farming and livestock rearing. Around 85% of the region's total population depends on agriculture and over 90% on livestock rearing. It is also the poorest region in the country, with a higher incidence of poverty than the national average (57.8% compared with 48.2% in 2011, rising to 67% compared with 45% in 2014, an increase of almost 9 percentage points) (WB, 2017). This impoverishment of the population is reflected in difficulties in accessing basic social services (education, health, water, and sanitation) and the high vulnerability of children, women and certain social groups to food and nutritional insecurity. Added to this is a population growth rate of 4% (INS, 2020), increasing the needs in terms of basic social services (education, health, water, and sanitation), already unsatisfied (OCHA, 2021), of an expanding population which is now putting strong pressure on limited natural resources to meet their needs. The region is also experiencing volatile and worrying insecurity, which has worsened the living conditions of the population, particularly those living on the borders with Nigeria. This situation, coupled with the closure of the Nigerian border for the period 2019-2021, has led to a rise in food prices in the region. These constraints on access are further factors exacerbating the vulnerability of households.

The region is also highly vulnerable to food and nutritional insecurity, particularly among children, women, and certain social groups. A recent study concludes that it combines all the generic indices of vulnerability, namely food insecurity, inequality, and poor health (LeMarois et al., 2021). It is nevertheless the leading producer of millet (22.7% of national production), cowpea (37.5% of national production) and tiger nuts (60% of national production). It is ranked second for sorghum and cowpea production. Maradi is also known for its sesame and vegetable production, despite difficult climatic conditions.

The potential of the region in terms of natural resources is multiple and varied. There are three types of soil: dune soils or "*jigawa*" (sandy tropical ferruginous soils) with low chemical fertility but good permeability and sensitive to erosion. These soils are used for rain-fed cultivation; tropical ferruginous soils or "*gueza*", which have a low permeability and are prone to run-off. Unlike *jigawa*, they are difficult to work; lowland soils or "*fadama*", hydromorphic and vertisols with a sandy-clay texture. They are rich in organic matter and suitable for growing sorghum and other crops such as horticulture and arboriculture. To the south, granitic outcrops appear, rapidly giving way to aeolian sands. Most of these soils are highly sensitive to the effects of the climate (intensity of rain and wind), as they are low in organic matter, and consequently suffer the loss of the most fertile surface layer. In addition, the region has several groundwater sources in the Hamadian continental aquifer system, the alluvial nappes of the *Goulbis* and *Tarka* rivers, which are limited in extent, and in the discontinuous aquifer systems of the southern Maradi basement. Unlike the Tillabéri region, Maradi has no permanent water, but benefits from easily mobilized water resources, thanks to the three major longitudinal valleys that cross it: the *Goulbi* de Maradi, the *Goulbi N'Kaba* and the *Tarka* valley. Seasonal run-off and the recharging of pools are naturally dependent on rainfall. There is a fair amount of silting, due in part to water erosion (Lake of Madarounfa). In view of the region's lack of surface water, the development of ponds and associated catchment areas would appear to be essential if the resource is to be exploited sustainably. The vegetation of the region is characterized by a grassy and shrubby steppe concentrated in classified forests, protected areas, and the most isolated areas of the south-west (Guidan Roumdji and Madarounfa departments), where rainfall conditions are favorable, but also in the northern part of the region (Dakoro). Wildlife resources are located in the Gadabedji Total Wildlife Reserve (Bermo Department), the *Baban-Raffi* protected forest (Madarounfa Department), which includes the Biodiversity Reserve. The Baban Raffi Forest has been registered as a biosphere reserve, covering an area of 3,419 ha, and containing a diversity of wildlife species:

gazelles, bustards, guinea fowl, migratory birds and patas monkeys, rodents (squirrel, hare). It is often visited by herds of elephants two to three times a year (MAG, 2019).

The climate in the Maradi region is Sudano-Sahelian. It is characterized by three distinct seasons: a cold and dry season from November to February; a hot and dry season from March to May; and a rainy season from June to September, which can exceptionally last until mid-October. Like the rest of the country, rainfall lasts little more than four months and is highly irregular, poorly distributed in time and space. Rainfall varies from less than 300mm in the north to more than 600mm in the south. Relative humidity peaks in August (the rainiest month of the year) and falls to a minimum in March. As a result, the average monthly maximum temperatures observed during the hot season can reach 40°C in April-May. On the other hand, minimum values, which can fall below 15°C, are recorded between December and January. Between these two extremes, there is an intermediate situation corresponding to the wintering period, characterized by variable temperatures with a maximum of 38.3°C in June and a minimum of 22.6°C in August, a period during which rainfall is abundant.

However, the region is experiencing the regular effects of climate change (CC) and extreme variability, such as the floods of 2021, which caused huge economic and social losses. The impacts of CC and the insecurity of recent years have destabilized the regional economy and increased the vulnerability of certain population groups, such as internally displaced people seeking a safer environment (OCHA, 2021).

2.2. Data source and sampling method

Multi-stage sampling (Balakrishman et al., 2014) was employed (Figure 3) for the selection of farmers in our sample. At the first stage, the regions of Maradi and Tillaberi were purposively selected enabling the country's agroecological zones to be considered: the Sahelo-Sudanian zone in Maradi and south of Tillaberi and the Sahelo-Saharan zone north of Tillaberi. They are also part of the largest agricultural regions and are highly vulnerable to CC (*Sections 2.1.1* and *2.1.2*). Cochran's sampling method (equation 1) (Cochran, 1977) was used to identify the number of farmers to be interviewed during a survey conducted to collect primary data.

$$n = \frac{z^2 p(1-p)}{e^2} \qquad \textbf{(1)}$$

e represents the level of precision, the marginal error chosen by the authors, *z* represents the *z*-value of the Normal Law corresponding to the degree of confidence (α), and *p* the proportion of the target population with the attributes of interest. In this case, 90% of the population of the Tillaberi region practices agriculture and 85% for the Maradi region, hence p = 90% for Tillabéri and p = 85% for Maradi, with an adopted marginal error of 5% for a confidence level of 95%. A reading of the Normal Law table gives a value of z = 1.96, corresponding to 95%. The results thus give the required minimum sizes of 196 farmers for the Tillaberi region and 138 farmers for the

Maradi region, for a total of 334 farmers to be interviewed. To take account of the impact of non-responses, which will lead to missing data for our analysis, we have overestimated the size of our sample. In total, 343 producers were randomly selected to administer a pre-established and pre-tested questionnaire. It is important to note that our selection took account of the reality of insecurity, especially in the Tillaberi region where the target could not be reached, and the gap had to be filled by data collection in Maradi. This substitution in the sample selection could potentially introduce selection bias, particularly when substitutes have different characteristics compared to the original participants they are replacing (Winship et al., 1992). Consequently, the final sample is caused to no longer be representative of the target populations. Although located in different agroecological zones, the two regions have been subject to similar climatic stressors (mainly intra- and inter-annual rainfall variations) (Asfaw et al., 2018; Assoumana et al., 2016), and small variation in responses are observed in view of limited means of subsistence and very limited political support (Asfaw et al., 2018; Gambo et al., 2016). Furthermore, the selected sites in this study have long been the target of certain projects that aimed at supporting community adaptation and resilience, while extending the same actions to all areas of intervention. The combination of these situations could potentially avoid selection bias in increasing the sample size in Maradi. *Table 1* summarizes the distribution of our sample, considering the readjustments made in the light of the insecurity situation.

The second stage concerned the choice of departments. The same criteria of agricultural production and agricultural vulnerability guided the selection of the department of Kollo in Tillaberi and those of Guidan-Roumdji and Bermo in Maradi. Then the proportional-to-size sampling technique (Skinner, 2016) was used to select the farmers for whom the questionnaire is randomly administered. The same selection criteria as above were used at this stage and led to the selection of the communes of Kollo and N'Dounga in the department of Kollo, Guidan-Roumdji in the department of Guidan-Roumdji and Gadabedji in the department of Bermo.

Table 1 : Sample by region and commune

<table>
<tr><td rowspan="3">Regions</td><td colspan="2">Tillabéri</td><td colspan="2">Maradi</td><td>Total</td></tr>
<tr><td colspan="5">Cochran sampling method</td></tr>
<tr><td colspan="2">171</td><td colspan="2">172</td><td>343</td></tr>
<tr><td>Departements</td><td colspan="2">Kolo</td><td>Guidan-Roumdji</td><td>Bermo</td><td></td></tr>
<tr><td rowspan="3">Communes[9]</td><td>Kollo</td><td>Ndounga</td><td>Guidan-Roumdji</td><td>Gadabedji</td><td></td></tr>
<tr><td colspan="5">Size-proportional sampling method</td></tr>
<tr><td>116</td><td>55</td><td>135</td><td>37</td><td>343</td></tr>
</table>

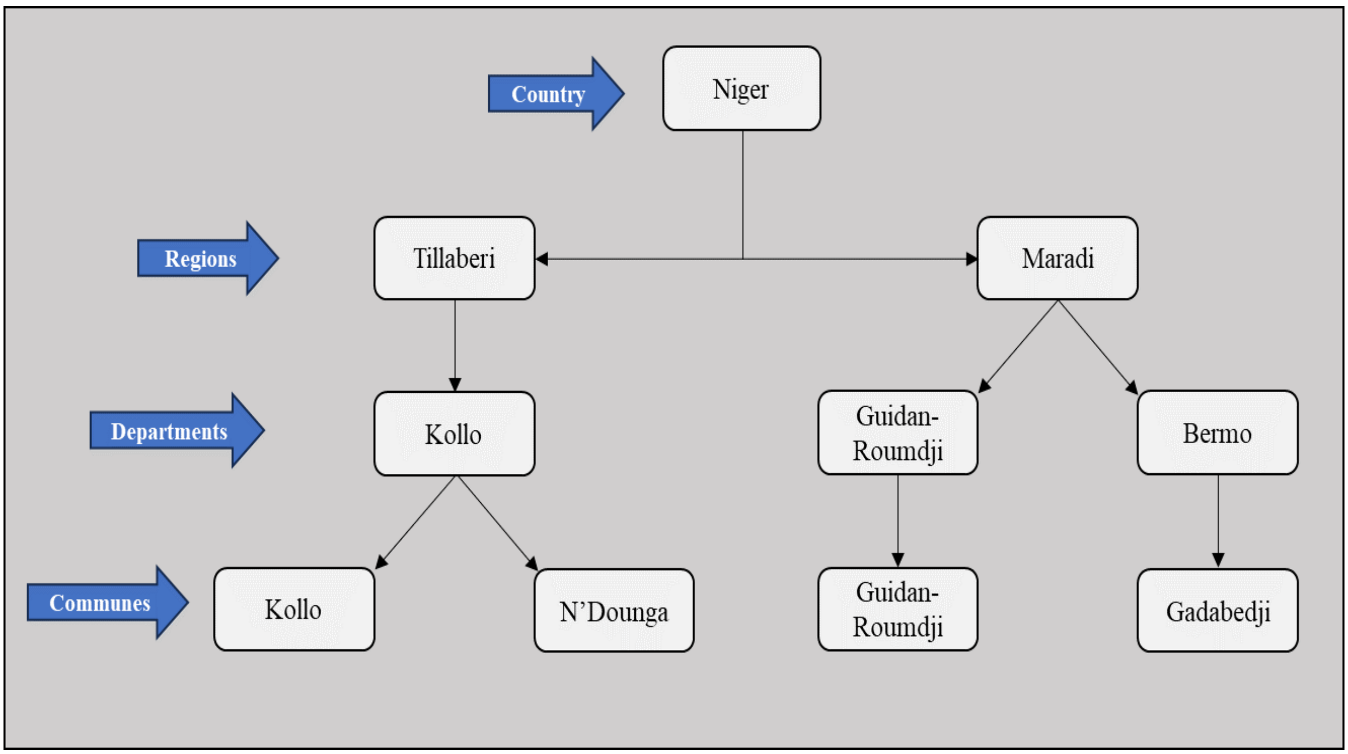

Figure 4 : Multi-stage sampling method

2.3. Analytical methodology

As introduced above, this work aimed at assessing the adaptive capacity (AC) of smallholder farmers in the selected sites for our analysis using an index-based approach and using indicators from the livelihood's framework. This section presents the mixed analysis method (summarized in Figure 4), combining theory and expert knowledge, as well as the method for calculating a composite AC index for each household surveyed.

[9] The weight of the communes comes from statistics on the populations of the communes of Kollo and Ndounga in the Tillabéri region (INS, 2022), as well as those of Guidan-Roumdji and Gadabedji in the Maradi region (INS, 2020).

2.3.1. Method of analysis

Adaptive capacity measures the "*potential*" to respond to CC-related events. It has the characteristic of being latent, and therefore difficult, if not impossible, to measure directly in the same way as concepts such as agricultural productivity. This is why various researchers and practitioners have developed or applied different methods and approaches to assess and analyze adaptive capacity, without any scientific consensus on the "*best*" method to adopt (Christiansen et al., 2018; Marzi et al., 2018). Most approaches in this context involve identifying the factors that contribute to adaptive capacity and the ability to use them when needed (Jacobs et al., 2015). These approaches consider factors as separate indicators that need to be chosen appropriately, and are then aggregated into a composite index, typically used to quantify, and characterize adaptive capacity (Hinkel, 2011; Zanmassou et al., 2020).

In general terms, indicators are defined as quantitative or qualitative measures derived from a series of observed facts that can reveal relative positions (e.g., of a country) in a given field (OECD, 2008). The composite index, on the other hand, is obtained by mathematically compiling separate indicators based on an underlying model (Nardo et al., 2005). In the field of environmental science, or more specifically adaptation to CC, the index development approach has proved particularly useful for measuring and analyzing complex, multidimensional concepts that cannot be captured by a single indicator (Nardo et al., 2005; OECD, 2008), such as adaptive capacity. They allow a greater number of variables to be incorporated, which ideally leads to a more complete model of reality (Vincent, 2004). Other advantages of composite indices are that they are easy to interpret and can be used for optimal resource allocation and priority setting (Adger and Vincent, 2005; Wang and Fu, 2019). Adaptive capacity is necessarily complex and multidimensional, since it involves a large number of factors that vary from one individual, household, community, or scale to another.

For this reason, it is undeniable that the construction of AC indices should be motivated by a coherent, robust, reproducible and usable conceptual and methodological framework in order to guarantee their adequacy with reality, as well as the quality of research results in terms of CC adaptation policy (Jacobs et al., 2015; Juhola et al., 2016). In this work, the analysis framework, summarized in the figure below (*Figure 5*) and detailed in the following points, has the benefit of appropriating those developed in the literature and adapting it to the local contexts of farming households in Niger. It is based on the frameworks proposed by authors such as Vincent (2007), Brown et al. (2010), Füssel (2010), Hinkel (2011), Juhola et al. (2016), and Jacobs et al. (2015).

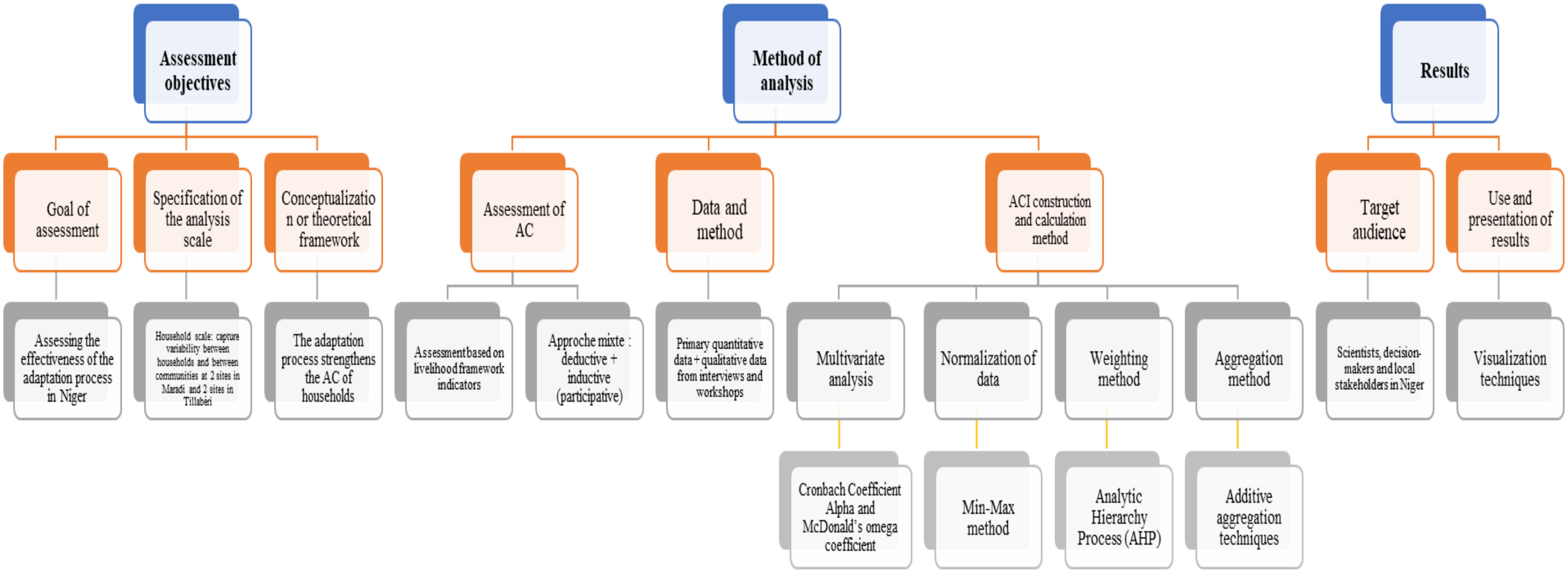

Figure 5 : Analytical framework adopted

Source: Authors, based on literature review

2.3.2. The purpose of the evaluation

This first chapter/section refers to the theoretical framework of the concept of AC to be evaluated, as developed earlier (see *section I*). It determines the purpose of the assessment, the assessment scale, and the conceptualization of AC. As a reminder, the adoption of an approach based on strengthening the adaptive capacity of households (and therefore reducing vulnerability) was specified as being appropriate for assessing the effectiveness of the adaptation process in Niger. The household scale was retained, as it is at this level that CC-related events, including extreme events, are most keenly felt. It is also the appropriate scale for the decision-making process, and the sites selected for this purpose are those of Kollo and Ndounga in the Tillabéri region, and Guidan-Roumdji and Gadabédji in the Maradi region.

2.3.3. The valuation method

With a view to assessing the AC of farming households in Niger by calculating indices, this section discusses the approach used to identify and select appropriate indicators tailored to local contexts in Niger, as well as the method used to calculate the AC index (ACI_i) for farming households i in given sites.

2.3.3.1. Indicator selection

From a literature perspective related to AC or vulnerability assessment, many indicators and index studies refer to the dichotomy of theoretical or inductive approaches, which researchers and practitioners contrast with data-driven or deductive approaches (see Brown et al. (2010) or Hinkel (2011)) for an in-depth understanding). Inductive approaches are based on a conceptual framework that highlights available theoretical knowledge about the nature and causes of AC, thus serving as a hypothesis base for selecting relevant indicators and determining their relationships (Vincent, 2007; Hinkel, 2011). However, the selection of indicator variables is prescriptive, representing a source of uncertainty regarding the representation of variables and the meaning of the relationship between them (Vincent, 2007). In addition, another underlying weakness is that secondary social and economic data from different social groups rarely help to highlight constraints and opportunities for strengthening local AC (Brown et al., 2010). Indeed, these approaches do not allow for a better understanding and consideration of local specificities and variabilities, which are essential factors for policymaking (Leith et al., 2012). As for data-based approaches, they develop a wide range of indicators and select among them based on their statistical relationships with observed results or expert judgement (Füssel, 2007; Vincent, 2007; Hinkel, 2011). The weaknesses of these approaches concern the limited objectivity of the experts and the fact that the indicators must be assessed in relation to a vulnerability or AC criterion (Below et al., 2012; Jacobs et al., 2015). These approaches are also conditioned by the availability of experts' specialist knowledge (Gbetibouo et al., 2010). However, they have the advantage of being context-specific, which makes it possible to identify specific opportunities for strengthening adaptive capacities (Jacobs et al., 2015).

Given the shortcomings of previous approaches, another recent group of researchers and practitioners have been treeing the selection of indicators based on a combination of empirical and theoretical findings (e.g., Choden et al. (2020), Azam et al. (2019), Abdul-Razak and Kruse (2017) and Below et al. (2012)). This mixed approach thus enabled the literature to be adapted to the uniqueness of the sites studied for a robust and appropriate selection of indicators.

In the context of this work, the use of the mixed approach resulted, firstly, in gathering indicators from an in-depth literature review on the assessment of adaptive capacity, particularly in Africa. The next stage involved validating the indicators at a workshop attended by 11 key experts (see *Appendix 1.1*) from institutions responsible for climate change adaptation issues. The aim of the workshop was to draw up a list of suitable indicators that reflect the local realities of farming households in the 4 selected sites. The 11 experts were carefully selected from 19 stakeholders who had previously been interviewed, using a pre-established interview guide as a basis (see *Appendix 1.2*). Two selection criteria were used: in-depth knowledge of climate change, its impacts on farming households in Niger and adaptation policies, and a particularly good knowledge of at least two of the four sites selected for this study. Table 2 summarizes the 21 indicators selected at the end of the workshop, according to each capital, with definitions and/or hypotheses justifying their selection. Appendix 1.3 summarizes the indicators as collected from the literature, as well as those validated and invalidated by the experts, followed by justifications. The following sections provide details of the indicators selected for each capital.

i. Financial capital: Represents the availability and accessibility of sources of income that contribute to the essential wealth of individuals, households, and communities for their agricultural activities (Nawrotzki et al., 2012). These resources are used to maintain or improve livelihoods (Reid and Vogel, 2006; UNDP, 2017). Thus, this form of capital assumes that a higher and more diversified level of income sources is likely to strengthen the adaptive capacity of households. The number of sources of income, the number of farm workers within households, access to formal and informal credit, public subsidies, and the number of animals owned by the household are the indicators used to represent financial capital. The positive relationship between diversification of income sources and adaptive capacity has been well documented and verified (Defiesta and Rapera (2014), Bryan et al. (2014), Abdul-Razak and Kruse (2017), Datta and Behera (2022) and Nelson et al. (2010); and many others). The diversity of income sources reflects an improvement in the living conditions of households, which can then reduce the negative impacts of current and future CC, recover from material losses, and take advantage of potential opportunities. On the other hand, the more households depend solely on agricultural resources, the more vulnerable they are to CC-related effects (Wall and Marzall, 2006; Gbetibouo et al., 2010). This was the case in the Maradi region, among other areas, where experts indicated that several producers were unable to adapt to the climatic shocks of previous years because of their sole source of agricultural income. In general, labor diversification has significantly improved the well-being of the most vulnerable Nigerien farming households who use it as a coping strategy in the face of CC and market shocks (Asfaw et al., 2018). Sufficient farm labor endowment has also been considered as an indicator to measure farmers' AC. It reflects greater financial capacity used to employ adequate labor on farms (Chepkoech et al., 2020). In addition, households with a greater ability to access sufficient labor can carry out farming activities in a timely manner and try out new labor-intensive technologies (Kansiime et al., 2018). Access to credit, while increasing cash flow, allows farmers to engage in capital-intensive technologies, thus enhancing their ability to adapt (Chepkoech et al., 2020). Better access to credit facilities also improves the flexibility with which producers can adjust their production strategies to cope with CC (Sahu and Mishra, 2013), reduce financial risks and cushion variations in household income (Bryan et al., 2015). For the Niger experts consulted, sources of credit come from village associations and 'tontine' systems and are of considerable importance in adapting to climate change, particularly in financing income-generating activities. Public subsidies often take the form of discounts on seeds and fertilizers (Defiesta and Rapera, 2014). In the case of Niger, experts explain that SPN2A has enabled reforms to be implemented that provide subsidies of up to 50%. These include free distribution of inputs, sales at moderate prices and targeted sales for the most vulnerable, thereby improving producers' adaptability to climatic shocks. Livestock holdings are also an indicator for measuring the AC of local farming households, as animals are the preferred form of savings for households, which do not hesitate to use them to finance their strategies and adapt to climate shocks.

ii. Social capital: As defined by DFID (1999) or UNDP (2017), this is the social resource base that farm households bring to bear to achieve their livelihood objectives. The hypothesis is that social capital contributes positively to household AC (Pelling and High, 2005; Gbetibouo et al., 2010), particularly in coping with CC-related events (Adger and Vincent, 2005). In this work, it is approximated by household size, participation in community or farmer group/organization activities and the gender of the household head. The positive link between household size and adaptation has been reported in some studies (Choden et al., 2020; Datta and Behera, 2022). These studies have shown that individuals from large families are more likely to create a mutual support and safety net system, and more likely to adopt adaptation practices to cope with CC-related effects. In addition, larger households are associated with greater labor availability, greater capital accumulation and better information networks (Chepkoech et al., 2020). Membership of social networks such as farmers' organizations or associations attracted particular attention from the experts, who said that there are several forms of farmers' organizations and associations in rural areas, particularly the farmers' platform. When they are functional and active, they produce benefits on farms, usually in terms of mutual aid. These forms of membership also provide access to useful information for adapting to CC, which may be available exclusively to members (Defiesta and Rapera, 2014; Jacobs et al., 2015; Choden et al., 2020). This indicator was relevant in several studies of small-scale farmers, particularly in Ghana, Burkina Faso, Kenya, and Benin (Abdul-

Razak and Kruse, 2017; Yaméogo et al., 2018; Chepkoech et al., 2020; Zanmassou et al., 2020). In the case of community-based organizations, participation by producers has provided access to important credit opportunities, seed sharing and information on weather conditions and markets for small-scale farmers in Kenya (Chepkoech et al., 2020). In Niger, these community organizations, when they are functional and active, are the government's preferred means of subsidizing local agricultural producers, according to the experts. In addition, gender has emerged as an important indicator of social capital, as it informs policy decisions about gender inequalities in decision-making and access to resources (Choden et al., 2020).

iii. Human capital: Encompasses all the skills, knowledge and working capacity that enable households to pursue different livelihood strategies and achieve their livelihood objectives (DFID, 1999). It is represented in this work by educational attainment, farming experience, and access to agricultural extension services. Education is considered a fundamental factor in improving AC in many studies. For example, educated Kenyan farmers were better able to process forecast information and use modern agricultural technologies to adapt to CC (Chepkoech et al., 2020). In the same vein, several other studies corroborate the positive correlation between level of education/instruction and AC (Gbetibouo et al., 2010; Defiesta and Rapera, 2014; Ng'ang'a et al., 2016; Choden et al., 2020; Jamshidi et al., 2020; Zanmassou et al., 2020; Datta and Behera, 2022). Thus, better-educated farmers are more likely to acquire knowledge and skills in managing natural resources and implementing farming practices that are resilient to CC, but also to access information for forecasting purposes. The same is true of farming experience, which has most often been found to be positively correlated with adaptation to CC (Dafiesta and Rapera, 2017). Experienced farmers are indeed better imbued with local knowledge on adaptation practices than less experienced ones (Abdul-Razak and Kruse, 2017). Farming experience is also often considered to be positively linked to age, and therefore to the likelihood of having accumulated resources over time, which makes it possible to invest in increasing the number of assets that contribute to increasing AC (Choden et al., 2020). According to the experts, this is also an important prevention factor. Access to agricultural extension services has already been introduced (*Section 1.1.2*) as a crucial factor in raising farmers' awareness and understanding. It provides information on forecasts and contextualized management advice (Bryan et al., 2015). In Niger, there are several agricultural advisory institutions: RECA (*Réseau national des Chambres d'Agriculture du Niger* in French), Plateforme Paysanne (for disseminating good practices), and the "*farmer field school*" approach implemented by several projects and NGOs (for technological innovations by farmers themselves).

iv. Physical capital: Concerns the basic infrastructure and production inputs needed to support livelihoods (DFID, 1999; UNDP, 2017). It is assumed that a better endowment of quality infrastructure can enable a better capacity to adapt to climatic stresses (Gbetibouo et al., 2010; Egyir et al., 2015). Physical capital is represented in this work by access to irrigation infrastructure, the quality of housing and roads, the distance separating the house from the agricultural plot and the market, and the possession of basic agricultural equipment. Access to irrigation infrastructure has been an important asset in adaptation to CC in several studies (Eakin et al., 2011; Egyir et al., 2015; Singh et al., 2017; Singh, 2020)). Improved irrigation facilities would make it possible to increase the crops available and withstand periods of climatic shocks (Chepkoech et al., 2020; Datta and Behera, 2022). Similarly, the quality of household housing has emerged as an important indicator that has a positive impact on physical capital, as it reflects better access to financial resources and proximity to markets (Choden et al., 2020). Furthermore, the quality of roads and other transport links determines the ability of rural populations to access numerous services such as health care or markets for the purchase/sale of livestock and inputs, which consequently increases their capacity to adapt in times of crisis. (Gbetibouo et al., 2010; Choden et al., 2020). In addition to the quality of roads, proximity to markets and agricultural plots are important indicators for improving physical capital. Distance from markets increases the difficulty of accessing and selling agricultural products and livestock, and therefore of generating income (Choden et al., 2020), while distance from agricultural plots offers fewer opportunities for accessing agricultural information and advice and has a negative impact on producers' income (Datta and Behera, 2022). Moreover, owning a variety of agricultural equipment has been a relevant indicator for improving physical capital in several studies (Defiesta and Rapera, 2014; Lockwood et al., 2015). The possession of equipment and means of production makes it possible to exploit better agricultural technologies and pursue different livelihood strategies (Nawrotzki et al., 2012).

v. Natural capital: this refers to the availability and accessibility of natural resources such as land, water or vegetation needed for agricultural practices and livelihood support (UNDP, 2017; Choden et al., 2020). The indicators used by experts to represent natural capital are soil fertility, the size of agricultural plots, the household's experience of natural hazards on the farm and the number of trees on the farm. Farmland fertility is a key factor that can influence adaptation to CC. This factor determined adaptation behavior in Ghana, where farmers perceiving the infertility of their land became less inclined to invest in more expensive inputs (Fosu-Mensah et al., 2012). According to Datta and Behera (2022), the less fertile the land, the lower the yields and the more vulnerable farmers become. In addition, a study conducted in five East African countries showed a link between household wealth and improved soil fertility (Shikuku et al., 2017). The total cultivated area is also considered as a natural resource in this work. The assumption is that the larger the farms, the greater the adaptive capacity, as this is associated with greater wealth (Dressa et al., 2009; Dafiesta and Rapera, 2014). The relevance of experience of natural hazards stems from the fact that the more producers are confronted with natural events such as floods and droughts, the more likely they are to be able to adapt to them (Zanmassou et al., 2020). Finally, crop production has emerged as another natural asset for supporting livelihoods, as it is assumed that crop cover helps to mitigate the loss of natural resources following a climate disaster (Reid and Vogel, 2006, Bryan et al., 2015).

Table 2 : Validated indicators for AC assessment

Components of the livelihood framework	Indicators	Sources	Definitions / Assumptions	Measurement unit	Percentage of the distribution*
Financial Capital (FC)	Number of income sources (FC1)	Gbetibouo et al. (2010) ; Bryan et al. (2015); Jacob et al. (2015) ; Abdul-Razak and Kruse (2017) ; Choden et al (2020); Datta et Behera (2020) ; Zanmassou et al (2020)	A farmer whose sources of income are more diversified has a greater capacity to adapt than a farmer whose sources of income are less diversified.	1_1 source	18.08
				2_2 sources	49.85
				3_More than 2 sources	30.61
	Number of farm workers (FC2)	Kansiine et al. (2018) ; Gbetibouo et al. (2010) ; Chepkoech et al.(2020)	Sufficient manpower enables farmers to carry out their agricultural work on time, and to try out new technologies that also require an investment in manpower.	1_1 worker	29.45
				2_2 workers	17.2
				3_3 workers	22.45
				4_More than 3 workers	29.45
	Access to formal or informal credit (FC3)	Deressa et al. (2009) ; Karanja et al. (2016) ; Chepkoech et al. (2020)	Farmers with access to credit are economically better able to adapt to climate change than those with less access to credit.	1_No access	97.67
				2_Access	0.87
	Public subsidies (FC4)	Defiesta and Rapera (2014)	Farmers with access to public subsidies for agricultural inputs are more resilient to climate change than those without access to public subsidies.	1_No access	91.55
				2_Access	7
	Number of animals owned by household (FC5)	Dafiesta et Rapera (2014)	As a form of savings for farm households, animals serve as financial resources available for financing adaptation strategies.	0	20.99
				1_1-5 animals	25.95
				2_6-10 animals	11.08
				3_More than 10 animals	40.52
Social Capital (SC)	Total number of household members (SC1)	Eakin et al. (2011); Zanmassou et al. (2020); Datta and Behera (2022)	Better access to family labor strengthens farmers' social capital.	Total number of people living in the household	98.54
	Participation in community or farmers' group activities (SC2)	Gbetibouo et al. (2010) ; Karanja Ng'ang'a et al. (2016) ; Abdul-Razak and Kruse (2017) ; Yaméogo et al. (2018) ; Choden et al. (2020);	Households belonging to a greater number of social groups and associations have better networks, which can help mitigate the adverse effects of climate change on their livelihood activities.	1_No	84.55
				2_Yes	13.99
	Sex of household head (SC3)	Choden et al (2020) ; Abdul-Razak and Kruse, 2017	The greater the inequality between the sexes in decision-making and access to land, the lower the level of social capital.	1_Female	2.33
				2_Male	96.21
Human Capital (HC)	Educational level of household head (HC1)	Deressa et al. (2008) ; Yohe and Tol (2002) ; Jacob et al (2015) ; Bryan et al (2015); Karanja et al. (2016) ; Zanmassou et al (2020); Choden et al (2020); Datta and Behera (2022)	Level of education is positively correlated with adaptive capacity. In other words, farmers with higher levels of education are more likely to accept and adapt to climate change than those with lower levels.	1_Informal/none	72.59
				2_Primary	13.12
				3_Secondary	11.08
				4_Tertiary	1.75

	Farming experience (HC2)	Yohe et al (2002) ; Defiesta and Rapera (2014) ; Karanja et al. (2016) ; Bryan et al (2015); Zanmassou et al (2020); Datta and Behera (2022)	The number of years' experience in agriculture is strongly correlated with the level of knowledge and skills in adapting to climate change and variability using technology.	Total number of years the head of household has been farming as an independent decision-maker	98.54
	Access to agricultural advice from extension services (HC3)	Jacob et al. (2015); Gbetibouo et al. (2010); Ruiz Meza (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Zanmassou et al (2020).	Access to agricultural extension services improves farmers' knowledge and skills in practices and technologies related to climate change and adaptation.	1_No access	68.8
				2_Access	29.74
Physical Capital (PC)	Irrigation infrastructure (PC1)	Eakin et al. (2011) ; Egyir et al. (2015); Singh et al. (2017) ; Chepkoeh et al (2020) ; Datta and Behera (2022)	Farmers with access to irrigation infrastructure are more likely to adapt to drought than those without.	1_No irrigation	70.26
				2_Manual irrigation	10.2
				3_Gravitation irrigation	17.49
				4_Drip irrigation	0.58
	House quality (PC2)	Choden et al (2020)	Owning a better-built home in terms of quality can improve living conditions and a household's ability to withstand the risks of environmental shocks, including climatic events.	1_Traditional house type (hut, shed, tent, tarpaulin)	49.27
				2_Banco house	14.87
				3_Modern house (stone, concrete)	34.4
	Road quality (PC3)	Byrne (2014), Egyir et al. (2015); Datta and Behera (2022); Choden et al (2020)	Access to a good road network improves farmers' ability to access markets for their input and output. Consequently, increasing the distance between the farm and good roads is inversely related to the infrastructure's ability to adapt to climate change.	1_No accessible	40.52
				2_Partially accessible	18.66
				3_Accessible	39.36
	Distance house-farm plot in km (PC4)	Below et al (2012); Datta and Behera (2022); Jacob et al. (2015)		1_<3 km	55.69
				2_4-6 km	27.7
				3_>6 km	15.16
	Distance home-to-market for inputs (PC5)	Bellow et al (2012); Jacob et al. (2015); Zanmassou et al (2020); Choden et al (2020)	Proximity to a market can strengthen adaptive capacity, as it increases opportunities to sell agricultural produce and thus generate cash income.	1_<1 km	46.65
				2_1-5km	44.61
				3_>5 km	7.29
	Number of types of farm equipment owned by household (PC6)	Dafiesta et Rapera, 2014 ; Lockwood et al., 2015	Ownership of agricultural equipment enables farmers to exploit better farming technologies and thus boost CA	0 type	0.58
				1_1-2 types	18.37
				2_3-4 types	41.69
				3_More than 4 types	37.9
Natural Capital (NC)	Soil fertility (NC1)	Below et al. (2012) ; Jacob et al. (2015) ; Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013).	Improved soil fertility ensures the survival and productivity of crops in a context of climate change.	1_Not fertile	53.94
				2_Fertile	44.61
	Plot size (NC2)	Jacob et al. (2015); Ruiz Meza (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013)	Farmers with larger farms are more adaptable	1_<=2 ha	37.9
				2_<=4 ha	20.99

			3_<=6 ha	20.99
			4_>6 ha	18.66
Experiences of natural hazards in the main household farms (NC3)	Jacob et al. (2015) ; Egyir et al. (2015) ; Bryan et al. (2015) ; Zanmassou et al (2020)	As climate change has a direct impact on crop yields, the more farmers are confronted with natural hazards, the more likely they are to be able to adapt to them.	1_No	58.6
			2_Yes	39.94
Number of tree types present on household farms (NC4)	Reid and Vogel, 2006; Bryan et al., 2015	Trees are considered natural fertilizers and protect farms from strong winds or flooding. They therefore enable households to adapt to the effects of climate change.	0 type	2.92
			1_1 type	26.53
			2_2 types	24.49
			3_3 types	15.74
			4_More than 3 types	28.86

Source: Authors

*The remaining 1.46% relate to non-respondent in the database.

2.3.3.2. Method of calculating the adaptability index

The main conceptual challenges relating to the analysis of household adaptive capacities are that it requires the aggregation of indicators into corresponding component values, then the aggregation of these component values into an overall AC index value, while considering the relative importance of each scale (indicators and components) when aggregating. Added to this are the disparate units of measurement of the individual indicators that make up each component. It is therefore essential to ensure (i) the reliability of the indicators selected, as well as the choice of appropriate methods for (ii) normalization, (iii) weighting, and finally (iv) aggregation.

i. Analysis of the internal consistency of the selected indicators: Cronbach's Alpha coefficient (1951)

A preliminary step in constructing an index is to assess the internal consistency of the indicators chosen for the cause. The aim is to assess the extent to which this set of indicators is sufficient or appropriate to measure the same concept that is the subject of the index construction. To this end, the estimation of Cronbach's alpha coefficient (C-alpha) is the most common (Nardo et al., 2005; OECD, 2008). C-alpha measures the proportion of the total variability of individual indicators due to the correlation of the indicators. It can be defined as follows:

$$\alpha = \left(\frac{I}{I-1}\right)\frac{\sum_{i\neq j} cov(x_i,x_j)}{var(x_o)}; \qquad i,j = 1,\dots,N$$

Where N denotes the number of individuals considered, I the number of indicators chosen, $x_o = \sum_{n=1}^{N} x_j$ the sum of all individual indicators. From this formula, it is easy to see that the C-alpha coefficient (α) increases with the number of individual indicators and with the covariance of each peer. A C-alpha equal to zero indicates that there is no correlation and that the individual indicators are independent, whereas it indicates perfect correlation of the individual indicators when it is equal to one. However, in the work of Nardo et al (2005) and OECD (2008), it is recognised that C-alpha is not a statistical test, but a reliability coefficient based on the correlation between individual indicators. Consequently, a high c-alpha, or equivalently a high 'reliability', indicates that the individual indicators are a good measure of the latent phenomenon. It is also compared with Nunnally's threshold of 0.7, as an acceptable reliability threshold.

In the specific case of our work, the estimated C-alpha is equal to 0.7093, indicating an acceptable level of reliability for the 21 indicators chosen.

ii. Normalization of indicators: the Min-Max method

One of the main challenges in constructing an index, particularly at the level of aggregation, lies in the disparate units of measurement of the different indicators, as we can see from Table 2. Aggregating indicators in such a case would be like adding up "apples and oranges". So, before any data aggregation, normalization is necessary because it makes the variables comparable (Chepkoech et al., 2020).

In this work, the Min-Max method was used because it has the advantage of being used with all weighting systems and for all aggregation systems (OECD, 2008). This method converts the indicator values to an identical interval [0, 1]. The values of each indicator are normalized according to the formula:

$$I_i = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

Where x_i is the particular value of the indicator to be transformed, x_{min} and x_{max} respectively the smallest and largest value of the indicator concerned, and I_i is the new normalized value. This step is followed by the aggregation of the normalized indicators, multiplied by their respective weightings based on a specific methodology.

iii. Weighting indicators using the AHP (Analytic Hierarchy Process) method

The aim of the weighting system is to assign relative importance to each criterion or component in the aggregation of the composite index. Policies aimed at improving the AC of farmers, and at the same time reducing their vulnerability to climate change, require information on the components of AC in order to prioritise their interventions. In the context of developing countries such as Niger, where policy-makers do not have the necessary resources for interventions, all the components of AC could end up with low scores (Zanmassou et al., 2020). In doing so, a weighting system must be sufficiently informed, explicit and robust in order to formulate adequate and consistent intervention policies (Nardo et al., 2005; Gan et al., 2017; Greco et al., 2018).

In the practice of composite index construction, AC assessments generally rely on three approaches to weighting indicators or components: the equal weighting approach, weights derived on the basis of statistical models (i.e. Principal Component Analysis PCA or Factor Analysis FA), and participatory approaches notably those based on expert judgement. In order to overcome the shortcomings of the first two approaches (see *Essay 2* for more details on these approaches, as well as their advantages and disadvantages), this work adopts the third form of approach involving expert opinions. Weighting approaches based on expert opinion are considered a conventional and appropriate means for obtaining a transparent weighting system at the individual level (Greco et al., 2018). They can be effective and very useful when the experts involved have a thorough knowledge of the national adaptation policy, in addition to the sites selected. Given that the components of adaptive capacity are linked to livelihoods, the weights will be easier for the experts to assign (Below et al., 2012). For this reason, the experts involved in the workshop to validate the AC indicators (*Section 2.3.3.1*) were used to assign weights as part of the implementation of the Analytic Hierarchy Process (AHP) method.

Developed by (Saaty, 1990), this method is a multi-criteria approach to decision-making based on expert judgement. It is particularly useful for solving problems relating to multidimensional latent concepts, in this case adaptability, as it structures a complex problem into simple hierarchies and groups (Ishizaka and Nemery, 2013). In addition, the AHP incorporates a consistency measure to guarantee the accuracy of the judgements made by experts (Nardo et al., 2005; OECD, 2008; Giri et al., 2020). Weights are thus derived rather than arbitrarily assigned. Recently, the AHP has been used in the assessment of vulnerability to climate change and adaptive capacity, particularly at the level of indicator weighting, by several studies (Sehgal et al., 2013; Udie et al., 2018; Giri et al., 2020; Datta and Behera, 2022).

Thus, the AHP was used in our work for the determination of the weights of the indicators and the components of the AC, including the analysis of the consistency of the experts' judgments through the following steps:

Step 1: Pairwise comparison of indicators and AC components. This step involved the experts making a pairwise comparison of the indicators (or components) to determine the relative importance of one criterion (component) compared to the others, making the exercise easier and more accurate (Ishiaka and Nemery, 2013). These comparisons consisted of verbal judgements provided by the experts, answering the question, firstly, "Which of the two is more important?", and secondly, "By how much?". The meanings of relative importance are expressed on a basic ordinal scale from 1 to 9 (*Table 3*), representing the number of times that one indicator (component) is more important than another. The comparisons resulted in a series of squared reciprocal matrices, called pairwise comparison matrices, and represented by *Tables 4, 5, 6, 7, 8*, and *9*. For example, the experts considered that, in terms of financial capital, the number of sources of income in a farming household is six times greater than the number of farmers in the household. Conversely, the number of farmers is 1/6 times greater than the number of sources of income.

Table 3 : Pairwise preference comparison scale

Intensity of importance	Description	Explanation
1	Equal importance	Two criteria contribute equally to the objective
3	Moderate importance	Experience and judgement strongly favor one criterion over another
5	Strong importance	Experience and judgement strongly favor one criterion over another
7	Very strong importance	A criterion is strongly favored, and its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one criterion over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgements	When compromise is needed
Reciprocals	Inverse comparison	

Source: from Saaty (1990)

Table 4 : Weighting process of different indicators of financial capital

Indicators	Step 1					Step 2		Step 3	
	FC1	FC2	FC3	FC4	FC5	Priority vector	Criteria weights	Overall score	Lambda
FC1	1	6	6	6	5	0.519481	0.5749241	3.0640170	5.3294286
FC2	1/6	1	3	3	3	0.220058	0.1870607	0.9969269	5.3294286
FC3	1/6	1/3	1	2	2	0.119048	0.1001993	0.5340052	5.3294286
FC4	1/6	1/3	1/2	1	2	0.08658	0.0764533	0.4074523	5.3294286
FC5	1/5	1/3	1/2	1/2	1	0.054834	0.0613625	0.3270272	5.3294286
CR = 0.07 < 0.1									

Table 5 : Weighting process of different indicators of human capital

Indicators	Step 1			Step 2		Step 3	
	HC1	HC2	HC3	Priority vector	Criteria weights	Overall score	Lambda
HC1	1	5	4	0.668896	0.686981	2.125531	3.094015
HC2	1/5	1	2	0.214047	0.186475	0.576958	3.094015
HC3	1/4	1/2	1	0.117057	0.126543	0.391526	3.094015
CR = 0.08 < 0.1							

Table 6 : Weighting process of different indicators of social capital

Indicators	Step 1			Step 2		Step 3	
	SC1	SC2	SC3	Priority vector	Criteria weights	Overall score	Lambda
SC1	1	2	1/3	0.307692	0.280936	0.946037	3.367442
SC2	1/2	1	1	0.230769	0.255248	0.946037	3.706349
SC3	3	1	1	0.461538	0.463816	0.946037	2.039683
CR = 0.03 < 0.1							

Table 7: Weighting process of different indicators of physical capital

Indicators	Step1						Step 2		Step 3	
	PC1	PC2	PC3	PC4	PC5	PC6	Priority vector	Criteria weights	Overall score	Lambda
PC1	1	4	3	4	5	3	0.357995	0.399598	2.642848	6.613769
PC2	1/4	1	3	3	3	2	0.219272	0.203256	1.34429	6.613769
PC3	1/3	1/3	1	1	1	1/4	0.070107	0.073388	0.48537	6.613769
PC4	1/4	1/3	1	1	1	2	0.09994	0.108123	0.715101	6.613769
PC5	1/5	1/3	1	1	1	1/4	0.067721	0.065332	0.43209	6.613769
PC6	1/3	1/2	4	1/2	4	1	0.184964	0.150303	0.994071	6.613769
CR = 0.09 < 0.1										

Table 8 : Weighting process of different indicators of natural capital

Indicators	Step 1				Step 2		Step 3	
	NC1	NC2	NC3	NC4	Priority vector	Criteria weights	Overall score	Lambda
NC1	1	1/3	5	3	0.347395	0.296463	1.268363	4.278322
NC2	3	1	4	4	0.44665	0.508845	2.177002	4.278322
NC3	1/5	1/4	1	2	0.128412	0.109104	0.466784	4.278322
NC4	1/3	1/4	1/2	1	0.077543	0.085588	0.366172	4.278322
CR = 0.1 == 0.1								

Table 9 : Weighting process of different components of adaptive capacity

Indicators	Step 1					Step 2		Step 3	
	FC	SC	HC	PC	NC	Priority vector	Criteria weights	Overall score	Lambda
FC	1	4	4	5	4	0.410334	0.479565	2.64605	5.517611
SC	1/4	1	1/3	3	3	0.172872	0.140308	0.774163	5.517611
HC	1/4	3	1	4	3	0.256459	0.234907	1.296127	5.517611
PC	1/5	1/3	1/4	1	3	0.109043	0.084744	0.467583	5.517611
NC	1/4	1/3	1/3	1/3	1	0.051292	0.060477	0.333687	5.517611
CR = 0.02 < 0.1									

Tables source: Author, based on data.

Step 2: The pairwise comparison matrices thus established were used to calculate the weights of the indicators and components. To do this, the eigenvector technique, using the power method, was used to derive the weights (Ishizaka and Nemery, 2013; Gan et al., 2017). It involves squaring the matrix, then dividing the sum of each row by the sum of all the elements in the matrix. The resulting column vector contains the normalized values and approximates the eigenvector. This step was repeated until the values of the eigenvector no longer changed. These were considered as the weight W_i of the criteria and components.

Step 3: A third step was carried out to check the consistency of the experts' judgements used to construct the pairwise comparison matrix and assign the weights. Weightings are only meaningful if derived from a coherent matrix (Nardo et al., 2005; OECD, 2008). To this end, the Consistency Ratio (CR) suggested by Saaty (1990) is calculated using the following formula:

$$CR = \frac{CI}{RI}$$

Where RI is the random index, and CI is the consistency index. CI is calculated according to the formula:

$$CI = \frac{(\lambda_{max} - n)}{n - 1}$$

The estimated CRs are shown in *Tables 4, 5, 6, 7, 8 and 9*, indicating the consistency of the pairwise comparison matrices and the weights assigned. A degree of inconsistency of no more than 0.10 is considered acceptable (Gan et al., 2017, Giri et al., 2020), hence the acceptability of our various results obtained.

iv. Aggregating the indicators into components and the components into a composite index of adaptive capacity ACI

Once the indicators have been normalized and weighted, they are integrated into the corresponding five (5) components, which are in turn aggregated into a composite index. The aggregation literature generally covers both compensatory and non-compensatory aggregation methods[10] (Greco et al., 2018), each of which has strengths and weaknesses (See *Essay 2* for more details on compensatory aggregation methods). Given that this work adopts a logic of full compensation in the construction of the ACI, i.e. a low value (score) of one indicator can be compensated by a sufficiently high value (score) of another indicator, the additive method of aggregation was adopted by this work.

With this method, weighted and normalized indicators are aggregated using an additive function (Nardo et al., 2005; OECD, 2008). The main feature of this method is the existence of preference

[10] Read the Manual on the construction of composite indicators (OECD, 2008), for a detailed guide to the various stages in constructing a composite index.

independence between the indicators. In operational terms, this indicates a trade-off between the indicators. This is why the linear additive method is often referred to as the "full compensation" method. It is a simple method, independent of outliers. In addition, the weights assigned to the indicators are considered as substitution rates, which make it possible to assess the marginal contribution of each indicator separately. The choice of the appropriate aggregation method is also closely linked to all the stages in the process of constructing the composite indicator, such as the choice of indicators, or the method of weighting the indicators. However, it is clearly explained in the work of the authors mentioned in this sub-section that the AHP method belongs to the group of compensatory aggregation methods. In addition, *subsection 1.2* of this paper supports the choice of the additive method for aggregating the components (assets) into an index of farmers' AC. It highlights the character of substitutability between assets, which is thus a fundamental element of the livelihood framework because it makes them more resilient, better able to adapt to unforeseen trends and hazards. For Jacobs et al (2015), substitution between different forms of capital is seen as a criterion of effectiveness in strengthening communities' adaptive capacities. For example, a large amount of natural capital makes it possible to convert, via markets, the plant and animal products it generates into financial capital, which in turn is easily convertible into other forms of capital: physical capital through the purchase of agricultural equipment; human capital through improved skills and educational opportunities, etc.

In previous studies, the adaptive capacity index was constructed by aggregating the indicators directly into a composite index, taking into account the weights assigned to each indicator. Analysis of the results provides useful information on farmers' varying adaptive capacities in the face of climate change, as well as the factors determining the constitution of their livelihood strategies. Then, formulations are made for policy interventions in favor of capital with low scores (Abdul-Razak and Kruse, 2017). However, the relative importance of the components (assets) of AC tends to be a result of the weights assigned to the indicators. Thus, this work does not exploit the information provided by the component weighting systems and may result in inappropriate policy implications (Zanmassou et al., 2020). This work therefore adopts a two-stage weighting while focusing on assets in the livelihoods framework that have also been weighted on the basis of the AHP.

In view of the above, additive linear aggregation has been adopted in this work and the indicators have been aggregated for each corresponding component using the following formula:

$$CP_{ij} = \sum_{q=1}^{21} w_q \, I_{ijq} \;;$$

$$\text{Avec } \sum_{q=1}^{21} w_q = 1, \text{ q = 1,…,21, i =1,…,N et j =1,…,5}$$

Where CP_{ij} captures the capital (component) j of the adaptive capacity of farm household i, w_q the weight of indicator q, and I_{ijq} the normalized indicator of the corresponding component j.

Then, the components were aggregated into a composite index of agricultural household AC, following the same aggregation method and through the formula:

$$ACI_i = \sum_{j=1}^{5} w_j \, CP_{ij} ;$$

$$\text{With } \sum_{j=1}^{5} w_j = 1$$

Where ACI_i represents the composite index of adaptive capacity of farm household i, w_j the weight assigned to component j. The index scores obtained are between 0 and 1. Presented directly, the levels of adaptive capacity of farm households by the index may limit its communication to policy makers (Juhola and Kruse, 2013). Consequently, they have been categorized, following Datte and Behera (2020), into three groups at equal intervals. Thus, a farm household is considered to have low adaptive capacity if $0 < ACI_i \leq 0{,}33$, moderate if $0{,}34 \leq ACI_i \leq 0{,}66$, and high if $0{,}67 \leq ACI_i \leq 1$.

In addition, the normality of the data was checked, and descriptive statistics were applied to analyze the socio-economic characteristics of farm households. Additional statistical tests were carried out to verify the hypotheses of differentiated CA between farm households and between communities (Choden et al., 2020).

III. Results and discussion

3.1 General characteristics of farm households

Table 10 gives an overview of the socio-economic and demographic characteristics of households at the selected sites. The majority of household heads surveyed were men (96.21%), compared with only 2.33% women. Among female heads of household, the majority were either widows (62.50%) or single (12.50%), the remaining (25%) having exiled husbands. The average age of the households surveyed was around 49, with a minimum and maximum age of 18 and 85 respectively. The number of people living in the households ranged from 2 to 30, with an average of around 9 per household. The large household size corroborates the population growth rates of the regions containing the selected sites (3.2% and 4% for the Tillabéri and Maradi regions, respectively). This is a factor traditionally cited as increasing the difficulties of satisfying needs in terms of basic social services in Niger, particularly regarding health, water and sanitation, as well as education. Difficulties of access to education, for example, are exacerbated by the health and security crises affecting these regions (OCHA, 2021; LeMarois et al., 2021). Thus, our sample was found to contain households with low levels of education, with more than half of household heads illiterate (72.59%), and only around 13% and 11% declared having attained primary and secondary levels of education, respectively. Furthermore, of households' members, respondents claimed that an average of 3 were involved in agricultural activities on the farms.

Most respondents reside in traditional housing such as huts, tents, and sheds (50%), while 15.09% live in banco houses. Only 35% of the respondents live in modern walled houses. Regarding land ownership, respondents reported owning between 1 and 7 farms, with an average of 2 farms per household. The farm sizes varied from less than 1 hectare to 7 hectares, with an average of 4 hectares per household. The inclusion of both used and unused farms in the survey accounts for the relatively high average number of farms, potentially introducing a bias in estimating actual farm sizes. However, this data is significant for understanding potential future exploitable land areas, which is crucial for assessing the households' capacity to adapt to climatic events that may impact the usability of their current farms.

Table 10 : Socio-economic and demographic characteristics of households

Variables	Category	Count	Percentage
HH head gender	Male	330	96.21
	Female	8	2.33
Marital status	Maried	324	94.46
	Widow	7	2.04
	Single	5	1.46
	Divorced	2	0.58
Level of education	Informal/none	249	72.59
	Primary	45	13.12
	Secondary	38	11.08
	Tertiary	6	1.75
House Type	Traditional	169	50.00
	Modern	118	34.91
	Banco house	51	15.09
Particulars	**Mean**	**Min**	**Max**
Age	48.932	18	85
HH size	9.577	2	30
HH farm labor	3.015	1	20
Farming experience	24.867	1	76
Farm plots	2.331	1	7
Farm size (ha)	4.424	.25	30
Off-farm activities	1.169	0	4

Source: Authors, based on survey data

The main activity of the households surveyed is farming. They declared having accumulated agricultural experience ranging from 1 year to 76 years as an independent decision-maker, i.e. an average of around 25 years per head of household. On average, the households consulted declared they were involved in an off-farm activity, i.e. trade (42% of households), not counting animal husbandry, which is an activity carried out by households on their farms, notably to produce organic manure and compost (92% of households used animals for compost production). Agriculture is essentially rain-fed, and only 28% of households reported using irrigation or market gardening.

3.2. Weighting of indicators and adaptive capacity components

The indicators and AC components were weighted using the Analytic Hierarchy Process (AHP) methodology, as outlined in previous sections. The results of the weighting scheme are summarized in *Tables 4 to 9*. To ensure the reliability of the indicators in measuring AC, Cronbach's alpha was calculated, yielding a value of 0.7093, indicating an acceptable level of reliability for the 21 selected indicators. Additionally, Consistency Ratios were calculated to assess the consistency of weights assigned by expert judgments, with all ratios falling below or equal to the 0.1 threshold, thus validating the derived weights.

The results indicate that financial capital received the highest weight (0.47), followed by human capital (0.23), social capital (0.14), physical capital (0.08), and natural capital (0.06). This suggests that access to financial, human, and social capital is considered the primary contributor to the adaptive capacity of farm households. Within these categories, the number of income sources received the highest weighting (0.57) for financial capital, the gender of the household head (0.46) for social capital, the level of education of the household head (0.68) for human capital, the type of irrigation (0.39) for physical capital, and the size of household holdings (0.5) for natural capital.

3.3. Analysis of farm household adaptive capacity scores and levels

In this study, adaptive capacity consisted of five determinants, namely financial capital, social capital, human capital, physical capital and natural capital. *Figures 5 and 6* illustrate the levels of AC of producers in the selected sites, as well as the levels of the components in the constitution of AC. In addition, complementary parametric and non-parametric tests, presented in *Tables 11, 12 and 13*, are carried out to determine statistical differences in farm households' access to the assets they need to pursue their livelihood strategies, on the one hand, and to test the association of farmers' levels of AC with climate risks at their locations, on the other. For instance, the Kruskal Wallis test was used when the normality assumptions were not met, and because it allows comparison of more than two independent groups, while the Pearson test of independence is used to determine the association of two (2) categorical variables.

Overall, 37.28%, 59.17% and 3.55% of households surveyed had a low, moderate and high level of adaptation, respectively (*Figure 5*). This implies an uneven distribution of surveyed households according to levels of adaptive capacity. Most households had a moderate level of AC, whereas a very low proportion of households acquired a higher level. *Figure 6 (a, b)* depicted that the biggest difference between producers with low adaptive capacity and those with medium and high adaptive capacity was in the accessibility and availability of natural capital, human capital and financial capital. Low-capacity producers had a human capital availability score of almost zero. The same differences applied to producers with moderate compared to those with high adaptive capacity. These results suggest that the producers at our sites were characterized by a very limited capacity to diversify their livelihoods, hence their high vulnerability to CC-related events. These findings are in line with the works of Abdul-Razak and Kruse (2017) in Ghana, Zanmassou et al. (2020) in Benin, Chepkoech et al. (2022) in Kenya and Jamshidi et al. (2020) in Iran, whose results showed the effectiveness of livelihood capital in explaining the adaptive capacity of farming households. Furthermore, a very low percentage of producers with high adaptive capacity to climate risks is often found in Sub-Saharan African countries (Egyir et al., 2015; Mekonnen and Kassa, 2019). However, the significance of the components varies between households and between communities in the aforementioned works.

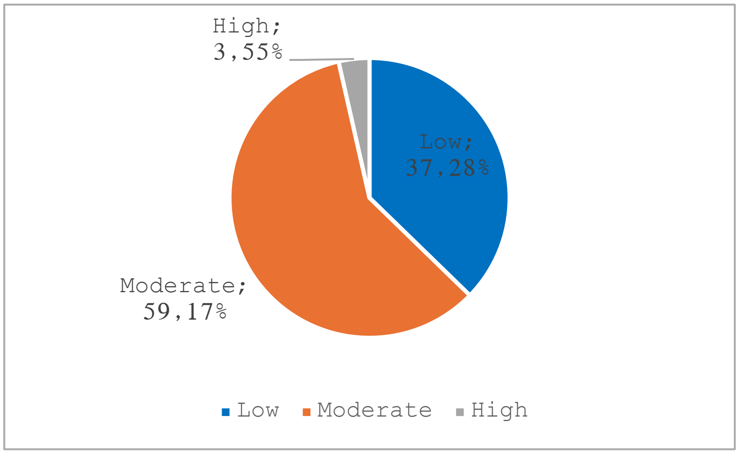

Figure 6: Overall percentage distribution of farmers' adaptive capacity on the selected sites (n=338, excluding the 5 nonresponse).

Figure 7 : AC levels across components scores. (a) Average scores of components (b) Median scores of components reported the x-axis.

The results of *Table 11* revealed that farmer adaptive capacity was built with moderate levels of social capital (0.53), financial capital (0.43), natural capital (0.42), physical capital (0.33), and a low level of human capital (0.12). Furthermore, the additional results in Table 12 showed that although access to and use of AC components differed significantly according to household location and adaptation levels, there was no significant association between producers' adaptation levels and the sites selected in our study. Bryan et al. (2015) also found that the average AC index of Australian wheat growers did not vary by region. This could be due to the method used or the indicators selected to calculate the AC index. Another explanation may be found in the fact that producers in Niger are essentially characterized by autonomous adaptations, based on their endogenous and traditional knowledge to cope with the climatic risks (mainly intra- and inter-annual rainfall variations) that they have been experiencing for a long time (Assoumana et al., 2016; Asfaw et al., 2018). Responses are thus limited and vary very little from one community to another in view of limited means of subsistence and very limited political support (Gambo et al., 2016; Asfaw et al., 2018). On the other hand, the sites selected for this study have long been the target of certain projects that aimed at supporting community adaptation and resilience. However, it emerged that the same projects generally operate in several localities and extend the same actions to all areas of intervention, hence their inconsistency in proposing actions that are incompatible with the climate threats specific to each locality (Tiepolo et al., 2018).

Table 11 : AC components' scores across study sites

Variables	All samples	Gadabedji	Guidan-Roumdji	Kollo	Ndounga	χ^2 value
			Medians			
Financial capital	0.43	0.49	0.43	0.37	0.49	12.19**
Social capital	0.53	0.54	0.54	0.52	0.52	1.33
Human capital	0.12	0.08	0.17	0.16	0.08	15.43**
Physical capital	0.33	0.18	0.31	0.33	0.35	12.99**
Natural capital	0.42	0.79	0.42	0.32	0.38	50.31***

**0.01 level of significance; ***0.001 level of significance

Table 12 : Categorization of adaptive capacity index across study sites

Adaptive capacity clusters	Range of scores	Gadabedji	Guidan-Roumdji	Kollo	Ndounga	F p-value
			Means			
Low	0.00-0.33	0.31	0.27	0.24	0.23	0.059
Moderate	0.34-0.66	0.46	0.49	0.47	0.48	
High	0.67-1.00	0.00	0.70	0.72	0.67	

The statistically significant differences in access to and use of AC assets revealed useful information for the decision-making process. The results revealed that there were no statistically significant differences in access to and use of social capital between the localities visited, although the scores were relatively high. This can be explained by the fact that social ties (networks, reciprocity, solidarity, cooperation, etc.) have traditionally shaped farmers' daily actions in the African rural context, irrespective of locality. They serve as important risk-sharing assets, making it possible to avoid or overcome the negative impact of CC-related events (Yameogo et al., 2018). A recent study in Niger showed that forms of social assistance in Niger, both formal initiatives and communal mechanism, support adaptation to climate change, though limited short-term coping strategies (Daoust et al., 2025). Furthermore, the results showed that farmers recorded very low human capital scores, irrespective of the localities visited. In general, analyses of farmers' adaptive capacity in Africa and Asia have consistently revealed low human capital scores (Gbetibouo et al., 2010; Antwi-Agyei et al., 2013; Defiesta and Rapera, 2014; Yaméogo et al., 2018; Jamshidi et al., 2020; Mogomotsi et al., 2020). In Niger, even the strategic documents federating actions in favor of the agricultural sector (SDDCI-2035, PDES, SPN2A) recognize that real efforts need to be undertaken to capacitate farm households with training and agricultural advice while working to significantly reduce gender inequalities. This suggests that efforts need to be directed towards planning much more specific actions to improve this capital.

Producers in Gadabédji performed relatively better than those in other sites, in terms of access to and use of natural and financial capital, while scoring very low on physical and human capital. The expected high score for natural capital is closely linked to the specific environmental characteristics of this locality. It is located in the only wildlife reserve in the Sahel, in a pastoral zone, called *Réserve Total de Faune de Gadabédji* (RTFG). It harbors a significant potential in renewable natural resources, making the area a key to biodiversity conservation and a rich grazing area and natural habitat for wildlife. These features made it registered as a UNESCO World

Heritage Site since July 2017 (UNESCO, 2018). Despite the high and moderate contribution of natural and financial capital, respectively, Gadabédji farm households were unable to make efficient use of resources due to very low human and physical capital scores. Also, the moderate level of financial capital did not give them sufficient financial capacity to acquire adequate physical capital equipment. Farmers in N'Dounga, Kollo and Guidan-Roumdji built their adaptive capacity with moderate levels of financial capital, physical capital and natural capital, and a very low level of human capital, with small statistically significant differences. These findings concur with those of Choden et al. (2020), who reported that adaptive capacity varies significantly according to socio-economic differences and access to different capital assets between farm households and between communities.

Comparative analyses that follow have identified specific factors that can better inform decision-making in prioritizing actions.

3.4. Comparative analysis of adaptive capacity indicator scores between households

The comparative analysis, based on the statistical results presented in Table 13, identified key determinants that can serve as levers to guide and prioritize agricultural policy actions aimed at improving the AC of households in the study sites. A series of constructed figures were utilized to better visualize the contributions of each indicator to the development of specific capitals. The assets of particular interest, as highlighted in the previous section, were financial capital, natural capital, and human capital. These assets were identified as critical due to their significant contributions to the overall adaptive capacity of households, suggesting that targeted interventions in these areas could effectively enhance household resilience and adaptability in the face of environmental and socio-economic challenges.

Table 13 : Comparison of groups based on adaptative capacity

Adaptive capacity components	Indicators	Clusters	Mean/Median ACI scores	Percentage of the distribution*	t value	F value
Financial Capital (FC)	Sources of income (FC1)	1	0.22	18.08		345.7***
		2	0.37	49.85		
		More than 2 sources	0.56	30.61		
	Farm worker on HH plots (FC2)	1	0.30	29.45		39.07***
		2	0.39	17.2		
		3	0.43	22.45		
		More than 3 workers	0.49	29.45		
	Access to credit (FC3)	No access	0.40	97.67	-1.17	
		Access	0.50	0.87		
	Access to public subsidy (FC4)	No access	0.40	91.55	-0.94	
		Access	0.43	7		
	Animal ownership (FC5)	0	0.31	20.99		38.97***
		1-5	0.34	25.95		
		6-10	0.39	11.08		
		More than 10 animals	0.49	40.52		
Human Capital (HC)	Level of education (HC1)	Informal / none	0.37	72.59		20.73***
		Primary	0.46	13.12		
		Secondary	0.53	11.08		
		Tertiary	0.51	1.75		
	Access to agricultural advice (HC3)	No access	0.36	68.8	-7.23***	
		Access	0.49	29.74		
Natural Capital (NC)	Soil fertility (NC1)	Not fertile	0.35	53.94	-7.75***	
		Fertile	0.46	44.61		
	HH plot size (NC2)	<=2 ha	0.34	37.9		21.10***
		<=4 ha	0.38	20.99		
		<=6 ha	0.44	20.99		
		>6 ha	0.49	18.66		
	HH experience with natural hazards (NC3)	No	0.42	58.6	2.23***	
		Yes	0.37	39.94		
	Number of tree types in the main farm of the HH (NC4)	0 type	0.31	2.92		3.34*
		1 type	0.38	26.53		
		2 types	0.38	24.49		
		3 types	0.41	15.74		
		More than 3 types	0.44	28.86		
Particulars		Correlation coefficient	Significance			
HH farming experience (HC2)		0.0386	0.48			

*0.05 level of significance; **0.01 level of significance, ***0.001 level of significance.
*****The remaining 1.46% relate to non-respondent in the database.

i. Financial capital: *Figure 8* illustrates the level of financial capital indicators. It shows that the indicator "number of sources of income" received the highest level of contribution (0.32), while the other indicators contributed almost nothing. However, its contribution remains low in the categorization of scores. The statistical results showed that there was a statistically significant positive difference between households AC with different sources of income. This suggests that households with more sources of income are more likely to get a high level of AC, compared to those relying solely on farm income. Households with a diversified portfolio of activities, including other off-farm jobs such as fishing, handicrafts, animal husbandry and petty trade, were more likely to recover from the negative effects of CC. In Niger, several researchers have demonstrated the positive and significant short- and medium-term impact of income diversification on CC resilience and the well-being of households (particularly vulnerable ones), including food security (WB, 2017A; Asfaw et al., 2018; GIZ, 2022). Our results corroborate the trend that households diversifying their income sources are more likely to adopt multiple livelihood strategies in times of stress and acquire a broader livelihood portfolio that can be used to reduce vulnerability to climate risks such as drought (Ellis, 1999; Nelson et al., 2010). The "number of workers on household farms" (0.095) contributed very little to the financial capital of Niger farmers. Around 30% of households surveyed had one active worker on the household farms and held a low average AC, compared with 70% that held workers equal to or greater than 2 and displayed a moderate average AC. Only 30% of the households had 3 or more workers on the farms. Adaptive capacity has positively and significantly improved with increasing numbers of workers in similar studies. Households with more workers are more likely to use new technologies and more labor-intensive measures and are therefore likely to be more effective in adapting with the effects of CC (Yameogo et al., 2018; Antwi-Agyei et al., 2018). Similar to the findings of Antwi-Agyei et al. (2018) in the northern region of Ghana, the labor shortage in Niger can be mainly attributed to the migration of able-bodied men, particularly young people. This affects farming operations and crop yields when many do not return, with significant implications for food security in these communities. Furthermore, according to the World Bank report (WB, 2019), if no concrete action is taken on climate and development, internal climate migration will affect 86 million people in sub-Saharan Africa by 2050, with effects more accentuated for poor and climate-vulnerable populations like those in Niger.

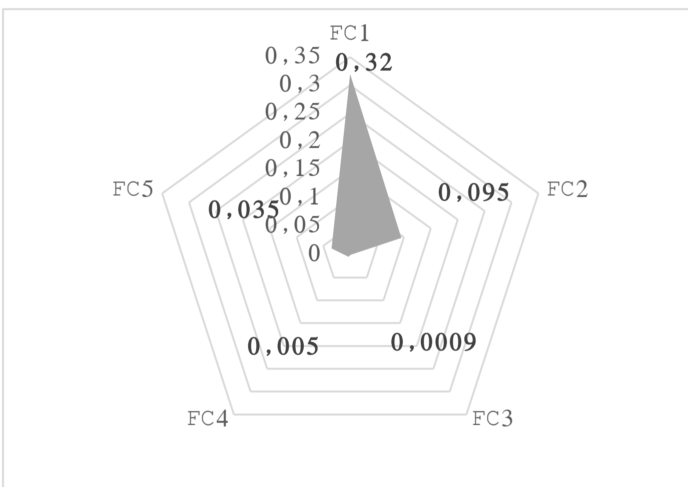

Figure 8: Scores of indicators of financial capital component

FC1: Number of income sources FC2: Number of farm workers; FC3: Access to formal and/or informal credit; FC4: Access to public subsides; FC5: Number of animals owned by the household.

The indicator "number of animals owned by the household" also contributed very little (0.035) to financial capital. The majority (around 66%) of producers claimed to keep animals for consumption, ploughing, but also for trading and the production of compost and organic manure. In addition, the test results showed that owning more animal units gives households greater AC. Animal units emerge as an important financial resource for households as they serve as insurance mechanisms for them by easily selling them for food purchases, they can also be used for the practice of adaptive measures such as manure spreading due to the greater availability of manure (Shikuku et al., 2017). Access to credit (formal and informal) as well as access to public subsidies contributed almost nil to the financial capital formation and depicted a positive but insignificant effect on AC. These results are the direct result of the combination of the absence of financial institutions in rural Niger and the existence of small-scale social safety net programs (Aker et al., 2009; Stoeffler et al., 2014; Gambo Boukary et al., 2016; WB, 2017).

ii. Human capital: *Figure 9* depicted that the indicators contributed very little to the constitution of human capital. The results of statistical tests showed that human capital increased with the level of education, households with no education having a low score. The latter made up the majority (74%) of households surveyed. In Niger, remarkably low levels of education, particularly in rural areas (WB, 2017A), have regularly been cited among the main constraints to effective adaptation to the adverse effects of CC and improved agricultural productivity (Assoumane et a., 2016; Asfaw et al., 2016, 2018; GIZ, 2022). This situation has not enabled farmers to maximize agricultural production by using all available resources, including climate information to better combat CC (Dressa et al., 2009; Egyir et al., 2015; Singh et al., 2020). In addition, a low level of education limits the ability of producers to engage in off-farm activities, better remunerated, and thus increase their income and subsistence activities (Paavola, 2008, WB, 2017B). Regarding the indicator "farming experience", one would expect farmers with more experience in farming to adapt better to the CC. In our study, the farmers surveyed were relatively well experienced, with only 18 (15%) having less than or equal to 10 years' experience as an independent decision-maker. However, the results of Spearman's correlation tests (*Table 13*) showed a very weak and non-significant correlation, suggesting that the number of years of farming experience did not influence AC of the producers. This result may be explained by the effect of inappropriate interventions by adaptation and resilience support projects/NGOs, which have traditionally targeted communities of our study sites and tend to pervert indigenous knowledge, so that it increasingly fails to serve as the main basis for implementing their adaptation strategies. Taking indigenous knowledge into account is considered fundamental to successful adaptation to CC in agriculture, livestock and fisheries (Dinesh et al., 2016). Another unexpected result was observed with regard to the indicator "access to agricultural advice". While 236 (around 70%) of households surveyed reported having access to farm advice, compared with 102 (20%), farmers with access showed a lower average AC score than those without access. Yet, access to agricultural advice has had a positive and significant effect on technical efficiency among farming households in Uganda (Kansiime et al., 2018), and is considered an important factor that enables African farmers to make informed choices for effective adaptation strategies and better manage CC-related risks (Fosu-Mensah et al., 2012; Ariom et al., 2022). In Niger, farmers' access to agricultural extension services has been structurally low (Assoumana et al., 2016). This is therefore mainly a limitation inherent in the data collected, as to the question to know from whom the respondents received agricultural advice (for seed use, irrigation practice, use of agricultural equipment, etc.), training or any other advice related to agricultural production, households confided that they receive from several types of agents (researchers, extension agents, NGOs/projects, private companies, etc.) and that they have difficulty distinguishing between these agents and the lessons they provide. This also explains the moderate level of AC despite access to agricultural advice.

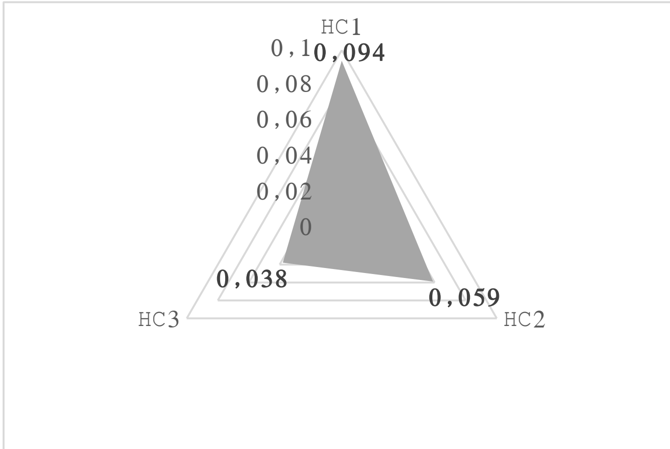

Figure 9 : Scores of indicators of human capital component.
HC1: Level of education; HC2: Farming experience; HC3: Access to extension services.

iii. Natural capital: Average scores for natural capital indicators are shown in *Figure 10*. As with human capital, scores reached very low levels. Household "farm size" was the indicator that contributed the most (0.205) to the natural capital of the households surveyed. The estimation results showed that farm size has a positive and significant influence on the AC of agricultural households. Dafiesta and Rapera (2014) and Jamshidi et al. (2020) also found that farmers with larger farms had greater adaptive capacity. These farmers are more likely to adopt new high-yield agricultural technologies, such as mixed cropping (Egyir et al., 2015). Our results also showed a significant association between the farm size of the households and the type of cropping system used on the farms, suggesting that households with larger farms adopted mixed cropping. They are also often considered as wealthy households who can afford to buy the necessary inputs (Egyir et al., 2015). The implication is that for small households to adopt integrated farming systems, external support will be required. On average, farmers who stated that their soils were fertile showed a higher, albeit moderate, AC score. More than half (around 55%) of the farmers surveyed stated that they produce on soils that are not fertile. The work of Fosu-Mensah et al., 2012 has also highlighted the importance of soil fertility for producers' AC, as this factor tends to influence the decision to adapt practices to climate risks. Our surveyed sites reflect the characteristics of Niger, in that very few producers have access to modern inputs such as chemical fertilizers and pesticides, and they mostly use organic inputs (mainly manure) or do not use any soil improvement products (WB, 2017). Yet, soil-improvement practices abound with significant returns on investment, albeit in the long term while requiring investment costs for the current period (Shikuku et al., 2017). These findings, combined with the poverty conditions of farm households who generally position themselves in a short-term perspective to decision-making, suggest that policy actions directly support the permanent availability of inputs for soil improvement, either through direct subsidies or facilitated access to the input market.

Unexpectedly, the experience of natural hazards on the farms of the households in our sites negatively impacted their AC, suggesting that households that have not experienced natural hazards have a higher AC compared to those that have experienced natural hazards on their farms. However, the empirical literature informs that experience of climatic stressors can motivate farmers to invest in risk-reducing adaptation strategies, such as crop residue management (Asfaw et al., 2014). In our study, this indicator is captured by asking surveyed farmers the following question: 'Have your farms been affected by a natural disaster such as a flood/drought in the last ten years in this community?' While 99% of households surveyed perceived climate changes/modifications (mainly in terms of insufficient rainfall, erratic rainfall, a prevalence of very hot days), around 59% of households said they had not experienced any natural disasters on their farms, and 40% answered in the affirmative. The latter had lower AC scores than their peers who had not suffered natural disasters. This result can essentially be explained by the poor conditions of the households and their inherent characteristics (low level of education, poor access to agricultural advice and credit, etc.) which make them even more vulnerable after a shock, further reducing their adaptive capacities. As a result, external support is urgently needed to help farmers affected by natural disasters to better adapt and take advantage of opportunities when they arise. Especially since households in most of our sites (in the Tillabéri region in particular) live in a part of the regional territory under constant threat of flooding, and where the poorest are forced to settle in areas unsuitable for crops, most often the banks of watercourses that are inevitably exposed to flooding (Tiepolo et al., 2016). As for the 'number of tree types on household farms', estimates showed that producers with a high number of tree types on their farms showed a higher AC score. Datta and Behera (2022), or Ariom et al. (2022) found that planting and managing several types of trees, particularly woody trees, enabled farmers to adapt against flooding on their farms and resist pest attacks, while generating additional household income.

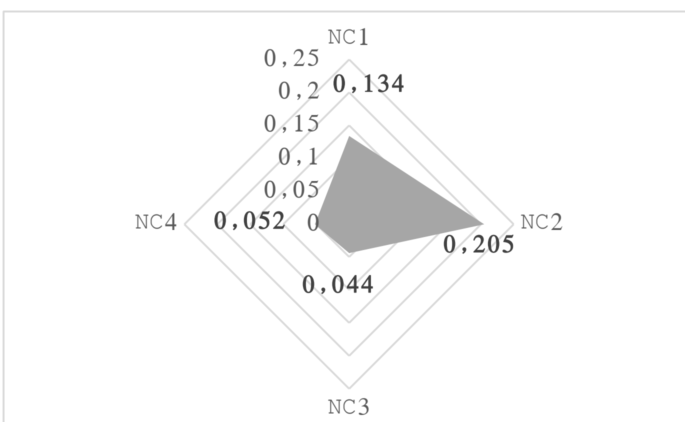

Figure 10 : Scores of indicators of natural capital component.

NC1: Soil fertility; NC2: Plot size; NC3: Experience of natural hazards; NC4: Number of tree types on the HH farm.

Conclusion and policy implications

This study was aimed to assess the adaptive capacity of farming households in Kollo and N'Dounga (Tillabéri region) as well as Gadabédji and Guidan Roumdji (Maradi region) in Niger. Operating within a methodological and analytical framework, this study enabled an in-depth analysis at all levels of aggregation. It highlights the relative importance of Nigerien households' livelihoods in line with the literature. The findings highlight critical disparities in asset portfolios among households, with low and moderate adaptive capacity associated with limited diversity and unbalanced portfolios, respectively. Diversification and balance between different assets are essential for farm households in the pursuit of livelihood strategies, enabling livelihood substitution strategies in the face of shocks and ensuring efficient use of resources80.

In practical terms, this implies that farm households with moderate AC (59.17%) faced critical constraints to convert high scores assets into very low ones, while those with low AC (37.28%) lack of sufficient level of all assets to combine in the pursuit of their livelihood strategy. For instance, in Gdabédji, very low levels of human and physical capital prevented households from making effective use of their substantial natural capital, even though financial capital contributed moderately. A similar pattern was observed in N'Dounga, Kollo, and Guidan Roumdji, where moderate levels of financial, physical, and natural capital were offset by very weak human capital. This analysis provides an important step forward, as it applies the Sustainable Livelihood Framework (Ellis, 1999; Nelson et al., 2010; Jacobs et al., 2015) in a way that considers the relative importance of livelihood assets—an approach often overlooked in earlier studies.

Comparative evidence from Kenya (Chepkoech, 2020), Ghana (Baffour-Ata et al., 2023), and Nigeria (Shakirat et al., 2022) also suggests that most households tend to have moderate AC. However, these earlier studies explained AC mainly through the performance of individual indicators, with limited attention to how the relative importance and interaction of livelihood assets shape AC. By emphasizing asset portfolios, this work provides a more nuanced understanding of adaptive capacity and its limitations in smallholder contexts.

Interestingly, physical capital did not emerge as a significant determinant of AC in this study. Nonetheless, earlier works in Niger consistently highlighted that poor access to and participation in markets limited farmers' ability to obtain high-yield inputs and technologies to improve agricultural productivity (Zakari et al., 2023), and to market their agricultural products effectively (Kalidou et al., 2024). This gap suggests a limitation of the study's methodology, which relied only on expert-validated indicators and may not have captured all locally relevant dimensions. Future research should adopt a more flexible design, testing alternative sets of indicators to enable deeper comparative analysis. Despite these limitations, the reliability of the findings was reinforced by the combined use of uncertainty and sensitivity analyses, which supported the overall consistency of the results. In doing so, the study provides both conceptual and methodological advances that can inform more context-sensitive and reliable assessments of household adaptive capacity.

The study revealed that low and moderate adaptive capacity households lacked critical human capital, particularly education and skills, which are essential for accessing information, technologies, and off-farm income opportunities. In Niger, remarkably low levels of education, particularly in rural areas (WB, 2017B), have regularly been cited among the main constraints to effective adaptation to the adverse effects of climate change and improved agricultural productivity (Röhrig et al, 2022; Asfaw et al., 2018; Assoumana et al., 2016; Asfaw et al., 2016). This situation has not enabled farmers to maximize agricultural production by using all available resources to better adapt to climate change (Egyir et al., 2015; Deressa et al., 2009; Singh, 2020). In addition, a low level of education limits producers' ability to engage in off-farm, better-paid, activities and thus increase their income and subsistence activities (WB, 2017A). It also emerged that these households did not receive sufficient access to agricultural advice through extension services to make informed choices on effective adaptation strategies and better manage climate change-related risks through climate information (Fosu-Mensah et al., 2012; Mazziotta and Pareto, 2013). Farmers' access to agricultural extension services has been structurally low in Niger (Assoumana et al., 2016), whereas it had a positive and significant effect on technical efficiency for farm households in Uganda (Kansiime et al., 2018).

Households with moderate adaptive capacity tended to diversify financial capital through multiple income sources, farm labor, and animal units. Households with a diversified portfolio of activities, including other jobs into non-agricultural activities like fishing, handicrafts, animal husbandry and petty trade, were more likely to recover from the negative effects of climate change. In Niger, several studies showed the positive and significant impact, in the short and medium term, of income diversification on climate change resilience and the well-being of farming households (particularly vulnerable ones) and food security (Röhrig et al., 2022; WB, 2017B; Asfaw et al., 2018). In addition, households with more workers are more likely to use new technologies and more labor-intensive measures and are therefore likely to be more effective in adapting to the effects of climate change (Yaméogo et al., 2018; Antwi-Agyei et al., 2018). Similar to the findings in the northern region of Ghana (Antwi-Agyei et al., 2018), labor shortage in Niger can be mainly attributed to the out-migration of active men, particularly young people. This affects farming operations and crop yields when many do not return, with important implications for food security in these communities. Moreover, according to the World Bank report (Rigaud et al., 2018), if no concrete action is taken on climate and development, internal climate change induced migration will affect 86 million people in sub-Saharan Africa by 2050, with effects more accentuated for poor and climate-vulnerable populations like those in Niger. Animal units have traditionally been an important financial resource for households in Niger for the provision of insurance mechanisms and supporting adaptive measures such as manure spreading due to the greater availability of manure (Shikuku et al., 2017).

It is often admitted that most rural livelihoods depend on natural resources, such as farm size. This suggest that farmers with larger farms had greater adaptive capacity (Jamshidi et al., 2020; Defiesta et al., 2014). These farmers are more likely to adopt new high-yield agricultural technologies, such as mixed cropping (Egyir et al., 2015). The results exhibited a significant association between the farm size and the type of cropping system used on the farms, suggesting that households with larger farms adopted mixed cropping. They are also often considered as wealthy households who can afford to buy the necessary inputs (Egyir et al., 2015). As a result, for smallholders to adopt integrated farming systems, external support will be needed. This external support is also a necessary factor in improving the soil fertility of household farms, some 54% of which reported producing on non-fertile soils. The study sites reflect the characteristics of Niger, for very few producers have access to modern inputs such as chemical fertilizers and pesticides, and they mostly either use organic inputs (mainly manure) or do not use any soil improvement products (WB, 2017b). While soil improvement practices have long-term benefits, their upfront costs pose challenges for resource-poor households (Shikuku et al., 2017). These findings, combined with the poverty conditions of farm households who generally position themselves in a short-term perspective to decision-making, suggest that policy interventions to improve input availability – through subsidies or market facilitation – are urgently needed.

The uncertainty analysis suggested that changes in the weighting and aggregation schemes have a significant influence on the values of the ACI index. In addition, the ACI is much more sensitive to changes in aggregation methods. These results highlight the importance of weighting and aggregation schemes in index construction. They are consistent with the results obtained in previous studies (Serrat, 2017; Marzi et al., 2018), who showed that the adaptive capacity index is sensitive to weighting and aggregation methods. In addition, the importance of using expert weighting allowing the perceived importance of indicators and components to be taken into account is well supported (Zanmassou et al., 2020). Concerning the sensitivity analysis, the results suggested that the ACI is highly sensitive to any change in the method of aggregating indicators into components, particularly when moving from linear to geometric aggregation. Therefore, the combined UA-SA analyses allowed to conclude that the ACI was developed on a relatively stable model.

The results suggest several policy implications. There is an urgent need for targeted interventions to strengthen the financial, human and natural capital of farming households, except for households residing in Gadabéji. Given that this locality had a high level of natural capital, interventions should target both financial and human capital. Policymakers should give priority to programs that promote income diversification, improve education levels and increase farm size and soil fertility through access to modern inputs and soil improvement practices. Collaboration with agricultural research and advisory institutions such as RECA (*Réseau National des Chambres d'Agriculture du Niger*), Regional Center AGRHYMET (regional training and application center for agrometeorology and operational hydrology), INRAN (*Institut National de la Recherche Agronomique du Niger*) and the *Plateforme Paysanne* (civil society organization bringing together farmers' organizations and active in all areas of the rural sector in Niger) will be crucial to the coordinated and effective implementation of policy actions. To effectively support farmers, it is essential to implement tailored programs that consider the specific needs and climatic conditions of target populations, while capitalizing on households' indigenous knowledge as *"indigenous knowledge is the backbone of successful climate change adaptation in agriculture"* (Dinesh et al., 2016). The results of this study provide a basis for the development of comprehensive and context-specific policies that strengthen the adaptive capacity and well-being of farm households in Niger.

However, another limitation of this study is the absence of longitudinal and spatially disaggregated data, which constrains the ability to assess changes in adaptive capacity over time and across different regions. As a result, our findings should be interpreted as a snapshot in time, and future research should adopt dynamic approaches to capture the evolving nature of adaptive capacity and integrate vulnerability and social justice considerations to ensure inclusive and effective policy outcomes.

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ESSAY 2: UNCERTAINTY AND SENSITIVITY ANALYSIS OF NIGER PRODUCERS' ADAPTIVE CAPACITY INDEX.

Abstract

The literature on index construction, particularly adaptive capacity indices, highlights the need for transparency and robustness assessment given the subjective choices involved in their design. Index approaches that fail to account holistically for uncertainty risk producing misleading policy conclusions. While most adaptive capacity indices either overlook uncertainty analysis or treat uncertainty and sensitivity analyses separately, this study contributes to the literature by integrating both analyses within a unified, iterative framework. Applied to the Adaptive Capacity Index (ACI) developed in Essay 1, uncertainty was assessed by testing alternative normalization methods, weighting schemes, and aggregation procedures using Monte Carlo simulations (10,000 draws), with the relative standard deviation (RSD) as the uncertainty metric. Sensitivity analysis was subsequently conducted using a first-order global approach to identify the main drivers of uncertainty at each stage of index construction. The results indicate that weighting and aggregation choices significantly influence ACI values, with aggregation methods exerting the strongest effect. In particular, the index is highly sensitive to changes in the aggregation of indicators into components, especially when shifting from linear to geometric aggregation. Overall, the combined uncertainty–sensitivity analysis suggests that the ACI is based on a relatively stable modeling framework.

Key words: Uncertainty analysis, sensitivity analysis, adaptive capacity index, relative standard deviation, Monte Carlo simulation.

Introduction

The adaptive capacity index developed in the previous section has the advantage of being developed on the basis of an original framework, combining a methodology based on the literature, quantitative (primary) data and qualitative data drawing on the opinion of Niger experts. This sound methodological and analytical framework has resulted in consistent conclusions that are appropriate to the contexts of Niger's producers and that can better inform the decision-making process. The eventual aim will be to guide political action to better enable farming households to cope with the negative effects of climate change.

However, a necessary and sufficient step is to ensure the robustness and transparency of the composite index calculated in this way. The justification for this step lies in the subjective nature of the choices made in the model underlying the construction of the index. Indeed, one of the main shortcomings and criticisms of composite indices concerns the subjective choices made by the developer at each stage of construction (Caccavale and Giuffrida, 2020). For example, Nardo et al (2005) stated that changes in the weighting system will almost always lead to a change in the ranking of countries (in the case of a composite index calculated at regional or global level), and therefore in the value of the index itself. In general, an index calculation approach that does not operate on a holistic basis that takes into account all the uncertainties that can influence the final result can lead to misleading and non-robust policy messages (Saisana et al., 2005; Dobbie and Dail, 2013; Greco et al., 2018). Uncertainty (UA) and sensitivity (SA) analyses carried out for other composite indices confirm that uncertainty is an unavoidable factor for composite indices (see for example Saisana et al., 2005[11]).

The aim of this trial is therefore to implement iterative uncertainty and sensitivity analyses (UA-SA) on the index of the adaptive capacity of producers in Niger. This 'synergistic' use will make it possible to answer the following questions: How do changes in the steps (technically input factors) involved in creating the ACI influence the final result or the value of the index? How much uncertainty is introduced by one or more input factors and to what extent do these factor(s) influence the overall result. Ideally, all stages in the creation of the ACI should be subject to uncertainty and sensitivity analysis (OECD, 2008). In this work, choices have been made and focus mainly on the method of normalization, weighting and aggregation. The following sections of this essay highlight these different choices and the operationalization of the UA-SA synergistic analysis.

The remainder of this paper is organized as follows. Section I identifies and discusses the input factors subjected to uncertainty and sensitivity analyses. Section II presents the analytical models employed, while Section III reports and discusses the results, leading to conclusions regarding the validity of the calculated Adaptive Capacity Index (ACI).

[11] These authors are regularly cited for their in-depth work on the United Nations' Technological Achievement Index (TAI), showing the need to implement uncertainty and sensitivity analyses.

I. Methods subject to uncertainty and sensitivity analysis

The aim of this section is not to provide a systematic review of the various stages in the construction of the ACI. Several of these stages have been extensively discussed in the previous essay and, in fact, the authors who will be involved in the discussions are reviewing them in depth. The aim here is to take stock of the methods most commonly used in the literature for the stages that will be the subject of UA-SA in this work. These stages are the normalization of indicators, the weighting methodology and the aggregation methodology. It should be remembered that our work has adopted a two-stage aggregation methodology: aggregation from indicators to components, and then from components to indicators.

1.1. Indicators normalization

Normalization is an important and necessary step in the index calculation process when the ACI indicators to be aggregated have different units of measurement. This step makes it possible to transform the indicators by making them standard, at the same level, and therefore comparable and dimensionless (OECD, 2008). Normalization is also motivated by the fact that some indicators may be positively correlated with the phenomenon being measured, while others are negatively correlated (Mazziotta and Pareto, 2013). One of the aims of normalization is to ensure that an increase in normalization indicators corresponds to an increase in the index. These justifications mean that the comparability of composite index values depends first and foremost on the Normalization method. This method must therefore be chosen carefully, taking into account the data and the objectives of the composite index (Nardo et al., 2005; Mazziotta and Pareto, 2013). For example, if the aim of constructing the composite index is to reward a few specific indicators because an extremely good result for these indicators is considered better than a large number of average results, the standardization method (or z-scores) is preferable (OECD, 2008). Alternatively, if the data used to measure the indicators does not have "sufficiently" extreme or outlier values that influence the transformation of the initial indicators, the developer can opt for a Min-Max normalization method that preserves the distribution of the indicators. This method has the advantage of being used with all weighting systems and for all aggregation systems (Nardo et al., 2005; OECD, 2008).

Singh and Singh (2020) conducted an uncertainty analysis to show the impact of 14 different normalization methods on the data quality and classification performance of machine learning algorithms. One of the main results is that one of the methods with poor performance is in fact the one that uses no normalization method at all. In the field of composite index construction, the normalization method to be chosen is considered to be interdependent on the different choices of methods to be made at the different stages of index construction. For example, it should be noted that the choice of normalization and aggregation methods are interdependent issues. Geometric aggregation prohibits the use of the transformation of indicators into z-scores because it is only for sets of positive values (Mazziotta and Pareto, 2010).

The Min-Max normalization methods (Abson et al., 2012; Epule et al., 2021; Shakirat et al., 2022) and the standardization or technically called z-scores (Coulibaly et al., 2015; Mesfin et al., 2020) are the most commonly used in the literature at our disposal. This work adopts the change of normalization methods between these two methods for UA-SA analyses.

The Min-Max normalization method is applied to indicators according to the function:

$$I_i = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

Where x_i is the particular value of the indicator to be transformed, x_{min} and x_{max} respectively the smallest and largest value of the indicator concerned, and I_i is the new normalized value. This normalized indicator thus takes values over an identical range [0, 1].

The standardization or z-scores method is implemented by subtracting the mean from the indicator values, then dividing by the standard deviation, as shown in the following formula:

$$I_i = \frac{x_i - \bar{x}}{\sigma}$$

Where x_i is the particular value of the indicator to be transformed, $\bar{x}$ the mean of all indicator values and σ the standard deviation. In doing so the indicator values are converted to a common scale with a mean of zero and a standard deviation of 1.

1.2 Weighting of indicators and components

Generally speaking, AC assessments are based on three (3) approaches to weighting indicators or components. Of these, the equal weighting approach is the most commonly used. This involves giving the AC indicators the same weight when aggregating the composite index. It is used when the indicators or components are considered to be of equal importance, or at least when there is no statistical or empirical evidence to justify using a different scheme (Nardo et al., 2005). Although this approach has the advantage of being simple and easy to replicate, it does not differentiate between essential and less essential indicators by treating them all in the same way (Greco et al., 2018). This implies the underestimation or overestimation of certain indicators, and therefore a discrepancy with reality. It could also reveal a lack of knowledge about the importance of components or the causal relationship between indicators (Wang and Fu, 2019). Furthermore, the use of the equal weighting system may lead to the phenomenon of "statistical double counting of weights", i.e. the inclusion of the same weight two or more times when two or more indicators, with a high correlation, measure more or less the same dimension (Nardo et al., 2005; OECD, 2008).

An alternative approach would be to use a data-based weighting system to overcome this problem. In this framework, indicator weights are derived on the basis of statistical models, such as Principal

Component Analysis (PCA) or Factor Analysis (FA). This approach is thus based solely on the characteristics of the data and on the analysis of correlations between indicators in order to avoid double counting (Gan et al., 2017). It groups together individual collinear indicators to form a dimension (composite indicator) that captures as much as possible of the information common to each indicator (OECD, 2008). However, this approach tends to produce physically inconsistent weights as the dimensions extracted can be difficult to define, particularly as unrelated individual indicators can be grouped together in the same dimension due to spurious correlations, and the weights thus derived are therefore based on correlations rather than the actual links between the indicators in the composite index (Gan et al., 2007). This approach is also a source of considerable bias, as it tends to favor indicators that are easy to measure, while punishing those that are statistically more difficult to identify and measure (Nardo et al., 2005). In fact, Gan et al (2007) explain that PCA and FA models were originally developed to examine the relationships between variables or indicators, and not to determine weights. Les limites susmentionnées des pondérations fondées sur l'égalité et les données peuvent alors induire en erreur la prise de décision si l'indice composite mesuré a pour objectif de saisir des informations au niveau individuel, telles que la CA des agriculteurs au changement climatique, où les pondérations doivent refléter l'importance perçue par les agriculteurs ou les experts de chaque composante pour informer les décideurs politiques (Zanmassou et al., 2020).

The third form of approach is weighting by expert judgement. This approach was extensively detailed in the previous essay, as was the process for deriving indicator and component weights (see *subsection iii of Section 2.3.3.2*). Equal weighting is generally achieved through a weighted arithmetic average of indicators and components. For reasons of simplicity, principal component analysis has been excluded from the AU-SA analyses.

1.3 Aggregating indicators into components, then components into an ACI index

The literature on aggregation covers a variety of methods, each with strengths and weaknesses. Two broad categories are often cited, comprising compensatory and non-compensatory methods. The biggest difference between these approaches is that compensatory methods, as their names suggest, allow compensation between aggregated indicators or components (Greco et al., 2018). In other words, low values of one indicator can be totally or partially compensated for by higher values of another indicator. This is not the case for non-compensatory methods, which are not dealt with in this work in view of the objective of compensation that characterizes the ACI construction stages[12].

The linear method, widely discussed in essay 1, uses an additive function to aggregate indicators or components. Unlike this approach, which assumes full compensation and preferential

[12] For more details on non-compensatory methods, see the OECD's Index Construction Manual (2008), or the various works by Nardo et al. (2005) and Greco et al. (2018), for example.

independence between indicators, the geometric aggregation method assumes only partial compensation (Gan et al., 2017). Thus, very low values of one indicator cannot be fully compensated with high values of another indicator. This is related to the geometric nature of this approach, which uses a multiplicative function for aggregation. However, both approaches adopt a compensation logic and the indicator weights are interpreted as substitution rates (Nardo et al., 2008).

The linear method is used to aggregate the indicators into components and then the components into an ACI index using the following formulations:

$$CP_{ij} = \sum_{q=1}^{21} w_q \, I_{ijq} \; ;$$

where $\sum_{q=1}^{21} w_q = 1$, q = 1,…,21, i =1,…,N et j =1,…,5

Where CP_{ij} captures the capital (component) j of adaptive capacity of farm household i, w_q the weight of indicator q, and I_{ijq} the normalized indicator of the corresponding component j.

$$ACI_i = \sum_{j=1}^{5} w_j \, CP_{ij} \; ;$$

where $\sum_{j=1}^{5} w_j = 1$

Where ACI_i represents the composite index of the adaptive capacity of farm household i, w_j the weight assigned to component j.

The geometric method is implemented according to the formulations:

$$CP_{ij} = \prod_{q}^{21} I_{ijq}^{w_q} \; ;$$

where q = 1,…,21, i =1,…,N et j =1,…,5

$$ACI_i = \prod_{j}^{5} CP_{ij}^{w_J} \quad ;$$

II. Setting up the uncertainty and sensitivity analysis mode

By definition, uncertainty analysis studies the way in which input factors propagate through the structure of the composite indicator and affect the indicator values (Saisana et al., 2005). Sensitivity analysis studies the extent to which each individual source of uncertainty contributes to the variance of the composite indicator (Saltelli et al., 2007). In the specific case of this study, a combined UA-SA uncertainty and sensitivity analysis is used to determine how a change in the input factors modifies the value of the ACI and to identify the factor for which the ACI is most sensitive.

The input factors relate to the various subjective choices made at each stage in the construction of the index. In this study, the choices of modifications relate to the normalization, weighting and aggregation stages. These modifications are formalized as follows:

$$ACI_i = f_{X_r}(I_{i,q} \; ; \; w_{i,q}),$$

Avec r = 1, 2, 3,…, R ; i = 1, 2, 3,..., 343 ; q = 1, 2, 3,…, 21

Where ACI_i represents the value of the adaptive capacity index for each Nigerien agricultural producer. This index is calculated on the basis of the underlying model f_{X_r}, according to different input factors X_r. In our case, we limit the index r = 3 representing the three input factors covered by UA-SA. Thus, X_1 will represent the choice of normalisation method (Min-Max or z-scores), X_2 the choice of weighting method (equal weights or AHP) and finally, X_3 the choice of aggregation method (linear or geometric). The ACI is calculated on the basis of q weighted Indicators ($I_{i,q}$) at the value $w_{i,q}$.

2.1. Uncertainty analysis

Several methods exist for carrying out an uncertainty analysis. Here, the analysis is carried out using a Monte Carlo experiment (Nardo et al., 2005; OECD, 2008) based on 10,000 samples to simultaneously explore the sources of uncertainty. Following Zanmassou et al (2020), the relative standard deviation (RSD) or coefficient of variation is used as an indicator of uncertainty:

$$RSD\ (\%) = 100 \times \left(\frac{Standard\ Deviation\ (SD)}{Mean}\right)$$

RSD measures the relative dispersion of ACI output values in the sense that low values (close to 0) of RSD mean a stable index and higher values (close to 100%) mean an unstable index.

2.2. Sensitivity analysis

Two approaches exist for a sensitivity analysis (see Iooss and Lemaître (2015) or Saisana et al. (2005) for in-depth information). There is the local approach which analyses the variability of the output (ACI_i) as a function of variations in a specific input factor (X_r). It is implemented through a simple partial derivative. Global sensitivity analysis, on the other hand, examines variations throughout the variability space of the input factors. One way of implementing it is through variance decomposition (Pianosi et al., 2016). This approach is called variance-based sensitivity analysis or Sobol indices (Saisanna et al. 2005). To do so, the variance decomposition is done through ANOVA (analysis of variance) while ensuring the normality and non-linearity of the ACI (Saltelli et al., 2017).

Given that the normality test carried out in essay 1 shows that the ACI does not follow a normal distribution and that we have adopted a linear construction of the ACI, the assumptions of Sobol's indices are violated. An alternative was to use the Kruskal-Wallis test simultaneously with the RSDs to analyze whether the distributions of the adaptability indices differed significantly according to the level of input factor. The results were then confirmed by applying the first-order Sobol indices.

III. Results and discussion

The uncertainty analysis was carried out using Monte Carlo simulation and the RSD as the uncertainty indicator. 10,000 simulations were carried out in order to calculate the ACI indices on the basis of the possible combinations of the input factors that were simulated. It was found that the combinations using the z-scores normalization method did not give any values for adaptive capacity. This is inherent in the z-score calculation method, which subtracts the mean from the indicator values and then divides them by the standard deviation of the range of values. Thus, when the values of the indicators vary considerably, as is the case with the ACI indicators, the standardized indicators tend towards zero or negative values. This is also the case when standardized indicators are aggregated geometrically. Geometric aggregation prohibits the use of the transformation of indicators into z-scores, as this is only possible for sets of positive values (Mazziotta and Pareto, 2015). Missing zero values were therefore excluded from the analysis. This resulted in a total of 16 indices. These were coded as shown in *Table 13*.

Table 14 : Code of indices from Monte Carlo Simulation

Indices	Indicator normalization method	Weighting schemes of indicators	Indicators aggregation method	Weighting schemes of components	Components aggregation method
ACI	Min-Max	AHP	Additive	AHP	Additive
ACI_MAAAG	Min-Max	AHP	Additive	AHP	Geometric
ACI_MAAEA	Min-Max	AHP	Additive	Equal weights	Additive
ACI_MAAEG	Min-Max	AHP	Additive	Equal weights	Geometric
ACI_MAGAA	Min-Max	AHP	Geometric	AHP	Additive
ACI_MAGAG	Min-Max	AHP	Geometric	AHP	Geometric
ACI_MAGEA	Min-Max	AHP	Geometric	Equal weights	Additive
ACI_MAGEG	Min-Max	AHP	Geometric	Equal weights	Geometric
ACI_MEAAA	Min-Max	Equal weights	Additive	AHP	Additive
ACI_MEAAG	Min-Max	Equal weights	Additive	AHP	Geometric
ACI_MEAEA	Min-Max	Equal weights	Additive	Equal weights	Additive
ACI_MEAEG	Min-Max	Equal weights	Additive	Equal weights	Geometric
ACI_MEGAA	Min-Max	Equal weights	Geometric	AHP	Additive
ACI_MEGAG	Min-Max	Equal weights	Geometric	AHP	Geometric
ACI_MEGEA	Min-Max	Equal weights	Geometric	Equal weights	Additive
ACI_MEGEG	Min-Max	Equal weights	Geometric	Equal weights	Geometric

The results of the uncertainty analysis using Monte Carlo simulation are shown in Table 11. The table shows that for 10000 simulations, there is a significant and critical difference between the indices that aggregated the normalized indicators using the linear method (ACI, ACI_MAAAG, ACI_MAAEA, ACI_MAAEG, ACI_MEAAA, ACI_MEAAG, ACI_MEAEA, ACI_MEAEG) and those that aggregated the indicators using the geometric approach (all the other indices). In other words, in case indicators were to be aggregated using the linear method the resulting indices meant that 50% of Niger producers showed moderate or low adaptive capacity and 50% showed moderate or high adaptive capacity. These results confirm those found in essay 1. The other indices show a very low median value (below 0.15) or close to zero, as can be seen in *Figure 11*.

Table 15 : ACI median scores and associated RSD from Monte Carlo simulation.

ACI with different input factor combinations	Median values	RSD (%)	Number of simulations
ACI	0.39	36.29	10000
ACI_MAAAG	0.32	46.79	
ACI_MAAEA	0.39	31.95	
ACI_MAAEG	0.31	44.54	
ACI_MAGAA	0.12	68.03	
ACI_MAGAG	0.05	96.17	
ACI_MAGEA	0.11	73.38	
ACI_MAGEG	0.04	103.55	
ACI_MEAAA	0.34	34.91	
ACI_MEAAG	0.30	43.44	
ACI_MEAEA	0.36	29.41	
ACI_MEAEG	0.33	38.19	
ACI_MEGAA	0.05	91.04	
ACI_MEGAG	0.03	84.39	
ACI_MEGEA	0.06	88.71	
ACI_MEGEG	0.04	83.59	
x^2	1.14***		

***0.001 level of significance

Furthermore, the indices that aggregated the indicators using the linear method had lower RSDs than the others (*figure 12*), with the exception of the indices that used the geometric aggregation method to aggregate the components into a composite index (ACI_MAAAG, ACI_MAAEG, ACI_MEAAG, ACI_MEAEG). The latter are therefore less stable and more sensitive to variations in the method of aggregating the components into an index.

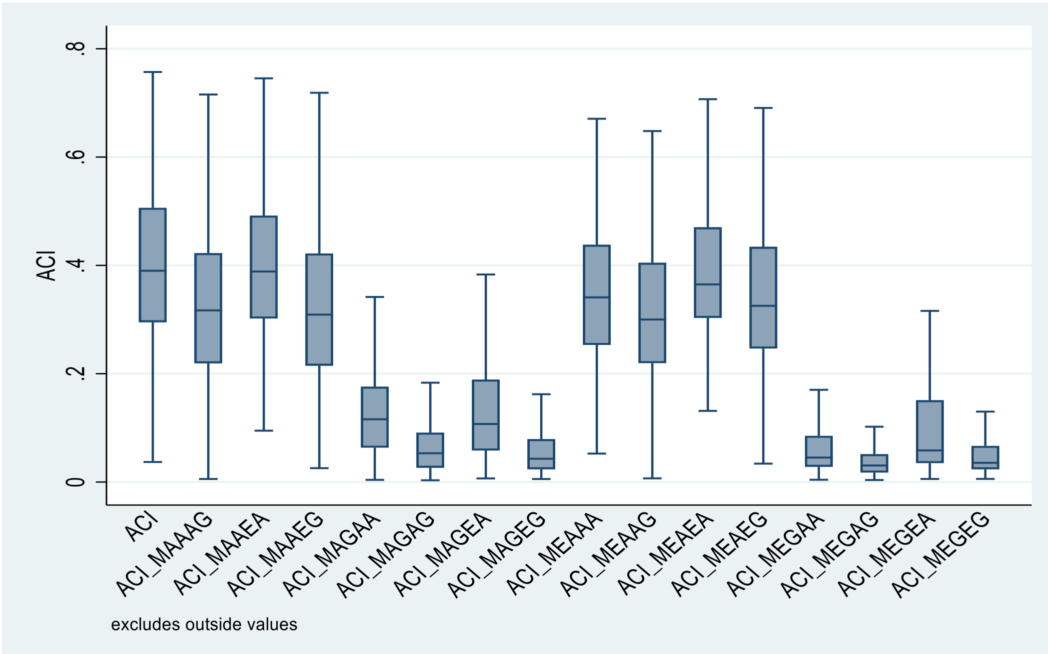

Figure 11: ACI by random combinations of input factors from 10000 Monte Carlo simulations.
The median values of indices that are based on linear aggregation of indicators are significantly different from all other indices that revealed very small median values.

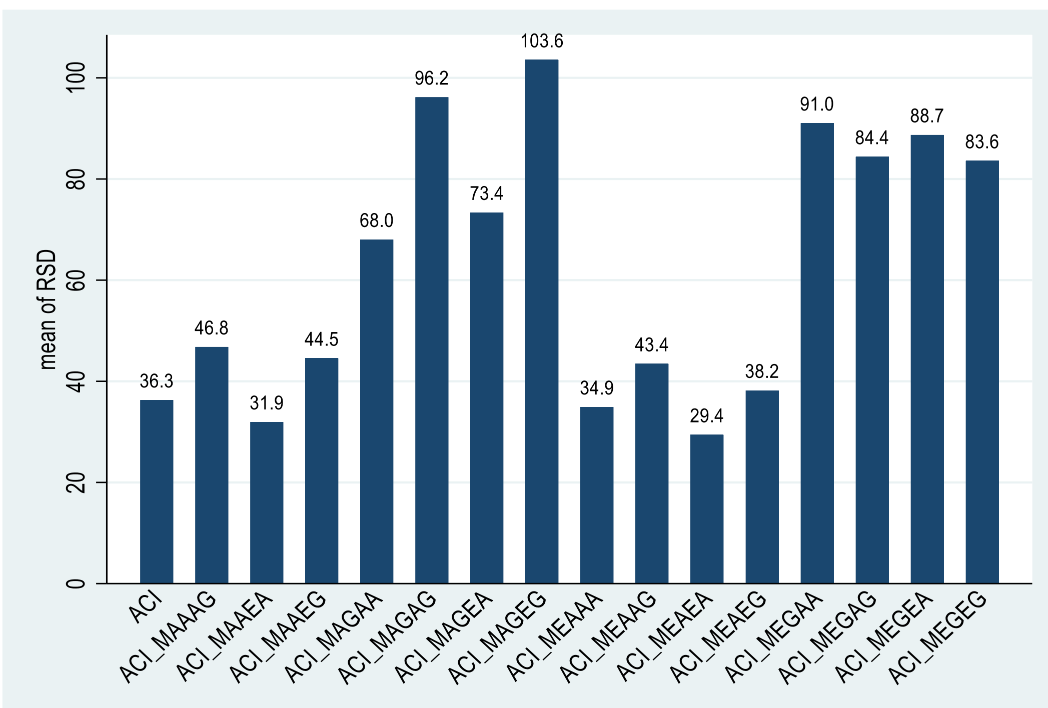

Figure 12: Relative Standard Deviation by ACI inputs factors combinations from Monte Carlo simulation**.**
Relatively stable indices are does that aggregate indices and components using an additive scheme.

These results lead us to conclude that changes in the weighting and aggregation schemes have a significant influence on the values of the ACI index. On the other hand, the ACI is much more sensitive to changes in aggregation methods. These results highlight the importance of weighting and aggregation schemes in index construction. They are consistent with the results obtained by Marzi et al. (2018) and Zanmassou et al. (2020), who showed that the adaptive capacity index is sensitive to weighting and aggregation methods. Zanmassou et al. (2020) also point to the importance of using expert weighting, which allows the perceived importance of indicators and components to be taken into account.

The global sensitivity analysis was conducted in order to gain a better understanding of which input factor has the greatest influence on the ACI and in what variation. The results of the Kruskal-Wallis test (*Table 15*) revealed that the largest significant difference lies between the RSDs of the linear (14.99%) and geometric (49.86%) aggregation factors at the indicator aggregation level. These results suggest that the change in the method of aggregating indicators is the factor that has the greatest influence on the variation in ACI values, and that the greatest variation is due to the geometric aggregation method. In terms of the other input factors, the differences in the RSDs remain similar, although significant. They are illustrated in *Figure 13*. To complete our analysis, the ANOVA results reported in *Table 16* confirm the previous results. The results show that the aggregation of indicators is by far the most influential factor in determining the ACI result - responsible for over 94% of the variation. It is followed by the aggregation of components, which is responsible for 3.8% of the variation. These results suggest that the ACI is highly sensitive to any change in the method of aggregating indicators into components, particularly when moving from linear to geometric aggregation. The logical conclusion of the combined UA-SA analyses is that the ACI is developed on a stable model.

Table 16 : Kruskal-Wallis test of influence of input factors on ACI output variation

Input factors	Indicators weighting scheme			Indicators aggregation method			Components weighting scheme			Components aggregation method		
	Experts weight	Equal weight	x^2	Linear	Geometric	x^2	Experts weight	Equal weight	x^2	Linear	Geometric	x^2
RSD (%)	65.96	77.28	54.453***	14.99	49.86	420.695***	69.03	73.26	4.018*	65.34	76.40	145.773***
Number of simulations	10000											

*0.05 level of significance; ***0.001 level of significance

Table 17 : Variance decomposition ANOVA of input factor variation to the total ACI output variation

Source	Partial SS	% of Total	df	MS	F
Model	0.310		4	0.077	351.25***
Normalization method	0.000	0	0		
Indicators weight	0.003	0.1	1	0.003	12.75**
Indicators aggregation	0.295	94.5	1	0.295	1336.68***
Components weight	0.000	0	1	0.000	1.86
Components aggregation	0.012	3.8	1	0.012	53.7***
Residual	0.002		11	0.000	
Total	0.312		15	0.021	
R-squared	0.992				
Adj R-squared	0.989				
Root MSE	0.015				

**0.01 level of significance; ***0.001 level of significance

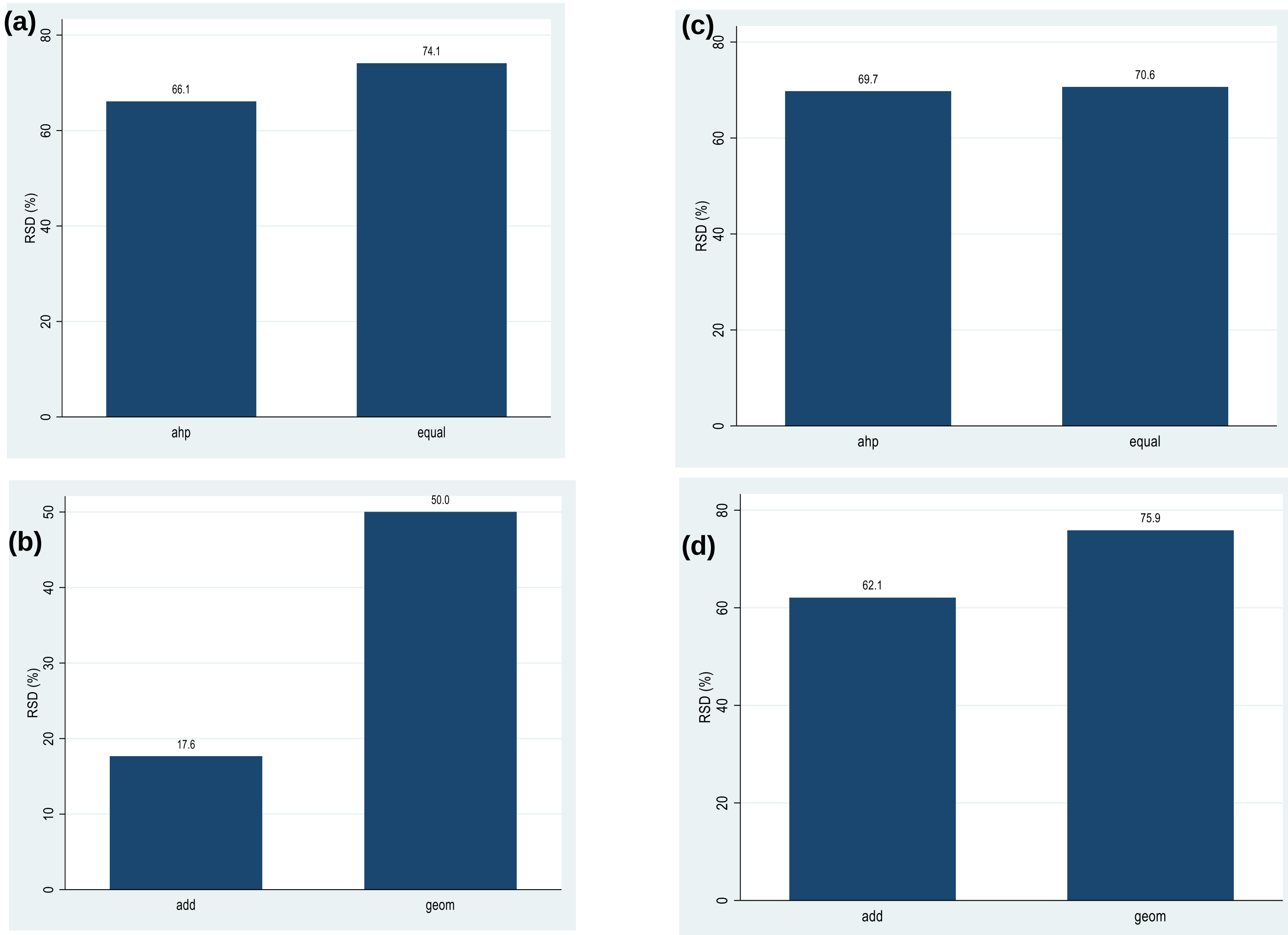

Figure 13 : Bar chart illustrating sensitivity analysis of input factors on ACI**.**

(a) Indicators weighting schemes variation; **(b)** Indicators aggregation methods modification; **(c)** Components weighting schemes variation; **(d)** Components aggregation methods modification.

Conclusion

Combined uncertainty and sensitivity analyses were conducted in this trial to ensure the robustness and transparency of the index of the adaptive capacity of Niger's agricultural producers. To this end, the normalization, weighting and aggregation methods were subjected to modifications in a Monte Carlo experiment simulated 10,000 times. The relative standard deviation (RSD) was used as an indicator of uncertainty, calculated for each level of the input factors subjected to the analyses. Finally, the Kruskall-Wallis test and the global first-order sensitivity analysis were conducted to examine the proportion of variation in the input factors responsible for the variation in the ACI.

The main results showed that changes in the weighting and aggregation schemes significantly influence the values of the ACI index, and that the ACI is much more sensitive to changes in aggregation methods. Furthermore, the results of the SA suggested that the ACI is highly sensitive to any change in the method of aggregating the indicators into components, particularly when moving from linear to geometric aggregation. These combined UA-SA analyses have led to the conclusion that the ACI is based on a stable, solid and reproducible model. However, there is still a need for future research to also examine the interaction between the input factors for a more complete but complex AS analysis.

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ESSAY 3: ANALYSIS OF THE IMPACT OF CLIMATE CHANGE-INDUCED LABOR DIVERSIFICATION

Abstract

The analysis of agricultural labor supply under conditions of structural and climatic change constitutes a central focus of this study. This issue has attracted growing attention from both the academic community and policymakers, particularly in light of the need to safeguard the primary livelihood of poor farming households in developing countries—livelihoods that are increasingly exposed to climate-related shocks—and to advance the overarching objective of poverty reduction in rural economies. The objective of this essay is to analyze the labor supply behavior induced by climate shocks in order to better inform policy-making process and enable more effective support for Nigerien producers. The essay based on a single-country static computable general equilibrium (CGE) model (DEMETRA) calibrated on a 2019 Social Accounting Matrix (SAM), to examine labor reallocation among Nigerien farming households following a climate-induced 20% decline in agricultural productivity. Two main findings emerge. First, climate-induced agricultural productivity shocks generate a broad-based decline in production across all sectors, reduce household incomes, and contract demand for goods and services, thereby affecting labor demand in multiple activities. These effects exhibit marked regional heterogeneity, particularly in the Agadez region. Second, households affected by the productivity shock demonstrate a short-term capacity to adjust by reallocating labor toward agricultural and food-processing activities in neighboring regions with relatively higher agricultural productivity. Agricultural labor thus responds to economic incentives linked to productivity differentials and is systematically redeployed as a strategy to smooth consumption in the face of declining incomes. The findings underscored the need an urgent development of irrigation infrastructure, as well the promotion of agro-processing activities.

Key-words: labor supply, labor diversification, Niger, DEMEMTRA, SAM

Introduction

Previous research has established labor diversification as a key adaptation strategy through which households seek to mitigate the adverse effects of climate change. Labor constitutes the primary source of income for most households worldwide and is particularly critical for poor households in Niger. At the same time, it represents an essential input in crop production and across the entire agri-food system. Among factors of production, labor is also one of the most persistently disrupted by climate-related shocks. Global evidence indicates that major climate change drivers, notably temperature and precipitation, exert substantial effects on per capita income, with disproportionately severe consequences for households in developing countries. Despite this growing body of literature, understanding of labor dynamics in the context of climate change remains fragmented (Hill et al., 2021; Feriga et al., 2024). This gap in knowledge, combined with Niger's high vulnerability to climate change, underscores the need for a comprehensive analysis of how climate change influences the reallocation of agricultural labor in the country. Climate change is projected to increase the frequency and intensity of extreme weather events, which recent studies have shown to significantly affect labor allocation decisions, including agricultural labor supply and migration patterns (Jessoe et al., 2018). Although the precise nature of future labor responses remains uncertain, these issues have been identified as a top priority for both researchers and policymakers (Hill et al., 2021).

Against this backdrop, the objective of this study is to examine household labor supply behavior in response to climate change–induced productivity shocks. The analysis is conducted using a static single-country computable general equilibrium model (DEMETRA), implemented through a simulation scenario that imposes a uniform 20 percent reduction in the agricultural efficiency factor across Niger's eight regions.

The remainder of the essay is organized as follows. *Section I* presents the demographic and labor market characteristics of Niger to highlight the relevance of climate change–induced labor reallocation. *Section II* discusses the theoretical and empirical mechanisms through which climate change may affect labor allocation decisions. *Section III* describes the methodological framework. *Section IV* provides a descriptive overview of Niger's economic structure and income distribution. Finally, *Section V* presents and discusses the results, before concluding with key policy implications.

I. Demographic and Labor Market Context in Niger

This section provides an overview of Niger's demographic and labor market structure in order to underscore the critical importance of examining the interactions between climate change and labor dynamics.

Niger is characterized by rapid population growth and a youthful demographic profile. National statistics estimate the population at over 23 million, growing at an annual rate of 3.7% in 2021, the highest in Africa (INS, 2023a). The country has one of the world's largest youth populations: individuals under 25 years account for approximately 70% of the total population, while those of working age (15–64 years) represent about 47% (DTDA, 2022). Fertility remains among the highest globally, declining only marginally from 7.8 live births per woman in the 1980s to 7.6 in 2019 (MESUDD, 2021; DTDA, 2021). These demographic dynamics are reflected in large household sizes, averaging 5.9 persons per household in 2017 (INS, 2016). Collectively, these patterns pose significant challenges for the country's socioeconomic development, notably in the provision of education, health care, food security, social protection, and employment, while exerting increasing pressure on scarce natural resources such as water and arable land.

Rapid demographic expansion also translates into considerable labor market pressures. Each year, over 500,000 young people enter the labor force (WB, 2017), intensifying competition for limited employment opportunities. The public sector—the main formal employer—has seen its labor demand grow by less than 2% annually, compared to an estimated 23.4% annual increase in labor supply (Saadatou et al., 2023). Despite these imbalances, unemployment, as defined by the International Labor Organization (ILO)[13], remains relatively low, estimated at 7.2% in 2017 (INS, 2016), primarily because most people cannot afford to remain without work in what the ILO describes as an economy "*too poor to be unemployed*" (Mueller, 2021). However, underemployment affects nearly one-third of the working-age population, with young people particularly vulnerable. The share of youth not in employment, not in education, nor in training (NEET) stands at 69%, significantly exceeding rates in neighboring countries (DTDA, 2021).

Spatial and sectoral characteristics further shape Niger's labor dynamics. Approximately 80% of the population resides in rural areas, mainly concentrated in the southern belt, which represents only 12% of the national territory but contains nearly all arable land (WB, 2017). Rural livelihoods are dominated by agriculture and livestock rearing, sectors that are highly dependent on climatic conditions and thus extremely vulnerable to climate variability. In addition to unemployment and underemployment, the predominance of informal self-employment—both agricultural and non-agricultural—illustrates the structural challenges facing Niger's labor market. The informal sector accounts for about 60% of GDP and employs more than 80% of the labor force (INS, 2016; WB, 2017; DTDA, 2022). It is characterized by limited institutional support, including weak social

[13] It refers to a person aged 15 or over who is without work, available for work within 15 days, and has actively sought work during the past four weeks or has found work that will start within three months (see for example INSEE).

safety nets, restricted access to finance, and insufficient agricultural extension services, all contributing to widespread economic precarity (KIT, 2020; Corta et al., 2021)). Employment in this sector is often seasonal, poorly remunerated, and insufficient to meet basic consumption needs, contributing to persistently low levels of labor productivity growth (WB, 2017; DTDA, 2021).

In a context of high population growth and pervasive informality, the capacity to generate decent and productive employment must outpace demographic expansion if development progress is to be sustained (GIZ, 2020). Otherwise, structural challenges such as food insecurity, poverty, inequality, conflict, and migration will remain entrenched. Against this backdrop, climate change represents a profound additional stressor. Niger's agricultural producers face chronic exposure to droughts, desertification, and erratic rainfall, all of which undermine agricultural and pastoral productivity and exacerbate income instability.

Taken together, Niger's demographic profile, labor market structure, and environmental vulnerability make it a compelling natural laboratory for studying how climate shocks influence labor reallocation in agrarian, climate-sensitive economies. The fragmentation of labor markets (Dedehouanou et al., 2018; Corta et al., 2021) necessitates strong institutional and policy support to enhance adaptability and resilience. Consequently, both academic inquiry and policy design addressing climate change in Niger must place labor dynamics at the center of analysis.

II. Climate change-labor reallocation mechanisms

Research on the diversification of rural farming household incomes has a long-standing tradition. In developing countries, the labor supply decisions of rural households have occupied a central place in both theoretical and empirical debates surrounding structural transformation—a process through which households reallocate labor across sectors (agricultural versus non-agricultural) and geographic spaces (rural, urban, or through internal and international migration) as labor productivity rises (Lewis, 1954; Harris and Todaro, 1970; Haggblade et al., 1989, 2010; Christiaensen et al., 2021). This reallocation supports the development of local and national economies by reducing the relative importance of agriculture and fostering the expansion of the non-agricultural economy, enabling households to access employment opportunities with higher returns to labor.

Given the empirical significance of both rural agricultural and non-agricultural sectors for economic growth and poverty reduction—particularly in low-income rural settings—the literature on structural transformation has stimulated extensive theoretical and empirical inquiry into the interdependencies between these sectors in order to better inform policy design (Barrett et al., 2001; Janvry et al., 2005; Anríquez and Daidone, 2010; Dorosh and Mellor, 2013; Brauw et al., 2014; Charlton and Taylor, 2016; Djoumessi et al., 2019; Dinkelman and Ngai, 2022). A recurring conclusion across these studies is that although participation in non-agricultural activities is generally positively associated with income and wealth in rural Africa (Barrett et al., 2001;

Dorward, 2013), agricultural and non-agricultural sectors are often complementary. Their growth dynamics are intertwined through investment, production, and consumption linkages across the rural economy (Davis et al., 2017). Both sectors form part of intricate livelihood strategies shaped by a wide array of factors that influence and constrain the movement of labor off the farm. Accordingly, numerous economic models have been developed to explain the "*push*" and "*pull*" factors underlying labor reallocation across sectors and space (Barrett et al. (2001), Haggblade et al. (2010), Harris and Todaro (1970) and Timmer (2009), among others).

The climate shocks analyzed in this study affect labor returns directly, reducing the relative attractiveness of agricultural activities and potentially intensifying the drivers of labor reallocation. These shocks may compel workers to seek opportunities outside agriculture or beyond their localities in an effort to stabilize income and maintain consumption levels (Branco and Féres, 2021). The following section outlines the mechanisms through which climate change may influence labor reallocation, thereby guiding the empirical investigation for the specific case of Niger.

2.1. Productivity shocks and labor reallocation

In developing countries, the diversification of income-generating activities is widespread (Barrett et al., 2001; Davis et al., 2017). Such diversification emerges endogenously from diminishing marginal returns to factors of production, particularly labor. Labor constitutes the principal input in agricultural production and serves as the primary means of subsistence for poor rural households, which typically operate small-scale, labor-intensive farms. From a theoretical standpoint, a negative shock to agricultural output reduces the marginal product and, consequently, the marginal value product of labor (Taylor and Charlton, 2019). This decline translates into lower incomes for subsistence-dependent farming households, compelling them to engage in alternative livelihood activities to smooth both income and consumption over time. Hence, diversification—beyond being a hallmark of structural transformation—also functions as a "*self-insurance*" mechanism for managing risk (Reardon et al., 1992, 1998; Barrett et al., 2001).

Recent empirical syntheses indicate that climate-related shocks, including extreme weather events, generally exert negative effects on labor productivity across diverse contexts, model specifications, scales of observation, and production systems (Dell et al., 2014; Feriga et al., 2024). Climate change therefore heightens vulnerability and income volatility, exacerbating poverty risks. In this regard, labor reallocation represents a key adaptive response for agricultural households (Emran and Shilpi, 2017; Jessoe et al., 2018). Assuming fixed total household labor time and frictionless mobility across sectors and space, households may opt to allocate their labor toward non-agricultural activities, particularly in manufacturing or services. Empirical evidence from Indonesia shows that shocks causing crop losses significantly reduce the number of hours worked on farms relative to non-shock years (Cameron and Worswick, 2003).

Similarly, Indian households experiencing persistent climate-induced declines in agricultural income were found to be 12% more likely to engage in non-agricultural employment (Blakeslee et al., 2020). Comparable patterns have been documented in Ethiopia, Malawi, and Uganda (McCullough, 2017; Musungu et al., 2023), Zimbabwe (Josephson and Shively, 2021), in Ethiopia (Musungu et al., 2023) as well as in India (Colmer, 2021), China (Huang et al., 2020) and Brazil (Branco and Féres, 2021), where elevated temperatures or drought events induced households to reallocate labor toward informal self-employment, service provision, or manufacturing. Non-agricultural jobs are typically less sensitive to climatic variability, and the additional income derived from such activities can offset agricultural income losses (Minale, 2018; Feriga et al., 2024). Urban labor markets similarly absorb displaced rural labor, as they are less directly affected by climatic conditions and tend to offer more remunerative employment opportunities (Brauw et al., 2014; Minale, 2018; Barrett et al., 2023).

Taken together, this body of research suggests that households are able to adjust their labor supply in response to climate-related shocks, thereby partially mitigating associated economic losses. Several studies further underscore the importance of distinguishing between short- and long-run behavioral responses, noting that labor reallocation is often transitory rather than permanent (Emerick, 2018; Minale, 2018; Feriga et al., 2024).

Conversely, when market imperfections—such as failures in insurance, credit, or labor markets—and mobility costs are present, households' capacity to smooth consumption and mitigate adverse climatic impacts is significantly constrained (Cameron and Worswick, 2003; Minale, 2018; Colmer, 2021; Liu et al., 2023). These mechanisms are further examined in *Section 2.3*.

2.2. Labor demand effect

The preceding section established that households can reallocate their labor toward non-agricultural activities or migrate to less-affected areas in response to climate-induced productivity declines. When general equilibrium mechanisms are considered, however, additional channels emerge through which climate shocks influence labor allocation.

Following the framework of Liu et al. (2023), suppose that productivity losses from climatic shocks occur exclusively in the agricultural sector, while productivity in non-agricultural activities remains unaffected. Under these assumptions, a decline in agricultural productivity reduces household income, thereby depressing demand for locally produced non-agricultural goods and services. This contraction in demand, in turn, lowers labor demand in the non-agricultural sector and may induce a reallocation of labor back into agriculture. Conversely, in the presence of "pull factors"—such as increases in agricultural productivity—household incomes rise, stimulating demand for local non-agricultural goods and services. As Emerick (2018) notes, this increased demand can draw labor away from agriculture and toward non-agricultural activities.

In both cases, two conditions strengthen the dominance of local demand effects. First, a high degree of consumption complementarity between agricultural and non-agricultural goods amplifies the demand response to changes in agricultural productivity (Foster and Rosenzweig, 2004). Second, differences in income elasticities reinforce these dynamics. Under Liu et al. (2023), agricultural goods have lower income elasticity than non-agricultural goods, whereas in Emerick (2018), agricultural goods exhibit higher income elasticity. Theoretical models of structural transformation often incorporate Stone-Geary preferences precisely to reproduce these patterns (Matsuyama, 1992; Kongsamut et al., 2001; Gollin and Rogerson, 2014; Herrendorf, 2014).

In this study, which focuses on the effects of climatic shocks on labor supply distribution, we adopt the assumptions proposed by Liu et al. (2023). Under these conditions, a reduction in agricultural productivity is expected to decrease the supply of non-agricultural labor in rural areas. Moreover, because of strong input–output linkages across sectors, a contraction in agricultural output can reduce labor demand in industries that rely on agricultural inputs (Acemoglu et al., 2012), such as agro-processing and agriculture-related manufacturing. A decline in agricultural income may also lower productivity in the non-agricultural sector by depressing demand for locally produced goods and services (Minale, 2018).

Empirical evidence from multiple developing countries supports these mechanisms. In Mexico, extreme heat has been associated with a 1.4% decline in rural employment over a 28-year period, largely due to reduced agricultural yields, with the most pronounced effects observed in non-agricultural employment because of falling demand for non-agricultural goods (Jessoe et al., 2018). In South Africa, droughts significantly affect employment patterns, with differentiated impacts across formal and informal labor markets (Brookes Gray et al., 2022). Comparable findings emerge from India, where reductions in household consumption of food and non-food items in response to temperature increases translate into contractions in local demand (Liu et al., 2023).

2.3. Liquidity and mobility cost of labor reallocation

The mechanisms outlined above rest on the critical assumption of perfect labor mobility across sectors. However, the movement of workers from agriculture to non-agricultural activities—or to urban labor markets—may be severely constrained when liquidity limitations and mobility costs are high. In practical terms, labor reallocation requires both the availability of more remunerative non-agricultural opportunities and sufficiently low costs associated with changing sectors or locations. When climate shocks reduce household income, the combined burden of liquidity constraints and mobility expenses can pose an even greater barrier to mobility (Liu et al., 2023). Empirical evidence shows that upfront migration costs constitute a major impediment preventing rural households from relocating (Barrett et al., 2001; Bryan et al., 2014; Kleemans, 2015; Letta et al., 2024). Because sectoral labor shifts often entail some form of migration, these constraints jointly decrease the likelihood that workers will transition into relatively unaffected non-agricultural sectors or areas. In the context of this study, we expect such frictions to be particularly binding in rural areas of Niger, where transportation infrastructure remains underdeveloped and access to formal credit is limited or absent.

III. Materials and method

Throughout this document, it has been shown that agriculture constitutes a central pillar of Niger's local economy and remains a primary source of income for a substantial share of the population. Consequently, productivity shocks affecting this sector are likely to generate significant spillover effects across the broader economy through general equilibrium channels. To account for these intersectoral linkages, the present study employs a static single-country Computable General Equilibrium (CGE) model to assess the impacts of negative productivity shock scenarios induced by climatic events and to capture the dynamics of the mechanisms discussed in the preceding sections.

3.1. The model

This study employs the Dynamic Equilibrium Model for Economic Development Resources and Agriculture (DEMETRA)[14], a single-country Computable General Equilibrium (CGE) model. DEMETRA is a development of the STAGE_DEV models (McDonald et al., 2016), which in turn is a variant of STAGE_2. The model is designed to assess the economic and distributional effects of policy and structural shocks, as well as the mechanisms through which sectoral policies transmit across sectors, agents, and regions. The model incorporates a set of additional behavioral relationships intended to more accurately capture the structural characteristics of developing economies, including the dual role of semi-subsistence agricultural households, a nested consumption structure, the endogeneity of functional income distribution, internal migration dynamics, and segmented factor markets.

In contexts where agriculture dominates economic activity and subsistence farming persists, DEMETRA provides a particularly suitable framework, owing to its detailed disaggregation of the rural economy by agricultural activity and household type. The model also strengthens the representation of structural rigidities—such as unemployment and underemployment—and accounts for time allocated to non-market activities outside the formal production frontier. Moreover, DEMETRA features an explicit modeling of labor markets and migration flows and differentiates between irrigated and rainfed agricultural systems. Subsistence farming is represented using distinct production technologies characterized by lower intermediate input and capital shares relative to commercial agriculture.

[14] See the DEMETRA model documentation for more insights.

The Niger-specific version of the model incorporates a detailed disaggregation of labor by types (farm, off-farm and mixed), household categories, and agricultural activities to reflect the diversity of agricultural production systems. The model operates under the assumption of perfect competition, implying that prices and quantities adjust freely without the influence of market power on either the supply or demand side.

Production technologies follow a nested structure. Intermediate inputs and primary factors are combined using Leontief technology to produce gross output, while value added is generated through a CES aggregation of labor and capital. Labor is assumed to be perfectly mobile across all production sectors, whereas capital is fixed within sectors. The labor force grows annually in line with population growth, while sectoral capital stocks evolve according to new investment flows.

Household consumption follows a Stone–Geary utility specification. Income sources differ across household types: farming households receive only a modest income share, wage-earning households depend primarily on labor income, and entrepreneurial households derive income from subsidies and remittances. Government revenues come from taxes, while public expenditures are fixed. Money serves solely as a medium of exchange, and monetary policy interventions affecting real economic activity are not modeled.

On the goods market, domestically produced and imported goods—sourced from Africa or the rest of the world—are treated as imperfect substitutes following Armington's assumption (Armington, 1969). The model distinguishes between subsistence and commercially oriented goods and employs an accounting framework that tracks production destined for self-consumption. Goods used for domestic self-consumption are exempt from consumption taxes, and factor use is similarly untaxed.

3.2. Market clearing

The market equilibrium conditions ensure the simultaneous clearing of all markets. In factor markets, equilibrium is achieved when factor demand, unemployment, and factor supply by institutions are equalized for all factors, and when the supply of each factor matches the supply provided by institutions. For analytical simplicity, the present study assumes full employment—that is, zero unemployment. Under this assumption, wages adjust endogenously to clear the market, while factor endowments remain fixed. It is important to note, however, that the model is sufficiently flexible to accommodate unemployment rates greater than or equal to zero, where unemployment is computed as the ratio of unemployed labor to total factor supply.

As previously indicated, DEMETRA incorporates household migration and labor mobility across sectors, thereby relaxing the restrictive assumption of rigid segmentation of representative household groups (RHGs) and production factors typically embedded in conventional CGE models. The behavioral hypothesis underlying this mechanism posits that RHGs respond to economic incentives associated with changes in relative returns. Accordingly, when representative households in one segment experience a relative increase in income compared with other RHGs, they become incentivized to relocate to the segment enjoying the improved returns. Relative incomes (YMIGR) are defined in Equation (1). Changes in these relative incomes are subsequently used to compute the per capita income migration driver (HMIGDRV), based on the benchmark-period relative income (YMIGRA), as shown in Equation (2).

$$YMIGR_{ins,insp} = \frac{YH_h}{POPN_h} \Big/ \frac{YH_{hp}}{POPN_{hp}} \; ; \forall inswmig_{h,hp} \qquad \textbf{(1)}$$

$$HMIGDRV_{ins,insp} = YMIGR_{ins,insp} \Big/ YMIGRA_{ins,insp} \qquad \textbf{(2)}$$

Here, $YMIGR_{ins,insp}$ denotes the relative income of the receiving RHG (*ins*) relative to the origin RHG (*insp*). YH and POPN represent the income and population, respectively, of the origin (*hp*) and host (*h*) RHGs.

The set $inswmig_{h,hp}$ defines the pairs of RHGs between which migration is possible, operationalized in the model through the specification of migration elasticities (*etam*). Following Liu et al. (2023), and in recognition of labor market fragmentation and the inadequacy of transport infrastructure in Niger, this study adopts migration elasticities of less than one for all movements, both across sectors and geographical spaces.

Migration incentives are further incorporated into the computation of the share of the migrant population (SHMIG). Equation (3) determines this share and allows for the inclusion of a constant term (MIGCONS) when exogenous migration determinants must be introduced. The variable component captures the combined effects of per capita income (HMIGDRV) and wages (FMIGDRV), moderated by the migration elasticity, which may be specified for each RHG–factor pair.

$$SHMIG_{f,h,fp,hp} = MIGCONS_{f,h,fp,hp} + (-1 + \left(HMIGDRV_{h,hp} * FMIGDRV_{f,fp}\right)^{etam_{f,h,fp,hp}}) \; ; \forall etam_{f,h,fp,hp} \qquad \textbf{(3)}$$

The quantity of factors migrating from institution hp to h, and from factor fp to f, is then determined as a function of the migrant population share and the initial supply of factor fsia held by institution hp for factor fp during the reference period (Equation 4).

$$FSI\_PGR_{h,l} = fsia_{h,l} + POPCHNG_h * \frac{fsia_{h,l}}{\sum_{ip} fsia_{h,lp}} \qquad \textbf{(4)}$$

The total factor supply by institution/RHG is updated in Equation (5), accounting for changes in factor supply due to population growth (Equation 4) and the net effects of migration.

$$FSI_{ins,f} = FSIP\_PGR_{ins,f} + \sum_{insp,fp} FSIM_{f,ins,fp,insp} - \sum_{insp,fp} FSIM_{fp,insp,f,ins} \qquad \textbf{(5)}$$

Finally, equilibrium in commodity markets requires that the supply of each composite commodity equals total domestic demand, which comprises intermediate demand from households, enterprises, and government, as well as final investment demand.

3.3. Data and scenario

The model relies primarily on the aggregated 2019 Social Accounting Matrix (SAM) produced by the National Institute of Statistics. This matrix is itself constructed from the Supply and Use Table (TRE), the Integrated Economic Accounts Table (TCEI), and data from the 2019 Harmonized Survey on Living Conditions of Agricultural Households (EHCVMA). Several structural refinements were introduced to enhance the representativeness of the Nigerien economy. These include: the disaggregation of the agricultural account to distinguish major crop categories; the disaggregation of households by rural–urban residence and by income quintile; the differentiation of labor by residence and labor categories (farm, off-farm and mixed); and the introduction of a land account that distinguishes irrigated from non-irrigated land across the country's eight regions.

Overall, the 2019 Niger SAM comprises 46 activities, including 16 regional household agricultural activities (eight related to crop production and eight to livestock production) and 30 additional activities spanning other primary sectors such as manufacturing, public administration, construction, and various service sectors. The SAM also accounts for 101 commodities, of which 31 correspond to household subsistence commodities and 70 to marketed commodities. Furthermore, it distinguishes 16 representative household groups, categorized by region (eight regions) and by place of residence (rural or urban).

Because there is no straightforward method to represent climate shocks directly within a CGE framework, modelers often resort to sector-specific agricultural models to simulate productivity impacts. In the context of this study on Niger, implementing the sectoral provisions of the National Adaptation Strategy and Plan for Climate Change in the Agricultural Sector (SPN2A 2020–2035) (MESUDD, 2020) required an agricultural modelling exercise to assess the potential effects of climate change on yields of the country's principal crops (Lona et al., 2019). That supporting analysis projects a 10–20% decline in yields for most rainfed crops by 2050, relative to 2020 conditions. Consequently, in the present study, the effects of climate change on labor reallocation are examined through a static CGE scenario in which factor efficiency is uniformly reduced by 20 percent to approximate the anticipated productivity shock, using General Algebraic Modeling System (GAMS).

IV. Economic overview and income distribution in Niger

This section characterizes the structure of the Nigerien economy through an examination of key aggregates derived from the 2019 Social Accounting Matrix (SAM). The descriptive analysis highlights several fundamental features of the economy, including household consumption patterns, income distribution, and sectoral composition.

Figure (14) presents the structure of Niger's foreign trade and domestic absorption in 2019. Domestic absorption amounted to approximately 113 percent of GDP, indicating that total consumption and investment exceeded domestic output. This imbalance reflects Niger's substantial reliance on imports, which accounted for roughly 28 percent of GDP, to satisfy domestic demand. By contrast, exports represented only about 12 percent of GDP, underscoring a persistent trade deficit characterized by significantly higher import volumes than export earnings.

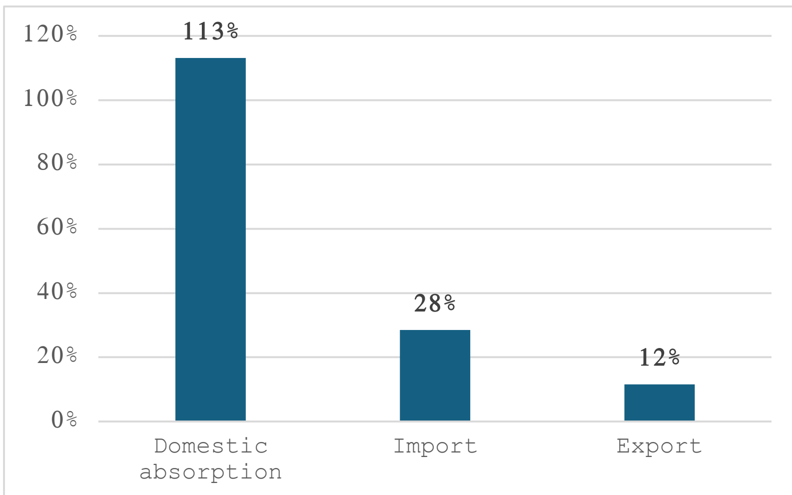

Figure 14: Domestic absorption, imports and exports of Niger in 2019, as a percentage of GDP.

At the household level, consumption patterns vary markedly by place of residence (*Figure 15*). Rural households account for a larger share of total consumption expenditure, representing approximately 58 percent of aggregate household spending. This pattern likely reflects the predominance of food consumption in rural household budgets and, consequently, a heightened vulnerability to shocks affecting agricultural output and food prices. *Figure 15(b)* further disaggregates household consumption by sector, irrespective of location, and indicates that approximately 37 percent of total consumption is allocated to goods from the primary sector, underscoring households' strong reliance on subsistence agriculture.

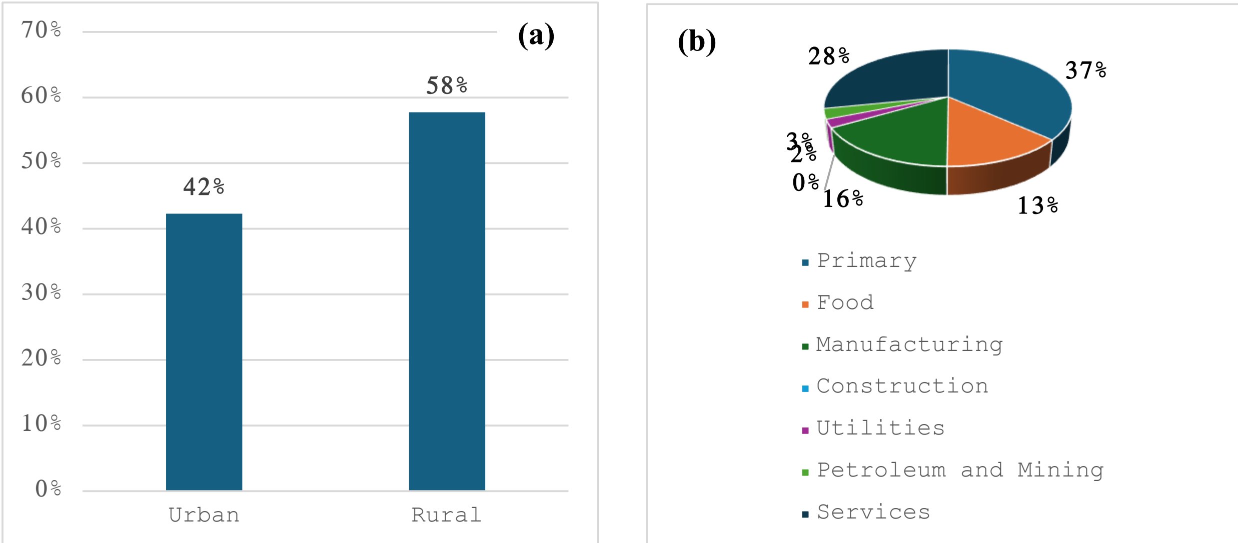

Figure 15 : Household consumption patterns according to place of residence (a), then across sectors (b).

Source: Authors, based on Niger SAM 2019.

Table 17 reports the distribution of income flows across labor and capital. The results indicate that household income in Niger is predominantly labor-based, with labor accounting for 74 percent of total income compared to 26 percent derived from capital. This composition reflects the dominance of labor-intensive activities, particularly in agriculture. The agricultural sector—encompassing both crop production and livestock—employs the largest share of the rural labor force, accounting for approximately 41 percent of the population. This proportion increases to 76 percent when households engaged in one or more secondary non-agricultural activities, mainly in industry and services, are included. This structure highlights the prevalence of livelihood diversification in rural Niger, where seasonal employment, migration, and self-employment often coexist within the same household as adaptive strategies in contexts characterized by high exposure to shocks and limited asset endowments. Recent studies have shown that self-employment outside the agricultural sector (Dedehouanou et al., 2018) and migration of all kinds (Corta et al., 2021; DTDA, 2022) remain important sources of income for Nigerien farming households. These subsistence strategies tend to complement agricultural activities, aiming to smooth income and lift people out of poverty (WB, 2017; Asfaw et al., 2018).

Table 18 : Distribution of factor income flows by aggregate activities (% of value added). Niger 2019

	Labor			Total Niger	
	Farm	Off-farm	Mixed	Labor	Capital
Rural Niger	**41%**	**25%**	**35%**	**74%**	**26%**
HH - Agadez	41%	34%	25%		
HH - Diffa	50%	25%	25%		
HH - Dosso	41%	26%	33%		
HH - Maradi	40%	15%	44%		
HH - Niamey	11%	81%	9%		
HH - Tahoua	53%	20%	27%		
HH - Tillabéri	36%	29%	35%		
HH - Zinder	29%	28%	44%		
Urban Niger	**3%**	**90%**	**8%**		
HH - Agadez	5%	92%	3%		
HH - Diffa	5%	84%	11%		
HH - Dosso	8%	59%	33%		
HH - Maradi	3%	80%	17%		
HH - Niamey	0%	99%	1%		
HH - Tahoua	11%	62%	27%		
HH - Tillabéri	8%	77%	14%		
HH - Zinder	1%	98%	1%		

Source : Athors, based on Niger SAM 2019

The table also reveals pronounced differences between rural and urban labor structures. Urban areas are dominated by non-agricultural activities, which employ approximately 90 percent of urban households. Income in urban settings is derived primarily from salaried or self-employed work in manufacturing, public administration, and service sectors, which tend to be less vulnerable to climatic shocks and generally offer higher returns. An exception is Niamey, where the non-agricultural sector predominates regardless of place of residence. As the administrative capital of Niger, Niamey exhibits an economic structure typical of capital cities, with limited reliance on agriculture. In light of these patterns, one might expect productivity shocks to exert broadly similar income effects across regions, with the notable exception of Niamey.

V. Results

In this study, climate change, as an exogenous shock, was implemented by reducing the agricultural production efficiency factor by 20% in the eight regions of Niger. This section presents the main results of the diverse impacts on labor reallocation, derived from the single-country DEMETRA static model.

5.1. Impact of productivity shock on production output and income

In economic theory, a reduction in factor efficiency—commonly modeled as a negative productivity shock—has direct implications for output levels and factor returns (Harris and Todaro, 1970; Timmer, 1988; Colmer, 2021). The simulation results presented in Figure 15(b) are consistent with these theoretical predictions. Specifically, the productivity shock leads to substantial contractions in agricultural output (–18%) and livestock production (–13%), with considerably smaller effects observed in other sectors. The magnitude of the decline in agricultural production, which closely mirrors the exogenous 20% reduction in agricultural productivity imposed in the model, underscores the pronounced vulnerability of Niger's agricultural sector to climate change–related shocks (ME/LCD et al., 2020; Röhrig et al., 2022; Zakari et al., 2022). Given the central role of agriculture in the national economy, Baptista et al. (2024) similarly estimate that climate change would exert a negative impact on aggregate production. In line with these findings, the present study reports an overall decline of approximately 7% in both GDP and government revenues (see *Appendix*).

As anticipated, the adverse effects of climate-induced productivity shocks on agricultural output are broadly similar across Niger's eight regions (*Figure 16(a)*), with estimated reductions ranging from 15% to 20%. Nonetheless, the regions of Dosso, Maradi, Tahoua, and Zinder exhibit the most pronounced contractions. These regions constitute major agricultural zones and are recurrently exposed to climate-related hazards, which exacerbates their susceptibility to productivity losses (Zakari et al., 2022). By contrast, regional impacts in the livestock sector display greater heterogeneity. The largest declines in livestock production are observed in Agadez, Diffa, Tillabéri, and Zinder. According to the Livestock Farming and Household Living Conditions survey (INS, 2023b), these regions are characterized by a high prevalence of livestock-rearing households, exceeding 50% of surveyed households. On average, livestock farming accounts for approximately 39% of household income in these areas, while poverty rates reached nearly 36% in 2021. This combination of income dependence and high poverty levels highlights the heightened vulnerability of these households and their limited capacity to absorb or adapt to climate-induced productivity shocks in the livestock sector.

Finally, it is important to note that productivity shocks originating in the agricultural sector also generate spillover effects on non-agricultural sectors, although the magnitude of these effects is comparatively modest (*Figure 16(b)*). These results point to the existence of intersectoral linkages through input–output relationships and local demand channels, which are examined in greater detail in the following section.

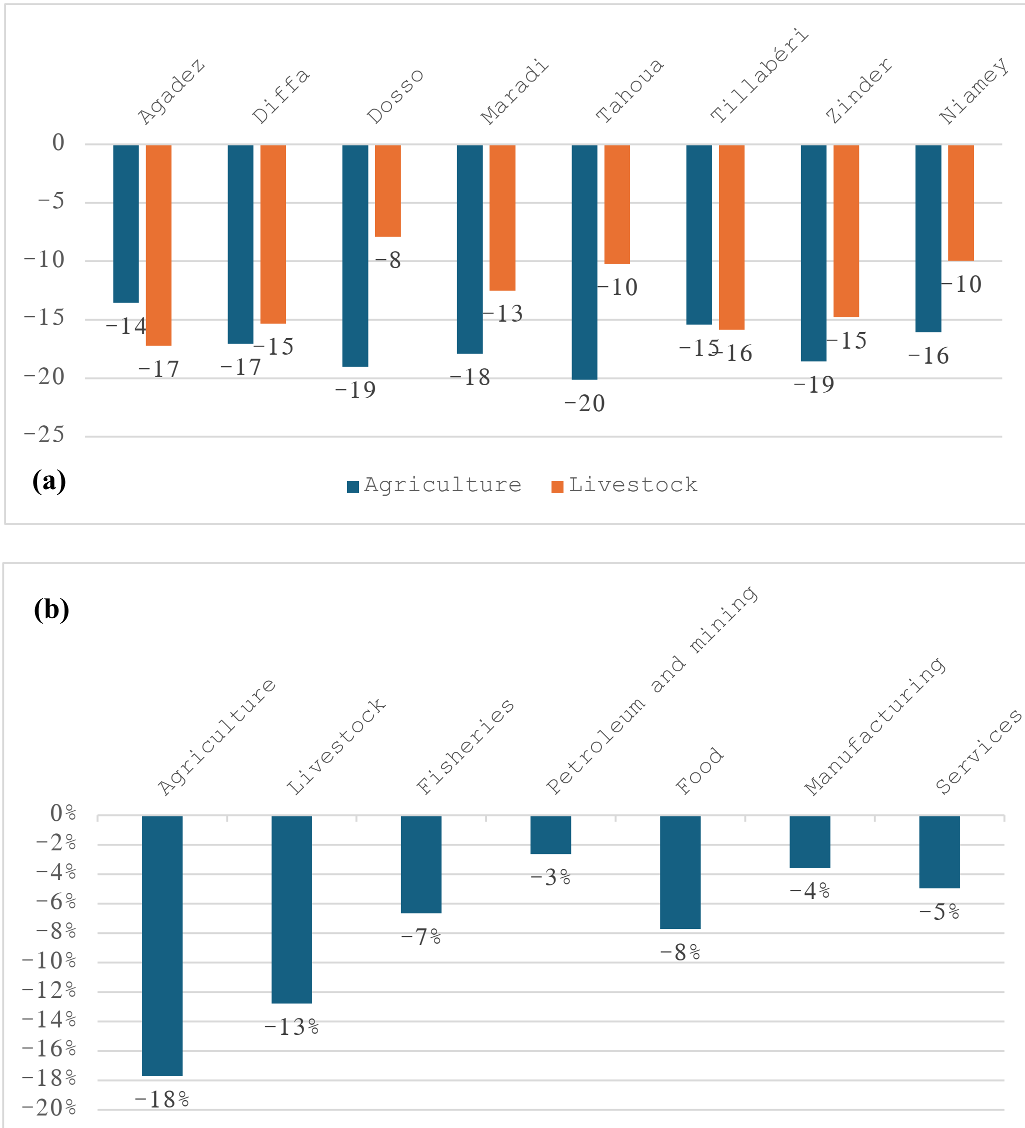

Figure 16: Productivity choc on domestic production across regions (a) and sectors of activity (b).

Source: Authors, based on scenario simulation.

Figure 17 presents changes in labor factor returns across regions and places of residence, disaggregated by type of labor. Overall, the results indicate that the agricultural productivity shock exerts a negative effect on household labor incomes across all labor categories, in both rural and urban areas. On average, labor incomes decline by approximately 6% (see *Appendix*).

As shown in the previous section, the productivity shock leads to a contraction in output across multiple sectors. This decline constitutes a direct and mechanical effect of reduced factor efficiency. Given the strong dependence of poor households in Niger on labor income, the associated reduction in the marginal value product of labor translates into lower returns to labor (Acemoglu, 2009; Charlton and Taylor, 2019). Comparable patterns have been documented elsewhere. In India, climate change–induced well depletion has resulted in persistent annual declines in agricultural incomes (Blakeslee et al., 2020). In South Africa, drought episodes have adversely affected labor incomes, particularly in tourism-dependent regions. More broadly, empirical evidence for sub-Saharan Africa suggests that rising temperatures reduce per capita income, with disproportionately large effects on poorer households (Dell et al., 2012, 2014).

An exception to this general pattern is observed in the Agadez region, which records positive labor returns in agricultural activities (2.8% in rural areas and 1.7% in urban areas). This result may appear counterintuitive, given that agriculture and livestock farming constitute the primary livelihood activities for much of the rural population in the region. However, several factors help explain this outcome. First, Agadez is the only region in Niger where agricultural production is predominantly based on irrigation, rendering it less exposed to adverse climatic conditions (CRA, 2018). Second, according to the national poverty profile (INS, 2023a), Agadez exhibits relatively favorable socioeconomic indicators, ranking after the Niamey region in terms of poverty incidence, food security, housing conditions, and access to basic social services such as energy, telecommunications, and education. These advantages suggest that households in Agadez possess greater physical, financial, and human capital, enabling them to better adapt to climate-induced productivity shocks and potentially benefit from labor inflows from more vulnerable neighboring regions. Moreover, the region is well known for its cash-crop vegetable production—which supplies urban markets, including Niamey, with potatoes, onions, and spices—as well as for its alfalfa production, which provides substantial support to livestock activities in both rural and urban areas (CRA, 2023). These characteristics likely underpin the observed gains in labor productivity, particularly in the livestock sector.

By contrast, the Niamey region—ranked ahead of Agadez in the national poverty profile (INS, 2023)—experiences negative effects of the productivity shock on labor returns in both rural and urban areas. As the administrative, industrial, economic, educational, and commercial center of the country, Niamey constitutes a major destination for rural–urban migration, attracting populations from rural areas and secondary cities in search of employment opportunities (Issaka, 2015; Dimé, 2020; Corta et al., 2021). This sustained inflow has contributed to challenges related to poverty, unplanned urban expansion, and security concerns, which in turn heighten the region's vulnerability to external shocks.

Finally, the finding that productivity shocks in the agricultural sector also reduce labor incomes in non-agricultural sectors points to the presence of broader general equilibrium effects. These cross-sectoral transmission mechanisms are examined in greater detail in the following section.

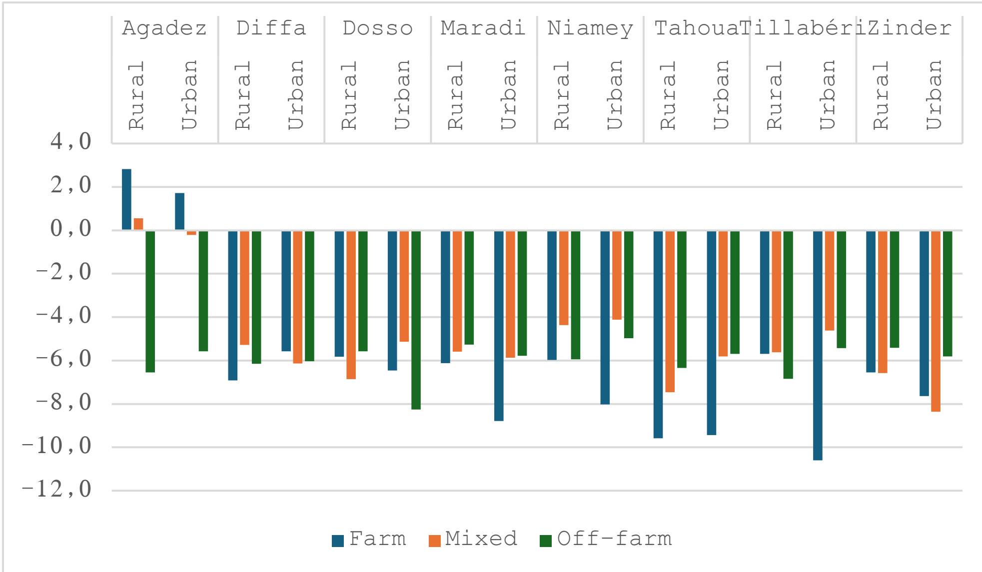

Figure 17: Impact of productivity shocks on factor labor return across region, area and labor type.

Source: Authors, based on scenario simulation.

5.2. General equilibrium effects

The preceding section documented declines in both production and income resulting from the productivity shock introduced in the model, with particularly pronounced effects in the agricultural and livestock sectors and in the Agadez region. These findings primarily reflect the direct effects of the shock and are consistent with established theoretical and empirical literature. However, the results also point to the presence of intersectoral linkages that can be more fully understood through the lens of general equilibrium mechanisms. As discussed in *Section 2.2,* a reduction in agricultural productivity lowers agricultural incomes, which in turn may generate a contraction in demand for non-agricultural goods and services.

Figure 18 illustrates the impact of the agricultural productivity shock on household consumption patterns in Niger. The results indicate a decline in consumption across both agricultural and non-agricultural goods, with a particularly sharp reduction in the consumption of agricultural products (primary goods and food), estimated at approximately 12%. This outcome is consistent with the observed decline in factor returns, which reduces household purchasing power. These findings align with the existing literature emphasizing the strong income and consumption linkages between agricultural and non-agricultural sectors in rural economies (Barrett et al., 2001; Davis et al., 2017).

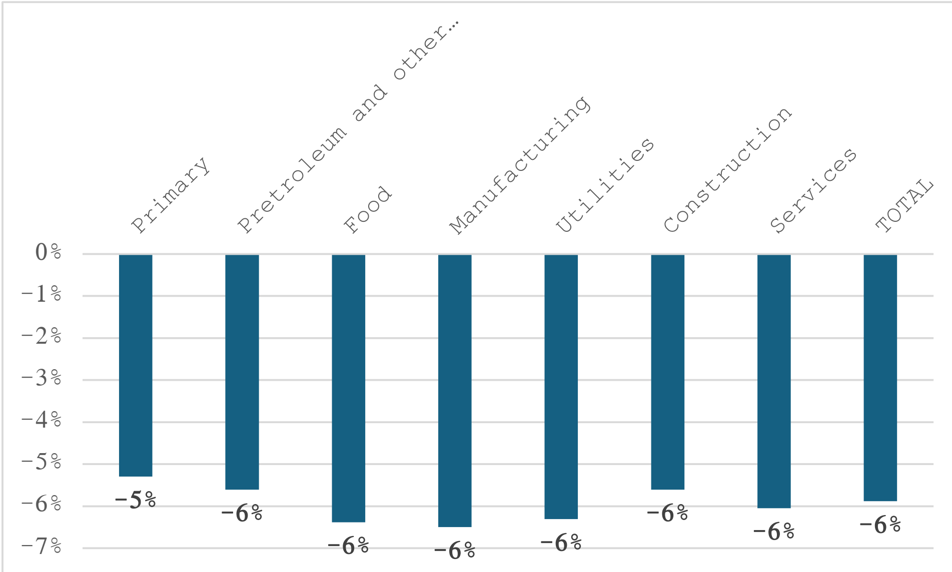

Figure 18: Impact of productivity choc on households' consumption patterns.

Source: Authors, based on scenario simulation.

The intersectoral relationship between agriculture and non-agriculture is illustrated in *Figure 19* and can be interpreted through general equilibrium labor-market adjustments. *Panel (a)* indicates that a negative productivity shock in agriculture induces a reallocation of labor toward agricultural and food-processing activities, while labor demand contracts in other sectors. This pattern reflects economy-wide income and demand effects: the decline in agricultural productivity reduces household incomes, thereby compressing demand for non-agricultural goods and services and, consequently, the demand for labor in those sectors.

Panel (b), which presents regionally disaggregated results, once again singles out the Agadez region. In this region, the productivity shock generates a markedly stronger increase in labor demand in agriculture and food processing relative to other regions. This outcome is consistent with the structural specificities of Agadez discussed earlier, notably the predominance of irrigated agriculture, greater resilience to climate variability, and relatively better endowments of physical and human capital. These characteristics appear to mitigate the adverse effects of the shock and enable the region to absorb labor reallocated from other activities.

Taken together, these findings support the study's initial hypothesis that, in the presence of strong income–consumption linkages, a decline in agricultural productivity leads to a contraction in non-agricultural labor demand through general equilibrium mechanisms. However, the divergent response observed in Agadez underscores the importance of regional heterogeneity in shaping labor-market outcomes and cautions against uniform interpretations of climate-induced productivity shocks across space.

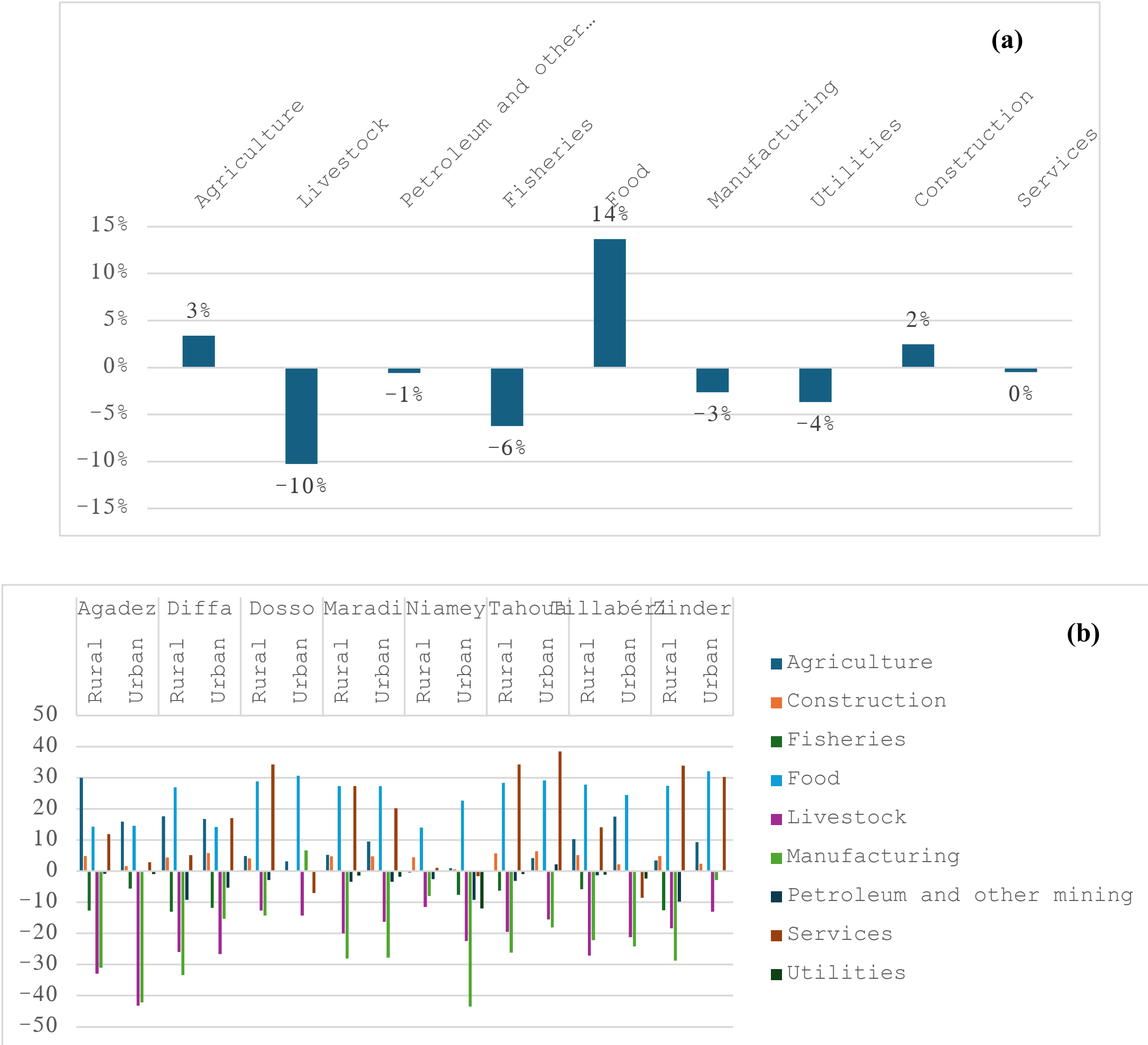

Figure 19: Impact of productivity shock on factor labor demand across activities (a) and across regions, area and labor type (b).

Source: Authors, based on scenario simulation.

5.3. The overall effects on labor reallocation

The results presented thus far indicate that agricultural and non-agricultural sectors in Niger are interconnected through income and consumption channels. The agricultural productivity shock generates a generalized decline in production across sectors, reduces household incomes, and contracts the demand for goods and services, thereby affecting labor demand in multiple activities, with notable regional heterogeneity—particularly in Agadez. This naturally raises the question of how labor supply responds to these economy-wide adjustments.

At the aggregate level, the simulation results indicate that the productivity shock leads to a modest decline in labor supply, on the order of 0.1 percent, while the reduction in overall labor demand is negligible. However, a disaggregated analysis reveals substantial spatial and sectoral variation. As shown in *Figure 19*, the shock induces a pronounced increase in labor supply in rural Agadez among households combining agricultural activities with secondary non-agricultural occupations, especially in food processing. In contrast, labor supply declines in rural Tahoua, while in other regions—such as Dosso and Diffa—no significant labor reallocation is observed following the shock.

Consistent with findings from Bangladesh (Emran and Shilpi, 2018), where the post-shock change in the overall share of agricultural employment was quantitatively limited, these results suggest that the observed decline in the labor force in rural Tahoua does not reflect a transition out of agriculture toward non-agricultural employment. Rather, agricultural labor supply increases following the productivity shock, but this adjustment occurs through spatial reallocation, with labor moving toward the neighboring Agadez region. In other words, household labor reallocation is predominantly temporary rather than permanent.

These findings underscore the role of irrigation—still underdeveloped in much of Niger—in enhancing the adaptive capacity of agriculture in Agadez. Irrigation appears to have enabled the region not only to buffer the adverse effects of climate change but also to absorb labor displaced from more vulnerable neighboring areas. By contrast, the mixed and limited responses observed in non-agricultural sectors point to potential labor market failures, particularly in meeting rising demand in sectors such as construction across multiple regions. Previous studies in Niger consistently highlight that constraints related to market access and participation limit farmers' ability to adopt high-yield inputs and productivity-enhancing technologies (Zakari et al., 2023), as well as their capacity to effectively commercialize agricultural output (Kalidou et al., 2024). These structural bottlenecks likely impede the ability of non-agricultural sectors to act as effective absorbers of labor in the aftermath of climate-induced shocks. This situation could push farming households that are unable to reallocate their labor into what is commonly referred to as the "*poverty trap*" or "*immobility trap*" (Barrett et al., 2001; Letta et al., 2024).

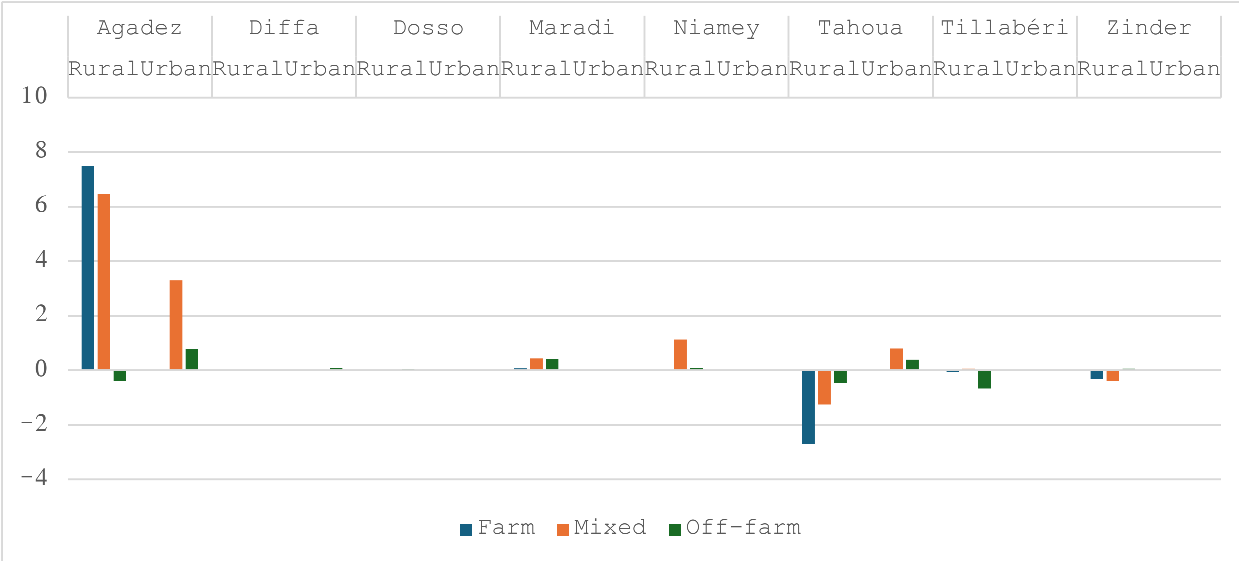

Figure 20: Productivity shock on labor reallocation across regions, place of residence and labor type.

Source: Authors, based on scenario simulation

Conclusion and policy implications

The analysis of agricultural labor supply under conditions of structural and climatic change constitutes a central focus of this study. This issue has attracted growing attention from both the academic community and policymakers, particularly in light of the need to safeguard the primary livelihood of poor farming households in developing countries—livelihoods that are increasingly exposed to climate-related shocks—and to advance the overarching objective of poverty reduction in rural economies.

To address this concern, the study employs an original single-country static computable general equilibrium (CGE) model, DEMETRA, to examine labor reallocation among Nigerien farming households following a climate-induced 20% decline in agricultural productivity. Two main findings emerge. First, the productivity shock generates a broad-based contraction in production across all sectors, leading to lower household incomes and reduced demand for goods and services, with consequent effects on labor demand across multiple activities. These impacts display marked regional heterogeneity, with particularly distinct outcomes observed in the Agadez region. Second, in the short run, households affected by income losses adjust by reallocating labor toward agricultural and agro-processing activities in neighboring regions characterized by relatively higher agricultural productivity. These results indicate that agricultural labor is highly responsive to productivity-driven economic incentives and is systematically redeployed in an effort to smooth consumption in the face of adverse shocks.

Nevertheless, the findings should be interpreted with caution, as the analysis is confined to short-term effects. Long-term responses may differ substantially, as they may incorporate endogenous adaptation or intensification processes induced by sustained climatic changes (Liu et al., 2023; Hill et al., 2023). Empirical evidence suggests that when such long-term adaptations are taken into account, the magnitude of the impacts may be attenuated (Musungu et al., 2023; Feriga et al., 2024). Moreover, the external validity of the results is inherently context-specific. While the findings suggest that regions exhibiting greater market integration, economic diversification, and labor mobility are better positioned to mitigate climate-induced economic losses, the focus on short-term climatic shocks implies that other factors of production—such as capital and land—are assumed to remain fixed. This modeling choice allows for the isolation of labor reallocation effects, rather than broader adjustments in factor endowments (Colmer, 2021).

An additional limitation arises from the assumption of full employment and the absence of empirically estimated labor supply elasticities, which could yield results more closely aligned with the realities faced by agricultural households. This constraint underscores the well-documented complexity associated with modeling agricultural labor supply (Hill et al., 2021).

Finally, the results highlight the distinctive role of the Agadez region, which appears less vulnerable to productivity shocks and demonstrates a capacity to absorb displaced labor within the agricultural and agro-processing sectors. Despite these notable characteristics, the region remains relatively under-researched, pointing to a clear need for further empirical investigation.

Overall, the findings carry important policy implications. Given the substantial benefits documented in the empirical literature, there is a strong case for expanding irrigation infrastructure in Niger, where irrigated land currently accounts for only about 2% of total agricultural area (ME/LCD et al., 2020). The study also underscores the strong interlinkages between agricultural and non-agricultural sectors through income and consumption channels, which render agro-processing activities particularly attractive to households affected by productivity shocks. These sectors should therefore be supported through integrated policies that account for local specificities. Finally, the results highlight the urgent need for a coherent rural market development strategy in Niger—an area that has long been largely delegated to NGOs and externally funded projects, with mixed outcomes to date.

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GENERAL CONCLUSION

The primary objective of this study is to contribute to the generation of robust empirical evidence to inform decision-making on climate change adaptation policies in Niger. Niger has long been identified as one of the countries most vulnerable to climate change and least equipped to cope with its adverse impacts. In a context characterized by limited policy support and weak social protection systems, climate-related shocks have structurally intensified pre-existing challenges, including poverty, food insecurity, and constrained livelihood options for poor farming households whose incomes are predominantly derived from agriculture. Under such conditions, there is an urgent need to strengthen agricultural management practices in order to prevent autonomous adaptation strategies adopted by households from exacerbating their vulnerability. To this end, the study employs a rigorous and context-specific analytical framework, combining index construction methodologies, uncertainty and sensitivity analyses, and a single-country static computable general equilibrium (CGE) model (DEMETRA) calibrated on a 2019 Social Accounting Matrix (SAM). This integrated approach is grounded in a solid theoretical foundation and tailored to the socio-economic realities of Nigerien households, thereby enabling the formulation of policy-relevant insights.

The analysis of household adaptive capacity reveals pronounced disparities in asset endowments across Nigerien farming households. A substantial proportion lack essential assets, particularly education and skills, which are critical for accessing information, adopting new technologies, and engaging in non-agricultural income-generating activities. Households with moderate levels of adaptive capacity are more likely to diversify into non-agricultural activities, significantly enhancing their ability to cope with climate-related shocks. The insights derived from this analysis, combined with a comparative assessment of potential policy levers, provide a solid foundation for evidence-based interventions. In this respect, the proposed index-based approach offers valuable guidance for identifying climate vulnerabilities and strengthening the resilience of Niger's agricultural sector.

The uncertainty analysis indicates that variations in weighting schemes and aggregation methods substantially influence the values of the Adaptive Capacity Index (ACI). In particular, the index is highly sensitive to the choice of aggregation technique, underscoring the critical role of methodological decisions in index construction. These findings are consistent with previous studies highlighting the sensitivity of adaptive capacity indices to weighting and aggregation choices. The results further support the relevance of participatory expert-based weighting methods, which incorporate stakeholders' perceptions of the relative importance of indicators and components. Sensitivity analysis confirms that the ACI is especially responsive to changes in the aggregation of indicators into components, notably when transitioning from linear to geometric aggregation. Taken together, the combined uncertainty and sensitivity analyses suggest that the ACI developed in this study is based on a relatively stable modeling framework.

In addition, the examination of labor supply behavior among Nigerien farming households yields two key findings. First, climate-induced agricultural productivity shocks generate a broad-based decline in production across all sectors, reduce household incomes, and contract demand for goods and services, thereby affecting labor demand in multiple activities. These effects exhibit marked regional heterogeneity, particularly in the Agadez region. Second, households affected by the productivity shock demonstrate a short-term capacity to adjust by reallocating labor toward agricultural and food-processing activities in neighboring regions with relatively higher agricultural productivity. Agricultural labor thus responds to economic incentives linked to productivity differentials and is systematically redeployed as a strategy to smooth consumption in the face of declining incomes.

Based on these findings, several policy implications emerge. There is an urgent need for targeted interventions aimed at strengthening the financial, human, and natural capital of farming households, with the exception of those residing in Gadabéji, where relatively high levels of natural capital suggest a greater need to focus on financial and human capital. Policymakers should prioritize programs that promote income diversification, enhance educational attainment, and improve farm size and soil fertility through access to modern inputs and sustainable land management practices. Effective implementation of such policies will require close collaboration with agricultural research and extension institutions. Moreover, tailored interventions that account for local climatic conditions and household-specific constraints are essential, while also recognizing the value of traditional knowledge, which constitutes a cornerstone of successful agricultural adaptation to climate change. In parallel, methodologies for constructing the Adaptive Capacity Index in Niger should emphasize participatory approaches to ensure that indicator weights accurately reflect local priorities and realities.

With respect to labor diversification, policies should actively support the expansion of irrigation infrastructure in Niger, where irrigated land currently accounts for only about 2 percent of total agricultural area. Furthermore, existing synergies between the agricultural and non-agricultural sectors should be reinforced through integrated policies that reflect local specificities and promote the development of agro-processing activities. Finally, there is a pressing need for the Nigerien state to implement a coherent rural market policy. Such efforts have historically been delegated to non-governmental organizations and externally funded projects, with mixed outcomes, underscoring the necessity of stronger public-sector leadership.

Despite its contributions, this study is subject to several limitations that warrant consideration in future research. The limited significance of physical capital as a determinant of household adaptive capacity suggests that the exclusive reliance on expert-validated indicators may have overlooked locally relevant dimensions. Future research should adopt a more flexible approach by testing alternative sets of indicators to enable deeper comparative analyses. In addition, the lack of longitudinal and spatially disaggregated data constrains the assessment of changes in adaptive capacity over time and across regions. Consequently, the results should be interpreted as a snapshot, and future studies should employ dynamic frameworks to capture the evolving nature of adaptive capacity, while explicitly incorporating issues of vulnerability and social justice to support inclusive policy design.

Similarly, the short-term perspective adopted to analyze climate-induced labor reallocation may obscure longer-term adaptation or intensification processes that unfold over time. Future research should therefore adopt a longer-term horizon. Another important limitation relates to the assumption of full employment and the absence of labor elasticity estimates, which restrict the model's ability to fully reflect the realities of agricultural labor markets. This limitation highlights the well-documented complexity of modeling agricultural labor supply in developing-country contexts.

Notwithstanding these limitations, the findings of this study provide a valuable foundation for the formulation of comprehensive and context-specific policies aimed at strengthening the adaptive capacity and improving the well-being of farming households in Niger.

Appendices

Appendix 1: Esssai1

Appendix 1.1: List of experts consulted to validate and score indicators

No	Full name	Institution	E-mail
1	Dr. Boubacar Ibrahim Fodi	DRP WASCAL Niamey	ibraboub@yahoo.fr
2	Pr. Seydou Traore	AGRYMET	seydou.traore@cilss.int
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4	Abdou Boko Boubacar	GIZ	abdouboko@gmail.com
5	Habou Maman Nourou	ONG Karkara	nouroudine75@gmail.com
6	Dr. Idrissa Mamoudou	ONG Garkua	mamoudouidrissa561@gmail.com
7	M. Adamou Oumarou	CC SAP	yarouh@gmail.com
8	Ranaou Maazou	FAO	maazou96@yahoo.fr
9	Patrick Delmas	RECA	delmas.reca.cowiram@gmail.com
10	Moussa Boureima	INRAN	moussaboureima@yahoo.fr
11	Charfa Salissou	CNEDD	salissoucharfa@gmail.com

Appendix 1.2: Experts interview questionnaire

<u>EXPERTS INTERVIEW GUIDE</u>

Introductory words

Dear Sir/Madam,

The main objective of my research is to investigate agricultural practices in Niger, in the context of climate change, to identify and propose practices that are efficient, cost-effective with environmental co-benefits for farmers. This is obviously due to Niger's quest for food self-sufficiency, the role of agriculture in the livelihoods of agricultural households, and the growing threat of climate change-related effects on them. I am convinced that this research cannot lead to meaningful economic policy implications without benefiting from your diverse experience in this field. This is why I am asking for a maximum of one hour time to discuss this issue, which requires in-depth analysis.

1. Please give us some information about your expertise: What is your level of knowledge of the agriculture, forestry and livestock sector in Niger?

(*Please refer to your day-to-day work: is it related to specific regions or do you have experience at national level in Niger*).

2. What do you think about climate change?
(*Definition, occurrence in Niger, effects/impacts on agriculture, etc.*)

3. Is this phenomenon perceptible and recognized by farmers in Niger?
(*Perception by farming households and consideration in their practices/behavior*)

4. What can you tell us about the impacts of climate change for agricultural households in Niger?

5. Are there any public and/or private institutions supporting farm households? If so, what form does this support take?

6. What can you tell us about the concept of Climate Smart Agriculture (CSA)?

7. Is it relevant to the Niger context?

8. How is it being implemented in Niger, both by public and private institutions, and by farmers themselves?
(*Implementation in terms of adaptation, mitigation and food security; results; evaluation of results, indigenous knowledge, adaptation in the short run / long run, etc.*).

9. In the various types of agricultural households you know, is the implementation of CSA effective?

--- cost-effective?

--- with environmental co-benefits?

--- uniform across all Nigerien contexts?
(*Adaptability/vulnerability, diversities according to the characteristics of farmers and their environment, etc.*).

10. The sites selected for this research are (....). They were selected based on the criteria of belonging to different agroecological zones, but also of their vulnerabilities to climate change. What can you say about the effects of CC on these specific sites and on the livelihoods of the farming households living there?

Concluding remarks

I sincerely thank you for your much-needed support. My conviction is to produce a document that closely reflects the context of farming households in Niger. To this end, I would like to have the opportunity to contact you later to attend a workshop that will enable us to deepen these discussions. Also, being one of the essential tools of research, allow me to solicit documents along the lines of our discussion for the purpose of desk review.

Thank you very much for your time!

Appendix 1.3: Indicators from the literature, validated during experts' workshop

Components of the livelihood framework	Initial indicators (literature review)	Sources	Definitions / Assumptions	Indicators selected following the workshop	Comments
Financial Capital	Diversity of revenue sources	Abdul-Razak and Kruse (2017); Choden et al (2020); Datta et Behera (2020)	A farmer whose sources of income are more diversified has a greater capacity to adapt than a farmer whose sources of income are less diversified.	Number of sources of income: agricultural, non-agricultural, migration, exodus, mutual aid	According to most participants, this indicator encompasses all the others and is more accurate. It's also easier to obtain reliable information, unlike monetary income, which is a sensitive subject for farmers and, in most cases, doesn't provide the real information. In addition, participants validated this indicator with examples from the Maradi region, among others, where many producers were unable to adapt to the climatic shocks of previous years due to their sole source of income from agricultural production. Definitions/assumptions column to be summarized for this indicator only.
	Number of household income sources				
	Income from non-agricultural activities, livestock and agriculture	Gbetibouo et al. (2010); Bryan et al. (2015); Jacob et al. (2015); Zanmassou et al (2020)	Access to agricultural, non-agricultural and livestock income influences the adoption of modern adaptation strategies.		
	Remittances (from family members)	Defiesta and Rapera (2014); Banerjee et al. (2017); Jha et al. (2018)	Farmers' remittances play an important role in strengthening their capacity to adapt to climate change.		
	Number of farm workers	Kansiine et al. (2018) ; Gbetibouo et al. (2010) ; Chepkoech et al.(2020)	Sufficient manpower enables farmers to carry out their agricultural work on time, and to try out new technologies that also require an investment in manpower.	Rather: Number of farmers or farm workers in the household	The same comment as in the definition / hypothesis column is validated.
	Access to formal or informal credit	Deressa et al. (2009) ; Defiesta and Rapera (2014) ; Bryan et al. (2015) ; Karanja et al. (2016) ; Chepkoech et al. (2020)	Farmers with access to credit are economically better able to adapt to climate change than those with less access to credit.	Validated indicator: Access to credit (formal and informal)	Same comments as in the definition / hypothesis column. For example, village associations or tontines are the most often cited in discussions because, when functional, they serve as sources of credit of considerable importance in adapting to climate change but for income-generating activities.
	Public subsidies	Defiesta and Rapera (2014)	Farmers with access to public subsidies for agricultural inputs are more resilient to climate change than those without access to public subsidies.	Validated indicator: Public subsidies	The same comment as in the definition / hypothesis column is validated. The participants added that the new reform of the agricultural sector, in line with the provisions of SPN2A, provides for subsidies of up to 50%. These include free distribution of inputs, sales at moderate prices and targeted sales to the most vulnerable.

	The last 2 indicators or the following: Diversification of credit sources	Ruiz Meza (2015); Defiesta and Rapera (2014); Gbetibouo et al. (2010); Bryan et al. (2015); Lockwood et al. (2015); Jacob et al. (2015); Zanmassou et al (2020)	Same assumptions as last 2 indicators	Indicator invalidated	No more relevant than the last two.
	Number of animals owned by household	Dafiesta et Rapera (2014)	As a form of savings for farm households, animals are available as financial resources for financing adaptation strategies.	New indicator validated: Number of animals owned by the household	Owning animals is seen as the savings for rural producers, who don't hesitate to sell livestock to adapt to shocks.
Social Capital	Total number of household members / access to family/household labor / number of relatives in the community	Eakin et al. (2011); Ibrahim (2014); Ali and Erenstein (2017); Abdul Razak and Kruse (2017); Zanmassou et al. (2020); Datta and Behera (2022)	Better access to family labor strengthens farmers' social capital.	Validated indicator: Total number of household members	The same comment as in the definitions / hypothesis column is validated.
	Membership of farmers' organizations	Gbetibouo et al. (2010) ; Karanja Ng'ang'a et al. (2016) ; Yaméogo et al. (2018) ; Choden et al. (2020); Egyir et al. (2015); Abdul-Razak and Kruse, 2017; Chepkoech et al (2020); Datta and Behera (2022)	Households belonging to a greater number of social groups and associations have better networks, which can help mitigate the adverse effects of climate change on their livelihood activities.	Validated indicator: Participation in community activities or farmers' groups/organizations.	Same comment as in the definitions / hypothesis column, which is validated. Examples such as farmers' organizations/associations and farmers' platforms exist in rural areas, and when they are functional and active, they produce benefits on the farm in terms of mutual aid. What's more, when functional, participation in community activities enables sharing of agricultural techniques and technologies and facilitates access to public subsidies, community associations being a favored means of public subsidies.
	Participation in community activities	Frank and Penrose Buckley, (2012); Abdul-Razak and Kruse (2017); Karanja Ng'ang'a et al. (2016); Chepkoech et al (2020) ; Yaméogo et al. (2018) ; Datta and Behera (2022)	Community organizations offer an important opportunity for money lending and seed sharing, as well as access to information on weather conditions and markets.		

	Presence of a community worker in the household	Ruiz-Mallén et al. (2017); Datta and Behera (2022)	Possession of a community position indicates a person's social standing, as they are more likely to have greater social capital and, consequently, greater access to common reserves for adaptation.	Indicator invalidated.	The indicator does not take equity into account, as very few producers hold community position in the sites identified.
	Sex of household head	Choden et al (2020) ; Abdul-Razak and Kruse, 2017	The greater the inequality between the sexes in decision-making and access to land, the lower the level of social capital.	Validated indicator	The same comment as in the definitions / hypothesis column is validated.
Human Capital	Level of education / Years of schooling	Deressa et al. (2008) ; Yohe and Tol (2002) ; Jacob et al (2015) ; Bryan et al (2015) ; Karanja et al. (2016); Zanmassou et al (2020); Choden et al (2020); Datta and Behera (2022)	Level of education is positively correlated with adaptive capacity. In other words, farmers with higher levels of education are more likely to accept and adapt to climate change than those with lower levels.	Validated indicator: educational level of household head	The same comment as in the definitions / hypothesis column is validated.
	Access to climate information	Lo and Emmanuel (2013)	Farmers with better access to climate information are better prepared to adapt to climate change than those with less access.	Indicator invalidated	Already taken into account in the indicators: Membership of farmers' organizations and Participation in community activities
	Farming experience	Yohe et al (2002) ; Defiesta and Rapera (2014) ; Karanja et al. (2016) ; Bryan et al (2015) ; Zanmassou et al (2020); Datta and Behera (2022)	The number of years' experience in agriculture is strongly correlated with the level of knowledge and skills in adapting to climate change and variability using technology.	Indicator validated with precision: Farming experience of household head	The same comment as in the definitions / hypothesis column is validated. Participants also see it as a prevention factor.
	Access to extension services / Visits to extension services	Frank and Penrose Buckley (2012); Jacob et al. (2015); Gbetibouo et al. (2010); Ruiz Meza (2015); Defiesta and Rapera (2014); Lockwood et al. (2015); Bryan et al. (2015); Zanmassou et al (2020).	Access to agricultural extension services improves farmers' knowledge and skills in practices and technologies related to climate change and adaptation.	Indicator validated with one modification: Access to agricultural advice	The same comment as in the definitions / hypothesis column is validated. Examples of farm advisory services are given: RECA, farmers' platform (dissemination of best practices), farmer field school approach (technological innovations by farmers themselves).

	Knowledge of modern adaptation strategies: seed varieties, soil moisture retention techniques, soil fertility retention techniques.	Mabe et al., 2012; Jacob et al. (2015); Gbetibouo et al. (2010); Ruiz Meza (2015); Defiesta and Rapera (2014); Lockwood et al. (2015); Bryan et al. (2015); Zanmassou et al (2020) ; Frank and Penrose Buckley (2012); Choden et al (2020)	The more farmers know about seed varieties, the more likely they are to adopt climate-resistant varieties / Knowledge of soil moisture retention techniques increases the propensity to adopt these technologies in times of drought / Farmers who know more about soil fertility retention techniques are better able to adapt to the negative effects of climate change, such as soil erosion, than those who know less about these technologies.	Indicator invalidated	Can be included in the education level.
	The last 3 indicators or: Access to climate change adaptation training	Choden et al (2020)	It enhances their knowledge and skills in adapting to the effects of climate change.	Indicator invalidated	No more relevant than the last 3.
Physical Capital	Irrigation infrastructure / Type of irrigation	Eakin et al. (2011) ; Egyir et al. (2015); Singh et al. (2017) ; Chepkoeh et al (2020) ; Datta and Behera (2022)	Farmers with access to irrigation infrastructure are more likely to adapt to drought than those without.	Validated indicator: Irrigation infrastructure	The same comment as in the definitions / hypothesis column is validated.
	House quality	Choden et al (2020)	Owning a better-built home in terms of quality can improve living conditions and a household's ability to withstand the risks of environmental shocks, including climatic events.	Indicator validated	The same comment as in the definitions / hypothesis column is validated.
	Road access / Road conditions	Byrne (2014), Egyir et al. (2015) ; Datta and Behera (2022); Choden et al (2020)	Access to a good road network improves farmers' ability to access markets for their input and output. Consequently, increasing the distance between the farm and good roads is inversely related to the infrastructure's ability to adapt to climate change.	Indicator validated with one modification: road quality	Same comment as in the definitions / hypothesis column, which is validated.

	Distance between house and agricultural plot / Distance between house and agricultural extension services.	Below et al (2012); Datta and Behera (2022); Jacob et al. (2015); Ruiz Meza (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013); Zanmassou et al (2020); Chepkoech et al (2020); Abdul-Razak and Kruse (2017)	Farmers who have access to reliable weather forecasts can plan their adaptation strategies to ongoing climate change.	Validated indicator: Distance between house and agricultural plot. Indicator invalidated: Distance between house and extension services.	Same comments as in the definitions / hypothesis column for the validated indicator. For the invalidated indicator, the intervention trend shows that this indicator makes no sense for a country like Niger, where there is a notorious shortage of these services, and where ICTs make it possible to decentralized access to agricultural advice, as is the case, for example, with RECA, which provides a number that can be contacted at any time for advice.
	Distance between home and market for inputs.	Bellow et al (2012) ; Jacob et al. (2015); Ruiz Meza (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013); Zanmassou et al (2020); Choden et al (2020)	Proximity to a market can strengthen adaptive capacity, as it increases opportunities to sell agricultural produce and thus generate cash income.	Indicator validated	Same comment as in the definitions / hypothesis column, which is validated.
	Distance from home to financial institution.	Jacob et al. (2015); Ruiz Meza (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013); Zanmassou et al (2020)	Farmers who are close to financial institutions are more likely to take advantage of agricultural credit opportunities, and thus to adapt to the effects of climate change.	Indicator invalidated	According to the participants, physical access to financial institutions is not an important reality for producers in Niger, as existing financing mechanisms, although very inadequate, already incorporate the use of ICTs.
	Number of types of farm equipment owned by household.	Dafiesta et Rapera, 2014 ; Lockwood et al., 2015	Ownership of agricultural equipment enables farmers to exploit better agricultural technologies and thus enhance their ability to adapt.	Indicator validated	Farm equipment, in particular carts, hoes, etc., are considered important assets for implementing adaptation practices.
Natural Capital	Land tenure / Land quality / Soil fertility	Below et al. (2012) ; Jacob et al. (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013) ; Zanmassou et al., 2020	The duration and type of land tenure influence the farmer's willingness to apply adaptive technologies. Long or reliable land tenure systems create an environment more conducive to adaptation than short or less reliable ones.	Validated indicator: soil fertility, which in the Niger context can be equated with land quality. Indicators invalidated: land tenure and land quality are included in soil fertility.	Same comment as in the definitions / hypothesis column for the indicator, which is validated. Land tenure as an indicator was not validated by the participants, for the simple reason that almost all rural producers in Niger do not possess a land title.

	Land ownership / Land security	Fosu-Mensah et al. (2012) ; Defiesta and Rapera (2014) ; Choden et al. (2020) ; Jacob et al. (2015); Ruiz Meza (2015); Egyir et al. (2015) ; Dannevig et al. (2015) ; Bryan et al. (2015) ; Zanmassou et al (2020) ; Chepkoeh et al (2020) ; Datta and Behera (2022)	Insecure land rights prevent farmers from making the investments needed to increase the productivity and economic value of their land / limited land ownership restricts access to formal financing mechanisms, as land is the most important guarantee for smallholders.	Indicator invalidated	These indicators were rejected for the same reason as the land tenure indicator.
	Plot size	Jacob et al. (2015); Ruiz Meza (2015); Defiesta and Rapera (2014); Bryan et al. (2015); Juhola and Kruse (2013)	Farmers with larger farms are more adaptable	Indicator validated	The same comment as in the definitions / hypothesis column is validated.
	Experience of natural hazards on the farm	Jacob et al. (2015) ; Egyir et al. (2015) ; Bryan et al. (2015) ; Zanmassou et al (2020)	As climate change has a direct impact on crop yields, the more farmers are confronted with natural hazards, the more likely they are to be able to adapt to them.	Indicator validated: Experiences of natural hazards in the main household farms	The same comment as in the definitions / hypothesis column is validated.
	Number of trees on household farms	Reid and Vogel, 2006; Bryan et al., 2015	La présence de végétation indigène influe sur la fourniture de services écosystémiques tels que l'atténuation de l'érosion et de la salinisation des sols, qui contribuent directement à la production agricole.	Indicator added	Trees are considered natural fertilizers and protect farms from strong winds or flooding. They therefore enable households to adapt to the effects of CC.

Appendix 1.4: Levene's test for equal variances

Variables	Categories	Mean	Std. Dev.	Freq.	W50	Pr > F
Household sex	Female	0.265	0.214	8	3.086	0.079
	Male	0.404	0.143	330		
Access to credit	No access	0.400	0.145	335	0.327	0.567
	Access	0.499	0.137	3		
Access to public subsidy	No access	0.398	0.145	314	0.335	0.562
	Access	0.428	0.150	24		
Participation in community and/or farmers-based group activities	No	0.389	0.141	290	1.711	0.191
	Yes	0.469	0.156	48		
Access to agricultural advice	No access	0.363	0.123	236	12.03	0.000
	Access	0.488	0.155	102		
Soil fertility	Not fertile	0.349	0.131	185	0.647	0.421
	Fertile	0.463	0.137	153		

Appendix 1.5: Post hoc tests

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Level of education						
Primary vs Informal/None	0.090	0.021	4.15	0.000	0.0325383	0.1481095
Secondary vs Informal/None	0.161	0.023	6.90	0.000	0.0994545	0.2237145
Tertiary vs Informal/None	0.145	0.055	2.63	0.054	-0.0016037	0.2931619
Secondary vs Primary	0.071	0.029	2.41	0.100	-0.0073341	0.1498552
Tertiary vs Primary	0.055	0.058	0.95	1.000	-0.0995889	0.2104993
Tertiary vs Secondary	-0.015	0.059	-0.27	1.000	-0.1725205	0.1409097

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Income sources						
2 sources vs 1 source	0.146	0.012	11.80	0.000	0.1163113	0.1758808
>2 sources vs 1 source	0.337	0.013	25.26	0.000	0.3056967	0.3700555
>2 sources vs 2 sources	0.191	0.010	18.52	0.000	0.1668702	0.21669

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Farm workers						
2 workers vs 1 worker	0.095	0.020	4.61	0.000	0.040308	0.1498614
3 workers vs 1 worker	0.130	0.019	6.82	0.000	0.079478	0.1806258
>3 workers vs 1 worker	0.187	0.017	10.60	0.000	0.140848	0.23493
3 workers vs 2 workers	0.034	0.021	1.60	0.657	-0.0228718	0.0928061
>3 workers vs 2 workers	0.092	0.020	4.50	0.000	0.0380276	0.147581
>3 workers vs 3 workers	0.057	0.019	3.04	0.016	0.0072632	0.108411

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Animal owned						
1-5 animals vs 0 animal	0.029	0.019	1.49	0.828	-0.023315	0.0826935
6-10 animals vs 0 animal	0.074	0.025	2.93	0.021	0.0070805	0.1411801
More than 10 animals vs 0 animal	0.172	0.018	9.42	0.000	0.1237857	0.2208941
6-10 animals vs 1-5 animals	0.044	0.024	1.82	0.418	-0.0203589	0.1092409
More than 10 animals vs 1-5 animals	0.142	0.017	8.34	0.000	0.0972539	0.1880473
More than 10 animals vs 6-10 animals	0.098	0.023	4.26	0.000	0.0369962	0.159423

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Type of irrigation						
Manual irrigation vs no irrigation	-0.005	0.025	-0.24	1.000	-0.0722477	0.0604634
Gravitation irrigation vs no irrigation	0.1233	0.019	6.19	0.000	0.0704722	0.1763231
Drip irrigation vs no irrigation	-0.070	0.098	-0.72	1.000	-0.3309304	0.1899943
Gravitation irrigation vs manual irrigation	0.129	0.029	4.40	0.000	0.0512677	0.2073119
Drip irrigation vs manual irrigation	-0.064	0.100	-0.64	1.000	-0.3312724	0.2021204
Drip irrigation vs gravitation irrigation	-0.193	0.099	-1.95	0.311	-0.4575417	0.0698102

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Farming equipment						
1-2 types vs 0 type	-0.026	0.091	-0.29	1.000	-0.2701198	0.2169329
3-4 types vs 0 type	0.031	0.090	0.03	1.000	-0.2382862	0.2445564
More than 4 types vs 0 type	0.138	0.091	1.52	0.774	-0.103081	0.3800945
3-4 types vs 1-2 types	0.029	0.019	1.54	0.749	-0.0215423	0.0809993
More than 4 types vs 1-2 types	0.165	0.019	8.42	0.000	0.1130514	0.2171491
More than 4 types vs 3-4 types	0.135	0.015	8.74	0.000	0.0942836	0.1764598

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
HH plot size						
<=4 ha vs <=2 ha	0.043	0.019	2.22	0.163	-.0085701	.0960988
<=6 ha vs <=2 ha	0.103	0.019	5.25	0.000	.0511353	.1558042
>6 ha vs <=2 ha	0.149	0.020	7.31	0.000	.0955076	.2043051
<=6 ha vs <=4 ha	0.059	0.022	2.67	0.048	.0003311	.1190797
>6 ha vs <=4 ha	0.106	0.023	4.60	0.000	.0449404	.1673436
>6 ha vs <=6 ha	0.046	0.023	2.01	0.269	-.014765	.1076383

Pairwise comparisons of means with equal variances

ACI	Contrast	Std.Err.	t	P>t	[95%_Conf	Interval]
Housing type						
Banco house vs traditional house	0.029	0.018	1.57	0.355	0-.0159556	0.0754369
Modern house vs traditional house	0.183	0.014	12.85	0.000	0.1489583	0.2175836
Modern house vs banco house	0.153	0.019	7.71	0.000	0.1055995	0.2014612

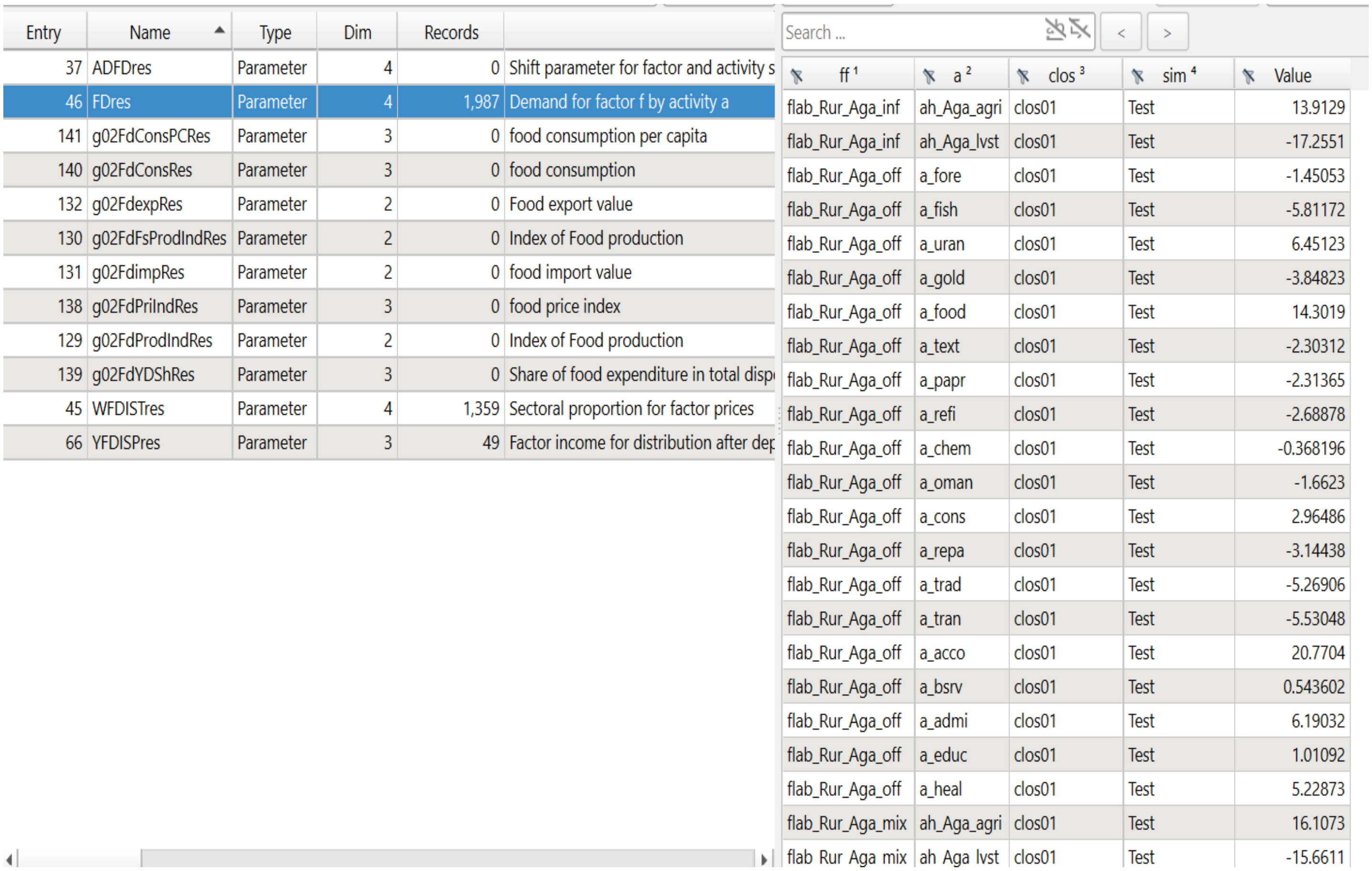
Appendix 2: Essay 3. GAMS software sets of output

Appendix 3.1: Scenario simulation coding

Welcome | model.gms | sta_experiment.gms | sta_lab_migratio

```
PPISIM(SIM)          = PPI0          ;

TMSIM(w,c,sim)       = TM0(w,c)      ;

QESIM(c,sim)         = QE0(c)        ;

ioqttqqSIM(m,c,sim) = ioqttqq.L(m,c)  ;

PWMRSIM(w,c,SIM) = PWMR0(w,c) ;

*-- --- 2b. Assign experiment parameters

* PWMRSIM(w,"c_maiz","Test") = PWMR0(w,"c_maiz") * 1.2 ;
* ADFAGfADJSIM("flab_Rur_Aga_Pr","Test") = 1.1 ;
* ADFDSIM("flab_Rur_Aga_Pr","ah_Aga_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Aga_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Dif_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Dos_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Mar_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Tah_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Til_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Zin_agri","Test") = 0.8 ;
ADFDSIM("fva","ah_Nia_agri","Test") = 0.8 ;

Parameter
closSwap(sim) parameter for sim specific closure swaps

;

 closSwap(sim)           = 0 ;
```

Appendix 2.2: Productivity shocks on labor demand output



Entry	Name	Type	Dim	Records	
37	ADFDres	Parameter	4	0	Shift parameter for factor and activity s
46	FDres	Parameter	4	1,987	Demand for factor f by activity a
141	g02FdConsPCRes	Parameter	3	0	food consumption per capita
140	g02FdConsRes	Parameter	3	0	food consumption
132	g02FdexpRes	Parameter	2	0	Food export value
130	g02FdFsProdIndRes	Parameter	2	0	Index of Food production
131	g02FdimpRes	Parameter	2	0	food import value
138	g02FdPriIndRes	Parameter	3	0	food price index
129	g02FdProdIndRes	Parameter	2	0	Index of Food production
139	g02FdYDShRes	Parameter	3	0	Share of food expenditure in total disp
45	WFDISTres	Parameter	4	1,359	Sectoral proportion for factor prices
66	YFDISPres	Parameter	3	49	Factor income for distribution after dep

Search ...

ff 1	a 2	clos 3	sim 4	Value
flab_Rur_Aga_inf	ah_Aga_agri	clos01	Test	13.9129
flab_Rur_Aga_inf	ah_Aga_lvst	clos01	Test	-17.2551
flab_Rur_Aga_off	a_fore	clos01	Test	-1.45053
flab_Rur_Aga_off	a_fish	clos01	Test	-5.81172
flab_Rur_Aga_off	a_uran	clos01	Test	6.45123
flab_Rur_Aga_off	a_gold	clos01	Test	-3.84823
flab_Rur_Aga_off	a_food	clos01	Test	14.3019
flab_Rur_Aga_off	a_text	clos01	Test	-2.30312
flab_Rur_Aga_off	a_papr	clos01	Test	-2.31365
flab_Rur_Aga_off	a_refi	clos01	Test	-2.68878
flab_Rur_Aga_off	a_chem	clos01	Test	-0.368196
flab_Rur_Aga_off	a_oman	clos01	Test	-1.6623
flab_Rur_Aga_off	a_cons	clos01	Test	2.96486
flab_Rur_Aga_off	a_repa	clos01	Test	-3.14438
flab_Rur_Aga_off	a_trad	clos01	Test	-5.26906
flab_Rur_Aga_off	a_tran	clos01	Test	-5.53048
flab_Rur_Aga_off	a_acco	clos01	Test	20.7704
flab_Rur_Aga_off	a_bsrv	clos01	Test	0.543602
flab_Rur_Aga_off	a_admi	clos01	Test	6.19032
flab_Rur_Aga_off	a_educ	clos01	Test	1.01092
flab_Rur_Aga_off	a_heal	clos01	Test	5.22873
flab_Rur_Aga_mix	ah_Aga_agri	clos01	Test	16.1073
flab_Rur_Aga_mix	ah_Aga_lvst	clos01	Test	-15.6611

Appendix 2.3: Productivity shocks on labor supply output

Entry	Name	Type	Dim	Records	
51	FSILres	Parameter	4	0	Factor supply for leisure
52	FSIMres	Parameter	6	0	Number of factors to f from f by ins
47	FSIres	Parameter	4	48	Factor supplies from institution ins by f
67	FSISHres	Parameter	4	0	Shares of factor f supplied by institutio
48	FSres	Parameter	3	142	Supply of factor f
130	g02FdFsProdIndRes	Parameter	2	0	Index of Food production
135	g02ProLvsFsRes	Parameter	3	0	Protein from livestock and fish and live
149	g07EnerSfSuRes	Parameter	2	0	Energy Self sufficiency
178	g10WageDifSklRes	Parameter	2	0	Wage differential skilled:unskilled
183	g14FsShRes	Parameter	2	0	Fisheries as a value share of GDP

Search ...

ff [1]	clos [2]	sim [3] Value
		Test
flab_Rur_Aga_inf	clos01	7.49903
flab_Rur_Aga_off		-0.398397
flab_Rur_Aga_mix		6.46035
flab_Rur_Dif_inf		-4.72064e-05
flab_Rur_Dif_off		-4.72064e-05
flab_Rur_Dif_mix		-4.72064e-05
flab_Rur_Dos_inf		-3.2218e-05
flab_Rur_Dos_off		0.0570425
flab_Rur_Dos_mix		-3.2218e-05
flab_Rur_Mar_inf		0.0740524
flab_Rur_Mar_off		0.417269
flab_Rur_Mar_mix		0.435754
flab_Rur_Nia_inf		0.00141557
flab_Rur_Nia_off		0.0826456
flab_Rur_Nia_mix		1.1283
flab_Rur_Tah_inf		-2.69561
flab_Rur_Tah_off		-0.470001
flab_Rur_Tah_mix		-1.24642
flab_Rur_Til_inf		-0.0636963
flab_Rur_Til_off		-0.667658
flab_Rur_Til_mix		0.0662549