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Mediation and moderation roles of resilience capacity in the shock–food-security nexus in northern Ghana

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ABSTRACT

This paper examines how resilience capacity mediates or moderates the relationship between weather shocks and household food security based on two waves of farm household survey and satellite-based weather data in northern Ghana and applying econometric models. Results show that resilience capacity moderate or mediates the negative effects of heat stress and drought on food security. However, the mediating role of resilience capacity in the shock-food security nexus is more stable and stronger than its moderating role. A standard deviation (SD) increase in heat stress reduces household food consumption by 0.71 SD, but resilience capacity effectively moderates this effect by approximately 0.61 SD. For drought, household food consumption is reduced by 0.67 SD, but resilience capacity effectively dampens this negative effect by approximately 0.60 SD. The mediation results, on the other hand, indicate that 537% of the total effect of heat stress on household calorie consumption is explained by the indirect effect through resilience capacity. Similarly, resilience capacity mediates about 74% of the total effect of heat stress on household food consumption. These results suggest that strategies that help improve resilience capacity, such as the adoption of sustainable intensification practices, are critical in enhancing food security in northern Ghana.

1. Introduction

Households in many African countries rely mainly on rain-fed agriculture, which is exposed to climate change and variability, and other socioeconomic shocks affecting their farming and food systems (Galarza, 2020). Due to the dire negative food security implications of these multiple shocks, the number of studies assessing resilience from the perspective of household food security has been growing since 2008 (see Ansah et al. (2019). However, there is no agreement among scholars on how resilience should be measured or analysed as it is conceptualized in different ways. In the emerging food security literature, resilience is mostly measured as a capacity (Alinovi et al., 2010; Alinovi et al., 2008; FAO, 2016) while Smith and Frankenberger (2018) define resilience capacity as *"a set of conditions, attributes, or skills that enable households to achieve resilience in the face of shocks"* (p.365). In this regard, resilience capacity is a latent variable with multidimensional attributes and indicators that can be measured through multivariate techniques, such as factor analysis and principal component analysis (D'Errico and Pietrelli, 2017). The common attributes of resilience capacity include access to basic services, assets, adaptive capacity and social safety nets, among others (Ado et al., 2019; Brück et al., 2019; D'Errico and Pietrelli, 2017; D'Errico et al., 2020; D'Errico et al., 2018; Dedehouanou and McPeak, 2020; Islam and Al Mamun, 2020; Murendo et al., 2020; Phadera et al., 2019; Smith and Frankenberger, 2018).

Empirically, resilience capacity has thus far been assessed in terms of its direct effect on food security by including it as an explanatory variable; or in terms of moderation by including the multiplicative product of shocks and resilience capacity in a regression (D'Errico et al., 2018; Murendo et al., 2020; Smith and Frankenberger, 2018). Jose (2013) defines moderation as the examination of the statistical interaction between two independent variables in predicting an outcome variable. A moderation variable, according to Baron and Kenny (1986), *"is a variable that affects the direction and/or strength of the relation between an independent, or predictor, variable and a dependent, or criterion, variable"* (p.

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1174). For instance, resilience capacity, if acting as a moderating variable, is expected to influence the direction and/or strength of the relationship between shocks and food security. This means, for instance, that households experiencing higher intensity of shocks should also report low levels of food security, but resilience capacity should influence this basic relationship. Jose (2013) argues that, in moderation analysis, the relationship between the moderator and the independent variable is not of direct focus but how the moderator and the independent variable interact to influence the outcome variable is of main interest.

The empirical literature on shocks, resilience and food security thus far indicates that the moderation condition is not completely met, as resilience efforts and interventions also focus on the link between the two variables. For instance, Brück et al. (2019) found that shocks also affect both resilience capacity and food security, thus pointing to a plausible mediating role of resilience capacity in the link between shocks and food security. Mediation, as defined by Baron and Kenny (1986), occurs when a third variable *"accounts for the relation between the predictor and the criterion"* (p. 1176). For instance, resilience capacity as a mediator is expected to explain the mechanisms through which shocks and food security are related. This hypothesis is plausible due to the multidimensional and latent nature of resilience capacity involving several indicators (Béné et al., 2012; Constas et al., 2014). These indicators are mechanisms that can be considered as predictors of resilience capacity (Knippenberg et al., 2019). The literature shows that several shocks affect food security through processes such as income loss, asset reduction or savings decumulation (Ansah et al., 2019). Households with assets or other accumulated savings may smooth consumption through these mechanisms, minimizing the impact of food prices on their food security (Ansah et al., 2021, 2022; Keil et al., 2008).

Further, the core objective in mediation analysis is to quantify a transmission mechanism in which a treatment and a mediator jointly cause an outcome of interest (Baron and Kenny, 1986). Resilience research focuses on the mechanisms through which individuals, households, communities and systems can develop robustness for withstanding the effects of shocks, and not on resilience per se, especially as resilience is a latent variable. D'Errico et al. (2020) argue that governments and humanitarian aid agencies often invest in specific interventions primarily to build the resilience of vulnerable households. Keil et al. (2008) also report that interventions designed to help farmers adapt or mitigate the impacts of climate change through provision of crop insurance, among others, contribute to enhancing household resilience capacity. In the context of farm households, agronomic practices that enhance their ability to adapt to the changing climatic effects on production systems are essential components of adaptive capacity (Béné et al., 2012; FAO, 2016).

There is limited evidence on whether resilience capacity mediates or moderates the relationship between shocks and food security. This study aims to address this gap. We analyze and compare the mediation and moderation roles of resilience capacity, measured through the Resilience Index Measurement and Analysis (RIMA) approach (FAO, 2016), which have not been addressed well in empirical literature. In this regard, we examine the direct effect of resilience capacity on household food security (proxied by household calorie consumption, household dietary diversity score, and per capita consumption expenditure), as well as its indirect, shock-moderating or mediating effects.

While many emerging studies use panel data methods to assess household resilience to weather shocks and how it affects food security (Brück et al., 2019; D'Errico et al., 2018; Galarza, 2020; Murendo et al., 2021; Murendo et al., 2020), our study fills a gap in the literature by analysing both within-household and between-household effects. Our econometric strategy relies on the correlated random effects (CRE) model and instrumental variable (IV) regression for moderation analysis, and structural equation modelling for mediation analysis to address these empirical gaps. The use of the CRE allows us to adequately measure the shock effects on food security, considering the effects of time-invariant factors. The IV approach allows us to address endogeneity due to unobserved heterogeneity and treatment. The structural equation model used in the mediation analysis allows us to assess the proportion of shock effects on food security that is mediated by resilience capacity.

2. Conceptual framework

Our conceptual model visualizes resilience capacity through the lens of mediation on one hand, and moderation on the other. Fig. 1 displays the conceptual links between shocks, resilience capacity, and food security.

Farmers usually meet their food security by directly consuming the crops they produce, buffer stocks and food they purchase from the market financed primarily through incomes they derive from marketed surpluses. Occasionally, some farm households may also obtain food supplies through gifts or barter. Shocks, manifested by droughts, floods, and extreme temperatures, negatively affect crop yields, reducing the amount of food available for household consumption as well income they generate from marketed surpluses. This direct effect of shocks on food security is represented by b_1 in Fig. 1. Without a third variable, b_1 measures the total effect of shocks (S_{it}) on food security (FS_{it}), but once a third variable is introduced, b_1 represents a direct effect only. The total effect, which consists of direct and indirect effects, may be mediated/moderated by resilience capacity (RC_{it}).

The position of resilience capacity as conceptually linking shocks and food security in the context of mediation is supported by literature, yet it

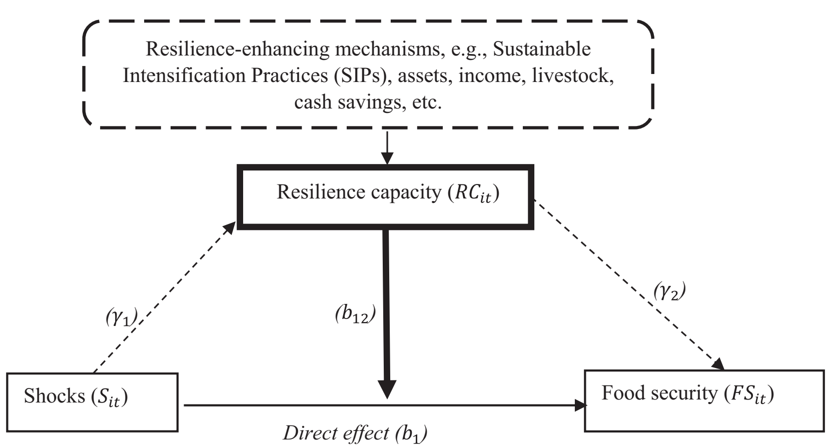

Fig. 1. Resilience capacity mediating/moderating the link between shocks and food security. Solid arrows represent moderation; broken arrows mediation.
Source: Adapted and modified from Andersson et al. (2020); Baron and Kenny (1986).

has not yet been explored. For instance, the literature thus far considered resilience capacity as an intermediate outcome that leads to achieving or improving an overall well-being result such as food security (Béné et al., 2012; Brück et al., 2019; Murendo et al., 2020). According to Jose (2013), mediation emphasizes the mechanism that operates between the two predictors (i.e., S_{it} and RC_{it}) and the outcome (FS_{it}). Thus, the interest in mediation is to examine the possibility that S_{it} predicts RC_{it}, which in turn predicts FS_{it}. Mediation explicitly examines the relationship between the independent variable (S_{it}) and the mediating variable (RC_{it}), as well as the ability of both S_{it} and RC_{it} to predict the dependent variable, FS_{it}. Complete mediation occurs if variable S_{it} no longer affects FS_{it} after RC_{it} has been controlled, making b_1 zero (Fig. 1). Partial mediation exists if the magnitude of b_1 is significantly reduced in absolute size when the mediator RC_{it} is introduced. The variable RC_{it} is thus considered the mechanism or process through which the impact of S_{it} on FS_{it} is realized.

On the other hand, moderation explicitly involves an interaction term between the two independent variables, S_{it} and RC_{it}. The inclusion of the interaction term as a third variable helps explain variability in the dependent variable, FS_{it} above and beyond the two additive effects contributed by S_{it} and RC_{it}. The interaction term provides important information about how shocks and resilience capacity jointly predict the food security. Therefore, in moderation analysis, the interest is not in the causal relationship between S_{it} and RC_{it}, but it is in the interaction between the two variables and its effect on FS_{it}.

Thus far, the literature on shocks, resilience and food security adopts the approach of moderation and less attention to mediation. To assess mediation or moderation, we focused on internally generated and externally sourced mechanisms or indicators such as assets, social safety nets, adaptive capacity, among others, of resilience that mediate or weaken the effect of shocks on food security. Resilience capacity is achieved through resilience-enhancing processes, including sustainable intensification practices (SIPs), assets, income, livestock, and cash savings, among others. Adoption of SIPs enhances households' adaptive capacity and consequently improves farmers' resilience capacity, which may dampen or intercede the effects of shocks on crop yields. This is the shock-mediating ($\gamma_2 * b_1$) or moderating (b_{12}) effect of resilience capacity. In Fig. 1, the direction of b_1 is expected to be negative whether RC_{it} is regarded as mediator or moderator.

3. Data and methodology

3.1. Data and variables

We used two waves of panel data conducted at onset and towards the end of the Africa RISING project in northern Ghana, spanning six years. The baseline survey data, collected in 2014, sampled 1284 farm households distributed across 50 communities in three northern regions of Ghana namely, Northern (former structure), Upper East, and Upper West regions. The survey was designed based on a quasi-randomized control trial method (Tinonin et al., 2016). A stratified two-stage sampling technique was used to select respondents. The first stage consisted of a random selection of control and intervention communities; in the second stage households within each community were randomly selected. Half of the selected communities were earmarked to receive intervention from the project while the other half were randomly sampled to serve as a control group. About 93% of the sample households in the baseline survey were interviewed during the endline survey (i.e., 450 households from control communities and 744 households from project intervention communities).

We relied on the two survey datasets to capture most of the variables in our analysis including, among others, resilience capacity, household food security, and household demography. We used three alternative (interrelated) variables as indicators of household food security namely, household calorie consumption, per capita food expenditure, and household dietary diversity score (DDS). For resilience capacity, we adopted the FAO's RIMA approach, specifically designed to explore the nexus between food security and resilience (Ansah et al., 2019; FAO, 2016). The RIMA approach uses the multiple indicator multiple cause (MIMIC) model, combining factor analysis with linear regression models to generate the latent indicators and the overall resilience capacity index (RCI) (see D'Errico et al., 2018; Smith and Frankenberger, 2018; FAO, 2016). For the baseline and follow-up surveys we constructed four pillars of resilience and RCI based on variables available in the datasets: access to basic services (ABS), assets (AST), adaptive capacity (AC), and social safety nets (SSN) (see Table A1 in the annex for details of the component variables of the four RIMA pillars).

In addition to the survey data, we used long-term meteorological data on precipitation and temperature to generate objective measures of shocks. Precipitation and temperature time-series data during 1981–2020 were obtained from the TerraClimate database (Abatzoglou et al., 2018). This database provides gridded monthly climate data from 1981 to the present with 4 km spatial resolution and global coverage. GPS locations of the survey households were used to extract monthly total precipitation and mean temperature from 2014 to 2020. Monthly time-series climate data for each household were aggregated to annual total precipitation and mean temperature, respectively. Long-term means (LTM) and standard deviation (SD) of the two variables were generated for the same period. Following Muthoni et al. (2019), the difference between annual total precipitation and LTM was divided by SD to derive the standardized precipitation anomaly. Precipitation anomalies indicate the difference between annual precipitation and LTM precipitation, with negative values representing periods of below-normal rains (droughts), and positive values representing above-normal rains (flood risk). Negative anomalies for temperature indicate cooling, while positive values reflect above-normal heating (heat stress) compared with LTM. Assuming that food security outcomes are more likely affected by the weather conditions of the cropping seasons prior to the time of data collection, we used standardized anomalies of 2013 for the baseline data and those of 2019 for the endline data. Following Azzarri and Signorelli (2020), we derive a measure of drought as standardized anomalous precipitation values below −2.0 and that of heat stress as standardized anomalous temperatures above 2.0. Thus, in the econometric models, we include shocks as dummy variables in the form of drought and heat stress.

3.2. Econometric strategy

Our econometric strategy aims mainly to test and explain the mediation and/or the moderation roles of resilience capacity between shocks and food security. We first discuss the strategy for testing moderation effects in Section 3.2.1 and that of mediation effects in Section 3.2.2 next.

3.2.1. Testing for moderation

In moderation, our main strategy is to examine the statistical interaction between shocks (heat stress/drought) and resilience capacity. Let FS_{it} denote food security outcome indicator for household i in period t; RC_{it} is a measure of household resilience capacity estimated following the RIMA approach based on multivariate analysis (FAO, 2016); and S_{it} is a vector of shocks, mainly drought and heat stress, X_{it} is a vector of control covariates such as the age of the household head, household size, sex of the household head, and education of the household head; A_i is an indicator variable denoting participation in Africa RISING interventions for at least three years since 2014; u_i is a unit-specific error term assumed to differ between units but constant for any particular unit; and e_{it} is a white noise idiosyncratic error term, and b_1, b_2, b_{12}, b_3 and b_4 are parameters to be estimated. The basic regression model to test our moderation hypothesis is the following:

$$FS_{it} = b_0 + b_1 S_{it} + b_2 RC_{it} + b_{12} RC_{it} S_{it} + b_3 X_{it} + b_4 A_i + u_i + e_{it} \tag{1}$$

Eq. 1 represents a multiple regression with three core predictive terms: the key independent variable (i.e., S_{it}), the moderating variable (i.e., RC_{it}) and the interaction term of the independent variable and the moderator (i.e., $RC_{it}*S_{it}$). Ignoring the control variables X_{it} and A_i, we have two main effects (b_1 and b_2) and an interaction effect (b_{12}). Note also that the basic relationship we are investigating is the association between shock and food security. We introduce resilience capacity because we are keen to know whether it might influence this basic relationship; we envisage a dampening effect (i.e., the negative impact of shock on food security is expected to be reduced by resilience capacity). The proposed moderation effect of resilience capacity, if it exists, should be evident in the interaction term ($RC_{it}*S_{it}$) predicting the outcome variable (FS_{it}). A standard *t*-test is used in assessing the operational and statistical significance of the interaction term (b_{12}). If positive and significant, we can conclude that resilience capacity dampens the negative effect of shock on food security. On the other hand, if b_{12} is negative and significant, then resilience capacity rather enhances or reinforces the negative effect of shocks on food security.

Although there are several options to estimate Eq. 1, researchers have typically used either the fixed effects (FE) or the random effects (RE) model, depending on the assumptions made about u_i and e_{it}. The FE approach admits a correlation between the independent variables and u_i, and hence eliminates it by group-mean centering the variables so that u_i disappears from eq. (1) completely. The FE model eliminates any between-household effects and only emphasizes within-household variation, which makes it unable to estimate the effects of time-invariant covariates. Further, FE assumes a zero correlation between the independent variables and e_{it}. The RE model, on the other hand, allows zero correlation between e_{it} and u_i, so that both time-varying and time-invariant effects are admissible. In other words, the RE model assumes that unobserved heterogeneity is uncorrelated with the observed explanatory variables, which is a very strong assumption and difficult to achieve in practice (Wooldridge, 2019).

The third estimation option is the correlated random effect (CRE) model. The CRE is becoming a popular choice because of its ability to unify the FE and RE approaches (Joshi and Wooldridge, 2019). It relaxes the assumption of non-zero correlation between u_i and the independent variables, and also permits the inclusion of both time-invariant and time-varying covariates. It does so by introducing the cluster means of all time-varying variables in an RE model. In this case, the coefficients for time-invariant variables correspond to those from an RE model, whereas coefficients for time-variant covariates are comparable to the FE estimates (Mundlak, 1978).

In the context of the CRE approach, Eq. 1 can be modified as follows:

$$\begin{aligned} FS_{it} =& b_0 + b_1 S_{it} + b_2 RC_{it} + b_{12} RC_{it} S_{it} + b_3 X_{it} + b_4 A_i \\ &+ b_5 \overline{RC}_i + b_6 \overline{S}_i + b_7 \overline{X}_i + v_i + e_{it} \end{aligned} \tag{2}$$

where $\overline{RC}_i, \overline{S}_i, \overline{X}_i$ denote the cluster means associated with RC_{it}, S_{it}, and X_{it}, respectively, which accounts for any correlation between these variables and the error term at the cluster level. The coefficient associated with this variable measures the difference between the within and between effects (Mundlak, 1978).

When the time averages of truly time-varying covariates are added, the CRE approach allows the effect of time-varying covariates to be estimated, thereby allowing between-household heterogeneity to be correlated with the time-varying covariates (Mundlak, 1978). Nonetheless, the CRE rules out the possibility that explanatory variables are correlated with time-varying innovations across any period. To address this, we use the control function approach and instrumental variable (IV) generalized least-squares random effects (GLS RE) regression models specified in Eqs. (3a), (3b), and (3c). The GLS RE accounts for the potential endogeneity in resilience capacity and treatment selection.

$$FS_{it} = b_0 + b_1 S_{it} + b_2 RC_{it} + b_3 X_{it} + b_{12} RC_{it} S_{it} + b_4 A_i + u_i + e_{it} \tag{3a}$$

$$RC_{it} = \alpha_0 + \alpha_1 Z_{1it} + \alpha_2 Z_{2it} + v_{1it} \tag{3b}$$

$$A_i = \delta_0 + \alpha_1 Z_{3it} + \delta_2 Z_{4it} + v_{2it} \tag{3c}$$

where Z_{it} are selected instruments; u_i is unit-specific error term assumed to differ between units but constant for any particular unit; and e_{it}, v_{1it} *and* v_{2it} are white noise idiosyncratic error terms. Since RC_{it} in eq. (3a) could potentially be endogenous due to correlation with u_i, we use access to model farmer and mobile phone ownership as instruments. Our exclusion restriction test supports these as valid instruments since they correlate strongly with resilience capacity but not with food security. The treatment variable (participation in the Africa RISING intervention) is also assumed to be endogenous due to potential sample selection, hence, as instruments, we use minimum and maximum distances to the nearest and farthest plots, respectively. These instruments also passed the exclusion restriction tests.

3.2.2. *Test for mediation*

The test for mediation effects of resilience capacity between shocks and food security follows the Baron and Kenny (1986) causal four-step strategy. The first step aims to demonstrate that there is an effect to be mediated by examining the correlation between the causal and outcome variables. Thus, we regress FS_{it} on S_{it} to obtain γ_1, controlling for other variables (Eq. 4a).

$$FS_{it} = \gamma_0 + \gamma_1 S_{it} + e_{1t} \tag{4a}$$

The second step aims to show that the causal variable is correlated with the intervening variable by regressing RC_{it} on S_{it} to obtain γ_2 as shown in Eq. 4b.

$$RC_{it} = \gamma_0 + \gamma_2 S_{it} + e_{2t} \tag{4b}$$

The third step aims to test whether the mediating variable affects the outcome variable ($b_1 > 0$) and whether there is a complete mediation ($b_2 = 0$) by regressing FS_{it} on S_{it} and RC_{it}.

$$FS_{it} = \alpha_0 + b_1 RC_{it} + b_2 S_{it} + e_{3t} \tag{4c}$$

While the situation of complete mediation is rarely observed in social sciences (see Baron and Kenny (1986); Preacher and Hayes (2008); (Jose, 2013), measuring the strength of mediation is appropriate which can be done by testing the significance of the indirect effect of RC_{it} ($b_1*\gamma_2$), which is the same as $\gamma_1 - b_1$. Resilience capacity is a mediator if (1) S_{it} significantly accounts for variability in RC_{it} and FS_{it}, (2) RC_{it} significantly accounts for variability in FS_{it} when controlling for S_{it}, and (3) the effect of S_{it} on FS_{it} reduces substantially when RC_{it} is entered simultaneously with S_{it} as a predictor of FS_{it}. Based on these, there can be no mediation, partial mediation, or complete mediation. The methods proposed for testing mediation include a z-test developed by Sobel (1987) (eq. 5a), or the bootstrap test (Zhao et al., 2010) of the indirect effects calculated as in eq. (5b).

$$z = \frac{b_1 * \gamma_2}{\sqrt{b_1{}^2 s_2{}^2 + \gamma_2{}^2 s_1{}^2}} \tag{5a}$$

$$Indirect\ effect\ size = b_1 * \gamma_2 \tag{5b}$$

where $s_1{}^2$ and $s_2{}^2$ are the standard errors of b_1 and γ_2, respectively.

A third approach to assessing the indirect effects is a Monte Carlo simulation procedure (Jose, 2013; Preacher and Hayes, 2008). A nonsignificant indirect effect indicates that RC_{it} does not mediate the shock–food-security relationship. It is also of interest to know the effect size of the mediation, which is based on the formulae specified in eqs. (5c) and (5d) (Mehmetoglu, 2018; Sobel, 1987).

$$\text{Ratio of indirect to total effect (RIT)} = \frac{b_1 * \gamma_2}{(b_1 * \gamma_2) + \gamma_1} \tag{5c}$$

$$\text{Ratio of indirect effect to direct effect (RID)} = \frac{b_1 * \gamma_2}{\gamma_1} \tag{5d}$$

The RIT can be interpreted as the proportion of the total effect of the independent variable (shocks) on the dependent variable (food security) that is explained by the mediator (resilience capacity). The RID can be interpreted as how large the effect is mediated compared to the direct effect of the independent variable on the dependent variable.

To implement the above tests, we adopted an improved estimation approach designed by Mehmetoglu (2018). This is a structural equation modelling technique that combines the first three steps of the mediation analysis and estimates all parameters simultaneously. We also performed postestimation tests after the simultaneous estimation.

4. Results and discussion

4.1. Descriptive results

Table 1 defines the core variables used in the econometric models and summarizes their values for each survey round and the corresponding differences between the two survey waves. The baseline values of total household calorie consumption and HDDS were higher than their respective endline values while the reverse was true for per capita consumption expenditure. The household heads' average age was about 48 years at baseline and 52 at the follow-up survey. The average household size at the baseline is higher by about one person than the one at the endline. Farm households in the sample generally have less than three years of formal education, increasing only slightly from baseline to endline survey. In both rounds of the survey, only a few households had female heads; the percentage of female-headed households was slightly higher in the follow-up than in the baseline (though not statistically significant).

The weather shocks were more severe during the endline than during the baseline. The heatmap in Fig. 2 shows that the average drier conditions in the endline period (Fig. 2b) coincide with significantly warmer conditions (Fig. 2d) in the same period. Comparing the shock conditions in the endline and baseline with their respective food security outcomes, we can infer that the relatively worse outcomes in the endline can be partly attributed to the extreme weather events that occurred.

Farmers' resilience capacity during the endline (75.79%) was significantly higher than their resilience capacity during the baseline (57.12%) suggesting that, on average, households' capacity to withstand shocks increased between the two periods. Fig. 3 displays the values of resilience capacity and its components at the baseline year (2014) and the endline year (2020). The figure shows that overall resilience capacity increased by about 33% between 2014 and 2020. The improvement in resilience capacity can be attributed partly to the increase in households' adaptive capacity and improved SSN. The average adaptive capacity of farm households increased by about 10% between the survey periods, and SSN increased by about 50% in the same period. In contrast, the ABS and AST pillars reduced on average by approximately 22% and 38%, respectively (see Fig. A1 for the spatial distribution of resilience capacity).

4.2. Empirical results on moderation and mediation

Tables 2 and 3 report results of alternative regression models for testing the moderation hypothesis. We consider CRE and IV regression results as the main results for discussion, and report FE and RE results as robustness checks. The overall, as well as between and within, variation in the dependent variables is moderately high ranging between 45% and 54% for the CRE and IV regression models implying that the independent variables fairly explained the observed variation in food security outcomes.

In all the moderation models, both heat stress and drought exert a significant negative influence on food security outcomes as expected, suggesting that farm households that experienced drought or heat stress tended to report lower food security outcomes than those that did not face these shocks. Whether we include only heat stress (models 10–12 in Table 3), drought only (models 13–15), or both as shock predictors (models 16–18), the direction of the effects remains largely similar for heat stress, but varies a bit for drought. Also, the estimated coefficients of resilience capacity (b_1) are positive in all the models, suggesting that increasing resilience capacity for a given farm household leads to significantly higher food security outcomes. The main effect of heat stress on food security is qualified by the significant interaction with resilience capacity in all the models. However, the modification of the main effect of drought on per capita consumption expenditure through its interaction with resilience capacity is not statistically significant. Like the CRE, the IV regression results confirm the significant main effect of resilience capacity on food security outcomes. Similarly, the main effect of heat stress on all food security indicators is significantly modified by its interaction with resilience capacity, while the interaction effect of resilience capacity with drought on per capita consumption expenditure is not significant.

We run different model specifications combining weather shocks to assess how the effects change when controlling for other shocks in the models. The overall result is that the effects of combined shocks are lower than when they are considered separately, indicating that multiple shocks bear greater effects than individual shocks alone, in line with the literature (Ansah et al., 2021).

The time variable is negative and significant which shows that food security outcomes were worse at the endline than at the baseline. This could be attributed to the severe weather conditions observed at the endline (Fig. 2). Also, the coefficient of resilience capacity in the FE model is negative, but after controlling for endogeneity it assumes the expected positive sign, indicating that controlling for endogeneity was necessary to identify the true correlation effects.

Table 4 reports the results for the mediation analysis alongside the standardized coefficients results from the moderation analysis. These results show that the conditions for mediation analysis are all met for both heat stress and drought as the main predictor of food security. The total effects, as well as the effect of shock on resilience capacity, or of resilience capacity on food security, are all statistically significant at the 1% level. The direct effects of both drought and heat stress are statistically significant for all food security indicators. However, the direct effects of drought in the moderation models are not significant for per capita consumption, whether based on the CRE or IV approach, and under individual or combined shocks. Therefore, while resilience capacity significantly mediates the association between the two shocks and all food security indicators, the results show a non-significant moderation effect of drought on per capita food consumption. The indirect effects confirm that resilience capacity significantly mediates the relationship between both shocks (drought and heat stress) and food security. However, like the direct effects, the moderation effect of resilience capacity between drought and per capita food expenditure is not significant in the IV models.

The significant mediation result across all models means that at least part of the statistical association between shocks and food security is transmitted indirectly through changes in resilience capacity. Consequently, the involvement of resilience capacity explains a significant proportion of the basic relationship between shocks and food security. Specifically, the standardized effect size of 0.060 for heat stress indicates

Table 1
Summary statistics of variables used for econometric analysis.

Variable	Definition	2020	2014	Difference
Household size	Number of people living in household	8.33 (0.15)	8.70 (0.15)	−0.37* (0.21)
Age of household head	Completed years of life of household head	51.21 (0.41)	47.69 (0.41)	3.52*** (0.58)
Education of household head	Completed years of education of household head	2.21 (0.12)	1.99 (0.12)	0.23 (0.17)
Female-headed household	Percentage of female–headed household	18.20 (1.08)	15.33 (1.08)	2.88 (1.53)
Household calorie consumption	Total household food consumption based on 12 food groups (kcal)	9815.31 (203.33)	11,362.6 (203.25)	−1547.29*** (287.50)
Per capita food expenditure	Per capita total consumption expenditure (Ghana cedis)	122.15 (2.78)	81.08 (2.77)	41.07*** (3.92)
HDDS	Household dietary diversity score based on consumption of 12 food items over the past 7 days	5.26 (0.06)	7.55 (0.06)	−2.29*** (0.08)
Heat stress	Dummy, 1 if annual temperature > 2 SD from long-term mean	0.45 (0.01)	0.00 (0.00)	0.45*** (0.01)
Drought	Dummy, 1 if annual precipitation > −2 SD from long-term mean	0.16 (0.01)	0.00 (0.00)	0.16*** (0.01)
RCI	Household resilience capacity (based on RIMA)	75.79 (0.34)	57.17 (0.34)	18.62*** (0.48)

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$; standard errors in parenthesis.

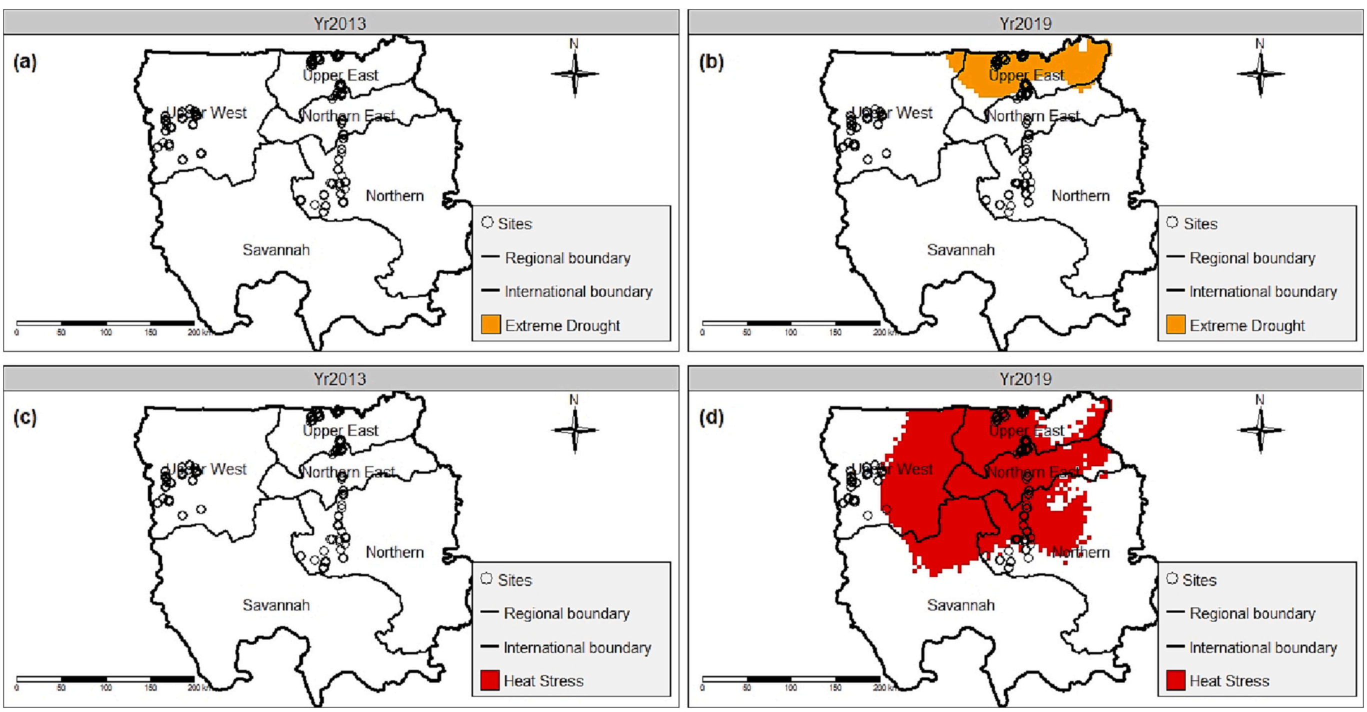

Fig. 2. Spatial distribution of drought (a, b) and heat stress (c, d) in 2013 (a, c) and 2019 (b, d) surveys.

that about 537%[1] (based on RIT) of the total effect of heat stress on household calorie consumption is explained by the indirect effect through resilience capacity. This result indicates a substantial proportion of the total negative effect of heat stress being mediated by resilience capacity, suggesting that such effects are not directly transmitted to household calorie consumption. Similarly, about 42% and 430% of the total effects of heat stress on per capita expenditure and HDDS, respectively, are explained by indirect effects through resilience capacity. Moreover, resilience capacity mediates about 74%, 39%, and 57% of the total effect of drought on household calorie consumption, per capita expenditure, and HDDS, respectively. The mediation results further depict the differentiated indirect effects, whereby the mediation effects for drought are smaller than for heat stress. This trend also holds in both the mediation and moderation models, but the trends for the direct effects are inconsistent across food security indicators.

The results show resilience capacity displays partial mediation between shocks and food security. The partial mediation is competitive for household calorie consumption and HDDS, while it is complementary for per capita expenditure.[2] The mediating role of resilience capacity is stronger than its moderating role. While the mediation effect is consistently significant for both drought and heat stress, the moderation

[1] The RIT larger than 100% is due to the relatively small negative direct effect but bigger and positive indirect effect, which leads to a smaller total effect than the indirect effect. Since RIT compares the indirect to the total effect, the resulting ratio exceeds 1.

[2] In competitive partial mediation, resilience capacity mediates the relationship between shocks and food security in such a way that both the direct and indirect effects are significant and point to opposite directions, while in complementary partial mediation, the significant direct and indirect effects point in the same path (Zhao et al., 2010).

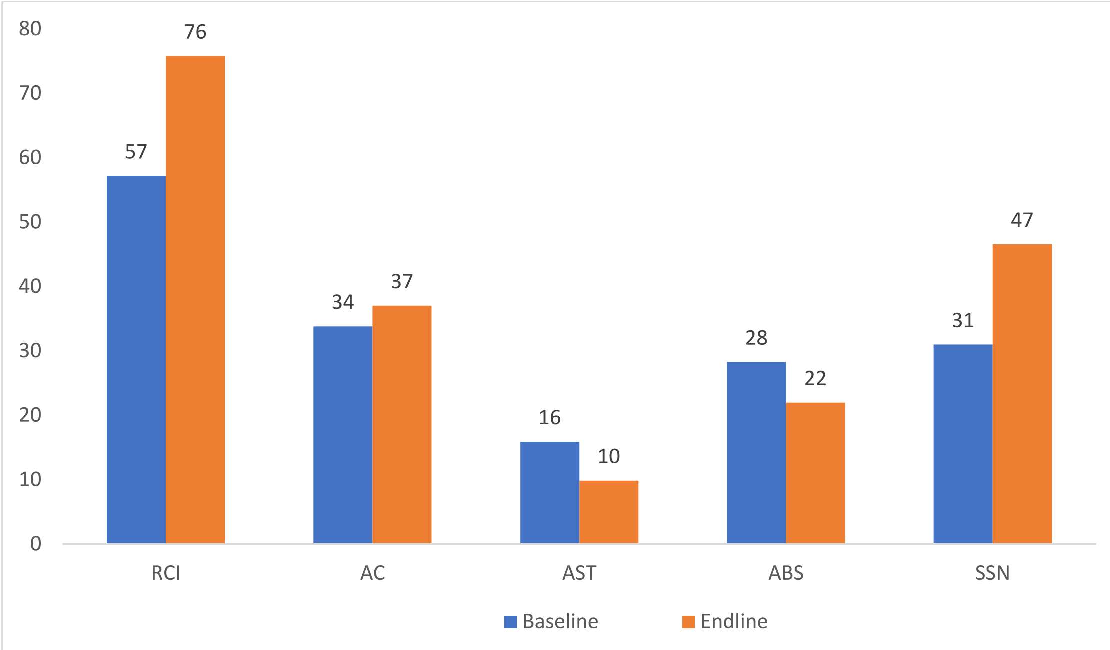

Fig. 3. Distribution of resilience capacity and its attributes at baseline and follow-up.

Table 2
Coefficient estimates from CRE, FE, and RE regressions for resilience capacity, shocks, and food security.

Variable	CRE			FE			RE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	HCC	PCE	HDDS	HCC	PCE	HDDS	HCC	PCE	HDDS
Resilience capacity index (RC)	0.028***	0.034***	0.110***	0.005***	0.024***	−0.014***	0.030***	0.032***	0.105***
	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.003)
Heat stress (HS)	−0.620***	−0.803***	−1.508**	−2.827***	−1.436***	−11.285***	−0.646***	−0.785***	−1.479**
	(0.211)	(0.215)	(0.715)	(0.323)	(0.281)	(1.302)	(0.211)	(0.215)	(0.715)
Drought (D)	−1.352***	0.338	−4.186***	−1.646***	−0.293	−8.882***	−1.276***	0.291	−4.373***
	(0.335)	(0.352)	(1.132)	(0.538)	(0.484)	(2.161)	(0.334)	(0.351)	(1.128)
HS * RC	0.008***	0.012***	0.020**	0.032***	0.017***	0.122***	0.009***	0.011***	0.020**
	(0.003)	(0.003)	(0.009)	(0.004)	(0.004)	(0.017)	(0.003)	(0.003)	(0.009)
D * RC	0.014***	−0.002	0.043***	0.021***	0.007	0.115***	0.013***	−0.002	0.045***
	(0.004)	(0.005)	(0.015)	(0.007)	(0.006)	(0.028)	(0.004)	(0.005)	(0.014)
Time	−0.765***	−0.368***	−4.204***				−0.818***	−0.335***	−4.096***
	(0.036)	(0.038)	(0.121)				(0.029)	(0.031)	(0.097)
Africa RISING intervention	−0.024	0.061**	−0.124*				−0.021	0.058**	−0.130*
	(0.021)	(0.024)	(0.073)				(0.022)	(0.024)	(0.073)
Household size	0.024***	−0.062***	−0.024	0.037***	−0.055***	0.059***	0.027***	−0.059***	−0.024***
	(0.005)	(0.005)	(0.016)	(0.005)	(0.005)	(0.021)	(0.002)	(0.002)	(0.007)
Female household head	−0.001*	0.001	0.000	−0.002**	0.000	−0.002	−0.001***	0.000	−0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.001)
Age of household head	−0.003*	−0.001	−0.010*	−0.007***	−0.003**	−0.034***	0.000	−0.004***	−0.009***
	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)	(0.002)
Education of household head	−0.005	0.009	−0.030	−0.016**	0.004	−0.091***	−0.009***	0.017***	−0.010
	(0.006)	(0.006)	(0.020)	(0.007)	(0.006)	(0.027)	(0.002)	(0.003)	(0.008)
Mean RC	0.004**	−0.002	−0.011*						
	(0.002)	(0.002)	(0.006)						
Mean household size	0.003	0.005	0.004						
	(0.005)	(0.006)	(0.018)						
Mean female household head	−0.000	0.000	−0.000						
	(0.001)	(0.001)	(0.002)						
Mean age of household head	0.004**	−0.004**	0.001						
	(0.002)	(0.002)	(0.006)						
Mean education of household head	−0.005	0.010	0.025						
	(0.006)	(0.007)	(0.022)						
Constant	7.108***	3.095***	2.619***	8.901***	3.390***	9.123***	7.290***	2.961***	2.284***
	(0.090)	(0.101)	(0.307)	(0.114)	(0.103)	(0.449)	(0.065)	(0.071)	(0.221)
Observations	2360	2385	2384	2360	2385	2384	2360	2385	2384
Number of HHID	1194	1194	1194	1194	1194	1194	1194	1194	1194
R^2-	0.5244	0.4789	0.5338	0.2984	0.4318	0.1392	0.5244	0.4789	0.5338

Table 3
Instrumental variable (IV) regressions for isolated and combined shocks, controlling for endogeneity of treatment (sample selection) and resilience capacity.

Variable	Isolated shocks						Combined shocks		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	HCC	PCE	HDDS	HCC	PCE	HDDS	HCC	PCE	HDDS
Resilience capacity index (RCI)	0.034***	0.042***	0.107***	0.034***	0.043***	0.106***	0.033***	0.042***	0.105***
	(0.004)	(0.004)	(0.013)	(0.004)	(0.004)	(0.012)	(0.004)	(0.004)	(0.012)
Heat stress (HS)	−1.163***	−0.604***	−3.266***				−0.757***	−0.833***	−1.875**
	(0.184)	(0.184)	(0.627)				(0.226)	(0.225)	(0.760)
Drought (D)				−1.741***	−0.240	−5.424***	−1.052***	0.486	−3.631***
				(0.303)	(0.317)	(1.009)	(0.376)	(0.385)	(1.264)
HS * RC	0.013***	0.010***	0.034***				0.008***	0.011***	0.019**
	(0.002)	(0.002)	(0.008)				(0.003)	(0.003)	(0.009)
D * RC				0.020***	0.006	0.061***	0.012***	−0.003	0.042***
				(0.004)	(0.004)	(0.013)	(0.005)	(0.005)	(0.015)
Time	−0.750***	−0.330***	−3.892***	−0.808***	−0.326***	−4.096***	−0.755***	−0.313***	−3.933***
	(0.034)	(0.035)	(0.115)	(0.028)	(0.028)	(0.092)	(0.037)	(0.039)	(0.125)
Household size	0.030***	−0.060***	−0.014*	0.029***	−0.058***	−0.020**	0.030***	−0.058***	−0.016**
	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)	(0.008)	(0.002)	(0.003)	(0.008)
Africa RISING intervention	0.302***	0.105	1.002***	0.242***	0.180*	0.472	0.274**	0.173	0.704*
	(0.091)	(0.097)	(0.317)	(0.093)	(0.107)	(0.318)	(0.112)	(0.125)	(0.384)
Female household head	−0.001***	0.001**	0.001	−0.001***	0.001**	0.001	−0.001***	0.001*	0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Age of household head	−0.000	−0.004***	−0.010***	−0.000	−0.004***	−0.010***	−0.000	−0.004***	−0.010***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
Education of household head	−0.010***	0.018***	−0.014	−0.009***	0.017***	−0.010	−0.009***	0.016***	−0.011
	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)	(0.003)	(0.003)	(0.009)
Constant	6.897***	2.302***	1.557*	6.910***	2.176***	1.901**	6.933***	2.281***	1.847**
	(0.251)	(0.261)	(0.857)	(0.246)	(0.260)	(0.820)	(0.251)	(0.264)	(0.845)
Observations	2349	2374	2373	2349	2374	2373	2349	2374	2373
Number of HHID	1194	1194	1194	1194	1194	1194	1194	1194	1194
R^2 (overall)	0.4585	0.4639	0.5179	0.4684	0.4663	0.5283	0.4594	0.4649	0.5277

HCC = household calorie consumption; PCE = per capita consumption expenditure; HDDS = household dietary diversity score; standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
Comparison of causal mediation analysis and moderation outcomes based on standardized coefficients.

Parameter	Heat stress			Drought		
	HCC	PCE	HDDS	HCC	PCE	HDDS
Total effect: *FS < − S (a)*	−0.011***	0.148***	−0.190***	−0.061***	0.123***	−0.071***
	(0.020)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
Direct effect: FS < − S,C (b)						
Mediation	−0.049***	0.085***	−0.068***	−0.105***	0.075***	−0.111***
	(0.017)	(0.017)	(0.017)	(0.015)	(0.015)	(0.015)
Moderation (main effect)						
CRE approach	−0.732***	−0.367***	−0.587***	−0.756***	−0.140	−0.638***
	(0.107)	(0.107)	(0.107)	(0.111)	(0.115)	(0.108)
IV approach	−0.711***	−0.356***	−0.593***	−0.673***	−0.141	−0.683***
	(0.114)	(0.108)	(0.107)	(0.124)	(0.122)	(0.116)
Indirect effect: (a − b)						
Mediation[a]	0.060***	0.062***	0.055***	0.045***	0.048***	0.040***
	(0.015)	(0.016)	(0.014)	(0.013)	(0.014)	(0.012)
Moderation (interaction effect)						
CRE approach	0.696***	0.472***	0.545***	0.648***	0.230**	0.540***
	(0.107)	(0.107)	(0.105)	(0.110)	(0.114)	(0.108)
IV approach	0.611***	0.491***	0.568***	0.599***	0.223	0.582***
	(0.121)	(0.114)	(0.114)	(0.122)	(0.120)	(0.114)
Shock on RCI (γ_1)	0.077***	0.074***	0.077***	0.057***	0.057***	0.056***
	(0.049)	(0.018)	(0.056)	(0.016)	(0.016)	(0.016)
RCI on food security (γ_2)	0.781***	0.846***	0.714***	0.786***	0.847***	0.718***
	(0.050)	(0.041)	(0.056)	(0.048)	(0.041)	(0.056)
Effect size of mediation						
RIT (proportion of total effect mediated)	5.366	0.422	4.296	0.739	0.389	0.567
RID	1.229	0.731	0.811	0.425	0.638	0.362
ACME	0.316***	0.317***	0.573***	0.203***	0.237***	0.259***
Type of mediation						
Baron and Kenny	Partial	Partial	Partial	Partial	Partial	Partial
Zhao et al	Competitive partial	Complementary partial	Competitive partial	Competitive partial	Complementary partial	Competitive partial

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; RIT = ratio of indirect to total effect; RID = ratio of indirect to direct effect, ACME = average causal mediation effect.

[a] Tests based on the Delta, Sobel, and Monte Carlo approaches for testing mediation all yield the same outcome.

outcomes show that resilience capacity consistently weakens the negative effect of heat stress on food security, but the effect is inconsistent for drought being statistically significant only for household calorie consumption and HDDS. In the moderation analysis, a standard deviation increase in heat stress directly reduces household calorie consumption by about 0.7 SD, but resilience capacity dampens this negative effect, increasing calorie consumption by between 0.6 and 0.7 SD. On the other hand, the mediation results show that the 0.05 SD reduction in household calorie consumption caused by the direct effect of heat stress is partially mediated (by 0.06 SD) by resilience capacity.

Our results complement empirical findings in developing countries regarding the nexus between resilience capacity and household food security. For example, D'Errico et al. (2018) found that higher levels of resilience capacity reduced the probability of experiencing food security losses among Ugandan and Tanzanian households. Similarly, D'Errico and Pietrelli (2017) reported a negative association between resilience capacity and probability of malnutrition in Malian households. In the face of drought, Murendo et al. (2020) reported direct effects of resilience capacity on HDDS and food consumption. Galarza (2020) also found a positive relationship between resilience capacity and food security, considering the number of weather shocks experienced by farm households. Our findings link these reports to an indirect mediation role for resilience capacity in the association between shocks and food security. Beyond the existing findings, our approach enables us to quantify the extent of mediation that is accomplished by resilience capacity.

Heat stress exerts negative effects on food security in all the estimated moderation models, whether or not we control for endogeneity. The standardized coefficients suggest that heat stress has a larger effect than drought on food security outcomes. The literature suggests that high temperatures threaten food production and availability directly through changes in agroecological conditions (Schmidhuber and Tubiello, 2007) or through reduction in crop yields (Tai and Val Martin, 2017). Recent findings show evidence of a warming trend in northern Ghana (Muthoni, 2020), which is expected to accentuate soil water loss through evapotranspiration adversely affecting crop growth and yields. With most farm households deriving their food needs from crop production, heat stress would also be expected to adversely affect their income generation capacity and reduce food security.

These results also agree with recent evidence that northern Ghana is experiencing significant warming, whereas changes in rainfall amount remains stable (Muthoni et al., 2020). While other studies in Africa observe that precipitation is the most important limiting factor for crop production (Niles et al., 2015), evidence shows that temperature is the main determinant of crop yields (Lobell et al., 2011; Zhao et al., 2017) and the value of crop production (Maggio et al., 2022). Hatfield and Prueger (2015) reported that temperature rise above optimal range during grain filling stage reduces maize yield by 80–90%. A combination of moisture and heat stress further exacerbates the effect on crop yield. For example, Lobell et al. (2011) demonstrated that about 65% of maize-growing areas in Africa would experience yield losses due to 10 °C warming under optimal rain-fed management, while 100% of these areas would be harmed by warming under drought conditions. In line with this evidence, this study shows that heat stress is the weather shock that matters most to the resilience of farm households in northern Ghana. As discussed by Muthoni et al. (2019) and Niles et al. (2015), the impacts of precipitation and temperature shocks vary based on several factors, including location, time, farming system, agroecology, and adaptive capacity of farmers.

Resilience research has called for interventions and policies that lead to improvements in land use systems for farm households in developing countries and has emphasized the need to promote resilience of low-inputs rain-fed farming systems to maintain their structure and productive potential amidst weather shocks (Galarza, 2020). Adoption of Sustainable Intensification Practices (SIPs) is one of the innovative agricultural solutions that is promoted to increase productivity on existing agricultural farmland while at the same time generating positive impacts on the environment and society (Kotu et al., 2022).

5. Conclusions and policy implications

This paper examines how resilience capacity enables farm households to cope with the negative effects of drought and heat stress on food security. Resilience was measured based on FAO's RIMA approach, and these measurements were used to examine how resilience capacity mediates or moderates the negative effects of shocks on household food security, accounting for both between-household and within-household effects, as well as endogeneity. The role of resilience capacity as a mediator between shocks and food security is consistent for both heat stress and drought, but its moderating role is inconsistent for the two shocks. The inconsistent moderation effect might be reflected in the indicators used in measuring resilience capacity. As resilience capacity, computed using the RIMA approach, is a composite of several indicators, the possibility that some of the indicators have synergistic effects while others are antagonistic is high.

Resilience capacity consistently mediates the negative impacts of drought and heat stress, suggesting that the total effects of these shocks are not completely transmitted to household food security. The role of resilience capacity is to serve as the channel through which shock impacts are transmitted to food security, by absorbing the negative impacts, modifying it and then transmitting the residual effect to food security. With sufficient resilience capacity, the negative impacts of shocks would be significantly reduced and food security improved. Nevertheless, the finding of partial mediation points to other mediators that are not yet included in the food security model (Zhao et al. (2010). Thus, future work should search for other potential mediators that still leave persistent negative and significant direct effects, even after mediation by resilience capacity.

This study shows that heat stress exerts a strongly adverse effect on household food security, and hence it demands policy attention. One viable policy option would be scaling up locally suitable SIPs (e.g., promoting heat- or drought-tolerant varieties and moisture conservation practices) among smallholder farmers, thereby improving resilience capacity. Attempts should also be made to boost farm households' knowledge of weather patterns and potential impacts on their livelihoods. This entails provision of accurate and timely weather information and early warning systems based on affordable and efficient dissemination mechanisms. As most of the communities involved in this study have very poor access to infrastructure and markets, a holistic strategy aimed at effectively improving resilience may bring a more sustainable and positive change regarding food security outcomes at household level.

Declaration of Competing Interest

The authors declare that there is no conflict of interest in this manuscript.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.

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