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Precipitation, temperature, and child undernutrition: evidence from the Mali demographic and health surveys 2012–2013 and 2018

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Abstract

Background Undernutrition among children remains a severe burden in Sub-Saharan Africa. Climate change is widely recognized as a major obstacle to improving children's nutritional outcomes. Mali, a landlocked country in West Africa, has one of the highest prevalence of child undernutrition in the region and is also considered one of the most vulnerable nations to climate change globally. This study, therefore, aimed to assess the effects of precipitation and temperature on child undernutrition in Mali, with a focus on climatic differences between the southern and northern regions.

Methods We pooled the two most recent cross-sectional datasets from the Mali Demographic and Health Surveys (DHS) 2012–2013 and DHS 2018, integrating them with climatic variables at the DHS cluster level. The study included data from 12,281 children under five years of age. Precipitation and temperature data were extracted from the Advancing Research on Nutrition and Agriculture's DHS-Geographical Information System database, which provides a comprehensive range of climatic and geographic variables at the DHS cluster level. We assessed the effects of precipitation and temperature over periods of three months, six months, one year, and two years before the survey on child undernutrition using multivariable multilevel logistic regression models.

Results In southern Mali, 25.0% of children under five were stunted (95% CI 23.7–26.3%), 24.9% were underweight (95% CI 23.7–26.1%), and 9.3% were wasted (95% CI 8.5–10.1%). In northern Mali, the prevalence rates were higher: 29.6% for stunting (95% CI 27.0–32.1%), 28.7% for underweight (95% CI 26.0–31.3%), and 10.5% for wasting (95% CI 8.8–12.3%). From the pooled data analysis, we found that higher average monthly rainfall over the last three months (AOR = 0.977, $p = 0.012$) and six months (AOR = 0.974, $p = 0.003$) preceding the survey was significantly associated with lower odds of wasting in northern Mali, predominantly comprising desert areas. Moreover, in addition to reducing wasting, rainfall over the one year (AOR = 0.985, $p = 0.010$) and two years (AOR = 0.984, $p = 0.009$) prior to the survey showed a significant effect in reducing the odds of underweight among children in the north.

Conclusions Increased precipitation had a beneficial effect on children's nutritional status, particularly in the northern part of Mali, where water scarcity is a persistent challenge. Amid growing concerns about declining rainfall due to climate change, the risk of child undernutrition is expected to rise in the northern part. To address this escalating

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threat, it is crucial to implement effective and timely measures to mitigate the impacts of climate change and improve children's nutrition.

Keywords Climate variability, Precipitation, Temperature, Children, Stunting, Underweight, Wasting, West Africa, Mali

Background

Child undernutrition remains a significant global public health challenge, disproportionately affecting Sub-Saharan Africa (SSA). In 2022, an estimated 31.5% (56.8 million) of children under five years of age in SSA were stunted (height-for-age z-scores < -2), while 6.0% (10.3 million) suffered from wasting (weight-for-height z-scores < -2) [1]. Early childhood undernutrition increases the risk of mortality, morbidity, infections, developmental delays, and cognitive deficits [2]. Later in life, poor childhood nutrition negatively affects educational attainment and labor productivity, thereby constraining socioeconomic development [3, 4]. Consequently, investing in child nutrition addresses not only immediate health concerns but also enhances human capacity in the long run [5].

Climate change, particularly variations in precipitation and temperature, presents a formidable barrier to improving child nutrition, especially in regions highly vulnerable to climatic fluctuations. Studies have consistently demonstrated that exposure to extreme weather conditions during pregnancy and early childhood adversely affects child nutritional outcomes in SSA [6, 7]. For example, high temperatures during fetal development significantly increase the risk of undernutrition, including severe stunting [8–11]. Similarly, exposure to drought in early childhood has been associated with long-term negative socioeconomic outcomes due to deteriorated nutritional status during critical growth periods, as evidenced by studies conducted in 19 SSA countries [11] and in Malawi [12]. For a more detailed review and a broader range of empirical studies on the impact of drought on child nutrition, refer to [6, 7, 13, 14].

Mali exemplifies the dual burden of undernutrition and climate vulnerability in SSA. As one of the world's poorest nations, ranking 188th out of 193 countries on the Human Development Index for 2023/2024 [15], Mali faces alarmingly high rates of child undernutrition. Despite progress in reducing childhood stunting (from 38% in 2012–2013 to 27% in 2018), underweight prevalence (from 26 to 19%), and wasting (from 13 to 9%), undernutrition remains a major contributor to nearly half of under-five mortality [16–18]. Regional disparities persist, with stunting rates highest in northern regions, such as Gao (33%), Mopti (30%), and Tombouctou (30%), compared to Bamako in the south (15%) [18]. Current projections suggest that Mali is unlikely to achieve the Sustainable Development Goals for childhood nutrition by 2030 [19].

Geographically, Mali's diverse climate zones range from the arid Sahara Desert in the north, which receives less than 50 mm of annual rainfall, to the Sudanian savanna in the south, which experiences up to 1,100 mm of rainfall annually between June and October [20]. This stark climatic contrast exacerbates regional vulnerabilities. With two-thirds of its land affected by severe desertification and an average annual temperature increase of 0.7 °C since 1960, Mali is highly susceptible to the adverse effects of climate change [20, 21]. Such environmental pressures are likely to further aggravate child undernutrition, particularly in the northern regions.

To address these challenges, this study evaluates the impact of precipitation and temperature on child undernutrition in Mali, emphasizing the climatic distinctions between the northern and southern regions. The manuscript is organized as follows: the Methods section details the data and statistical analysis, the Results section presents the findings of the data analysis, and the Discussion section interprets the findings and concludes with policy implications.

Methods

Data

We utilized the two most recent cross-sectional data from the Mali Demographic and Health Survey (DHS): DHS 2012–2013 [22] and DHS 2018 [23]. The surveys applied a two-stage stratified cluster sampling, covering regions classified as southern (Bamako, Kayes, Sikasso, Segou, and Koulikoro) and northern (Gao, Kidal, Mopti, and Tombouctou) Mali as shown in the map (Fig. 1). Table 1 summarizes the surveys and sampling methodology.

In DHS 2012–2013, clusters were selected nationally with probability proportional to size, excluding three northern regions (Gao, Kidal, and Tombouctou) due to military occupation [22]. In DHS 2018, all regions were included, with 379 clusters sampled nationally [23]. A total of 26 households per cluster were surveyed for both rounds, and additional 35 households per cluster were surveyed in three northern regions (Gao, Kidal, and Tombouctou) during DHS 2018. DHS 2012–2013 included 10,105 households surveyed from November 2012 to February 2013, while DHS 2018 encompassed

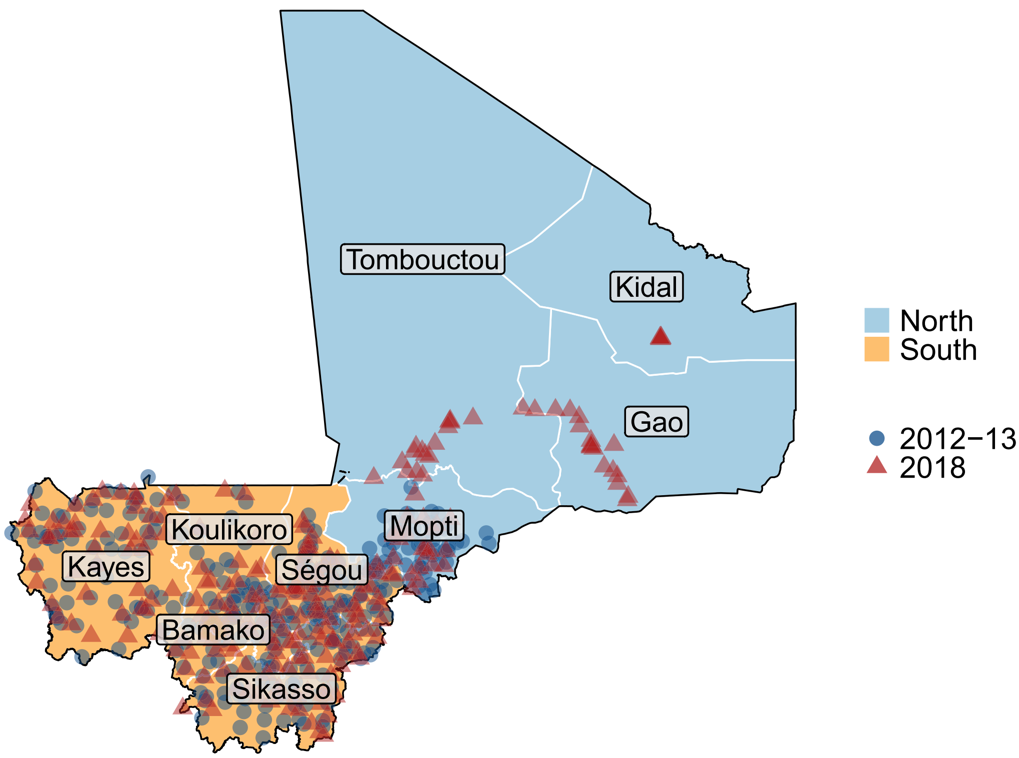

Fig. 1 Map of Mali classified by geographical parts (North and South)

Table 1 Summary of the surveys of Mali DHS 2012–2013 and DHS 2018

	DHS 2012–2013	DHS 2018
Survey period	November 13, 2012–February 5, 2013	August 6–November 18, 2018
Primary sampling units (clusters)	585	379
Households per cluster	26	26 or 35
Households surveyed	10,105	9510
Women (15–49 years) surveyed	10,424	10,579
Children aged < 5 years	9582	9275
Children aged < 5 years whose nutritional status were measured	4344	8193

9,510 households from August to November 2018 [22, 23].

All women aged 15–49 years living in these households were individually surveyed. Nutritional data on children under five years of age were collected from half of the surveyed households in DHS 2012–2013 and all households in DHS 2018. This study analyzed a pooled sample of 12,537 children under five years of age (4344 from DHS 2012–2013 and 8193 from DHS 2018).

There is now a variety of literature on different databases and indicators that can be used as proxies for climate variability [24–26]. In such a situation, we utilized the Advancing Research on Nutrition and Agriculture (AReNA)'s DHS-GIS (Geographical Information System) dataset [27]. This dataset integrates monthly precipitation and temperature data at a 0.5°×0.5° degree resolution from the Climatic Research Unit Timeseries, based on over 4000 weather station records [28]. Although empirical studies using the AReNA DHS-GIS dataset remain limited, research on child health has been conducted in Bangladesh [29] and SSA countries [30]. We linked the monthly precipitation and temperature data to the children in the DHS based on the survey rounds and clusters.

Statistical analysis

To examine the effects of precipitation and temperature on the likelihood of child undernutrition, we employed multivariable multilevel logistic regression models. Specifically, we applied a two-level multilevel model incorporating mother-level and cluster-level random effects. In our research sample, 33.4% of mothers had more than one child under the age of five. Given this proportion, accounting for mother-level clustering is statistically justified, as a significant portion of the children share common maternal factors such as biological characteristics, health status, and caregiving practices, which may lead to intra-mother correlations in nutritional outcomes. Ignoring these correlations could result in biased estimates and underestimated standard errors. Similarly, the cluster-level random effect controls for unobserved cluster-level characteristics, including traditional beliefs, cultural practices, legal policies, and other local and geographical factors that may influence child nutrition.

Statistical analysis was conducted using Stata version 16. We applied the svy (survey) commands to adjust for unequal sampling probabilities, clustering, and stratification in calculating sample characteristics, given that DHS employed a two-stage cluster sampling design. We used complete-case analysis, which is the default approach in Stata. Missing data in the DHS datasets were minimal [31], and no imputation was performed, as the analysis focused solely on available cases.

Outcome variables

For child undernutrition outcome variables, we used three anthropometric measures: height-for-age z-score (HAZ), weight-for-age z-score (WAZ), and weight-for-height z-score (WHZ). These measurements correspond to the standard deviations from the median of the reference population as defined by the World Health Organization [32]. A child with a HAZ, WAZ, or WHZ more than two standard deviations below the median of the reference population is classified as moderately stunted, underweight, or wasted, respectively. HAZ is a long-term index representing a child's linear growth, with stunting indicating chronic undernutrition. WAZ identifies underweight children and serves as an index of both acute and chronic undernutrition. WHZ is a short-term index, with wasting indicating acute undernutrition. Wasting typically results from a recent nutritional deficiency, and its prevalence can fluctuate seasonally based on food availability and disease incidence.

Explanatory variables

Precipitation and temperature variables at the DHS cluster level served as the primary predictors. Regarding precipitation, considering that the outcome variables of stunting, underweight, and wasting have long-term, acute, and seasonal characteristics, we used the average monthly precipitation from four different periods preceding the survey: three months, six months, one year, and two years. Next, we calculated the difference between the average monthly rainfall and the long-term average rainfall over a 40-year period (1980- 2019), using this as a proxy for rainfall variability, following previous studies [33]. A positive value indicates that the rainfall for that month was higher than the long-term trend, whereas a negative value indicates that it was lower. Additionally, we defined a "dry climate" variable as a binary variable, assigning a value of 1 if the annual average precipitation was less than 200 mm, and 0 otherwise [34]. For temperature, we used the average temperature from three-month, six-month, one-year and two-year periods preceding the survey, as with precipitation variables.

Control variables

To account for potential confounding factors, all regression models incorporated child-, mother-, and household-level characteristics. Child-level variables included sex (boy or girl) and age categories (0–11 months, 12–23 months, 24–35 months, 36–47 months, and 48–59 months). Mother-level variables encompassed age categories (15–19 years, 20–24 years, 25–29 years, and 30–49 years) and educational attainment (none, primary, secondary, or higher education). Household-level variables included the religion (Muslim or other) and ethnicity (Bambara, Peulh, Soninke/Sakole/Marka, or other) of the household head, as well as asset quintiles. In the DHS, asset quintiles are derived using wealth indexing, which uses household asset data and principal component analysis to assign wealth scores. Households are then ranked based on these scores and divided into five groups, representing different wealth levels [22, 23].

As another control variable, we created dummy variables for the months during which the household surveys were conducted in each DHS round, given the high seasonal variability in Mali's climate and the seasonal nature of wasting, one of the child undernutrition indicators. Specifically, the household survey for the DHS 2012–2013 was conducted from November 2012 to February 2013, while the DHS 2018 survey took place from August to November 2018. In Mali, the rainy season spans from June to October, and the rest of the year constitutes the dry season [20]. The household survey for the DHS 2012–2013 was conducted during the dry season, whereas about half of the DHS 2018 survey period overlapped with the rainy season. By using the survey months as control variables, we were able to account for the seasonal timing of data collection.

Results

Sample characteristics

Table 2 summarizes the characteristics of the study participants. The pooled sample included 12,281 children under five years of age, with 33.7% from the DHS 2012–2013 and 66.3% from the DHS 2018. Geographically, 78.5% of children were from the southern regions, and 21.5% were from the northern regions. Nationally, 25.7% of children were stunted, 25.5% were underweight, and 9.5% were wasted. Nutritional disparities

Table 2 Sample characteristics

	Total	South			North		
	All years	All years	2012–13	2018	All years	2012–13	2018
Outcome variables (%)							
Stunting	25.7	25.0	32.4	21.1	29.6	40.2	25.5
[95% CI]	[24.6–26.9]	[23.7–26.3]	[30.1–34.6]	[19.7–22.5]	[27.0–32.1]	[34.3–46.2]	[23.1–28.0]
Underweight	25.5	24.9	29.9	22.2	28.7	35.9	25.8
[95% CI]	[24.4–26.6]	[23.7–26.1]	[27.7–32.1]	[20.9–23.5]	[26.0–31.3]	[30.4–41.4]	[23.2–28.7]
Wasting	9.5	9.3	11.4	8.2	10.5	13.2	9.5
[95% CI]	[8.8–10.2]	[8.5–10.1]	[9.8–13.0]	[7.3–9.0]	[8.8–12.3]	[8.9–17.5]	[7.8–11.3]
Predictors							
Average monthly precipitation (mm) (preceding the survey)							
Over the last 3 months	131.9	139.9	62.5	180.9	88.6	43.9	106.1
Over the last 6 months	112.6	119.7	145.9	105.9	73.5	112.3	58.3
Over the last year	79.4	84.4	83.5	84.9	52.1	58.8	49.5
Over the last 2 years	71.6	76.3	72.3	78.4	46.3	48.6	45.3
Rainfall deviation from the 40 year-average (mm) (preceding the survey)							
Over the last 3 months	67.9	71.1	-6.4	112.3	50.6	0.7	70.1
Over the last 6 months	48.6	51.0	76.9	37.2	35.5	69.1	22.4
Over the last year	15.4	15.7	14.6	16.2	14.2	15.6	13.6
Over the last 2 years	7.7	7.5	3.4	9.8	8.3	5.4	9.4
Average temperature (℃) (preceding the survey)							
Over the last 3 months	28.5	28.2	27.4	28.5	30.5	29.2	31.0
Over the last 6 months	29.5	29.3	27.5	30.2	31.1	29.3	31.9
Over the last year	28.5	28.4	28.0	28.5	29.5	28.8	29.7
Over the last 2 years	28.7	28.5	28.2	28.7	29.6	29.2	29.7
Dry climate (annual total rainfall < 200 mm) (%) (preceding the survey)							
Over the last year	0	0	0	0	3.1	0	4.2
Over the last two years	0.1	0	0	0	3.9	0	5.3
Covariates (%)							
Girl	48.9	49.0	48.7	49.2	48.2	47.8	48.4
Child's age							
0–11 months	20.7	20.5	18.3	21.7	21.4	18.0	22.7
12–23 months	21.1	21.1	19.8	21.8	21.3	20.4	21.7
24–35 months	19.0	19.1	20.1	18.5	18.8	18.4	19.0
36–47 months	20.4	20.6	22.0	19.9	19.1	22.0	17.9
48–59 months	18.8	18.7	19.8	18.1	19.4	21.2	18.7
Mother's age							
15–19 years	27.7	28.2	26.4	29.1	25.1	26.1	24.8
20–24 years	28.2	28.6	29.4	28.1	25.9	25.3	26.1
25–29 years	21.9	21.6	22.8	21.0	23.6	24.8	23.2
30–49 years	22.2	21.6	21.3	21.8	25.4	23.8	26.0
Mother's education							
No education	76.5	74.9	81.9	71.2	84.8	91.3	82.3
Primary	10.9	11.4	9.6	12.4	8.4	6.1	9.4
Secondary	11.5	12.4	7.7	14.8	6.5	2.5	8.1
Higher	1.1	1.3	0.8	1.6	0.2	0.2	0.3
Religion of household's head							
Muslim	92.6	92.0	91.9	92.0	96.3	91.9	98.0
Ethnicity of household's head							
Other	42.5	35.6	32.9	37.1	79.7	78.0	80.4

Table 2 (continued)

	Total	South			North		
	All years	All years	2012–13	2018	All years	2012–13	2018
Bambara	33.9	39.0	39.5	38.7	6.0	7.8	5.3
Peulh	13.8	14.2	15.0	13.7	11.8	12.6	11.5
Sarakole/Soninke/Marka	9.9	11.2	12.6	10.5	2.5	1.7	2.8
Household asset quintile							
Lowest	21.1	17.5	19.5	16.4	40.7	37.1	42.1
Lower middle	21.1	19.9	20.2	19.8	27.7	27.6	27.7
Middle	20.8	21.3	19.2	22.5	18.1	23.2	16.1
Upper middle	19.6	21.4	22.4	20.9	9.6	5.9	11.1
Highest	17.4	19.8	18.7	20.4	4.0	6.2	3.1
DHS Round							
2012–2013	33.7	34.7	100	0	28.1	100	0
2018	66.3	65.3	0	100	71.9	0	100
DHS survey month							
January	12.2	14.4	41.5	0	0	0	0
February	0.1	0.1	0.3	0	0	0	28.5
August	21.0	21.1	0	32.3	20.5	0	44.3
September	27.4	26.6	0	40.8	31.8	0	25.3
October	15.8	15.4	0	23.6	18.2	0	2.0
November	8.3	9.5	21.2	3.3	1.4	0	0
December	15.2	12.8	37.0	0	28.1	100	0
Observations	12,281	9645	3679	5966	2636	665	1971

Category variables are represented as percentages, while continuous variables are represented as means

were observed between regions, with children in the northern regions exhibiting higher rates of stunting (29.6% vs. 25.0% in the south) and underweight (28.7% vs. 24.9% in the south). Significant improvements in child nutrition were observed over time, particularly in the north, where stunting rates decreased from 40.2% in 2012–2013 to 25.5% in 2018. Similarly, stunting in the south declined from 32.4% to 21.1%.

Regarding household characteristics, most mothers had no formal education (76.5%), and 12.6% had completed secondary or higher education. Muslim households predominated (92.6%), and 33.9% of household heads identified as Bambara, followed by Peulh (13.8%), and Sarakole/Soninke/Marka (9.9%).

Climate conditions varied significantly between the south and north. For instance, the average monthly precipitation over the three months preceding the survey was 139.9 mm in the south and 88.6 mm in the north across both survey years. Similarly, the deviation from the long-term rainfall trend over the three months preceding the survey was 71.1 mm in the south and 50.6 mm in the north. Precipitation over the six months, one year, and two years preceding the survey followed similar trends, as detailed in Table 2. The average temperature was consistently higher in the north, averaging 31.0 °C in 2018, compared to 28.5 °C in the south.

Regression analysis

This section presents the regression results in a structured manner. We first examine the effect of precipitation over the last three months preceding the survey (Table 3), followed by longer time periods of six months, one year, and two years (Table 4), and finally, deviations from long-term precipitation trends and dry climate conditions (Table 5).

Table 3 presents the results from the multivariable multilevel logistic regression analyses examining the effect of precipitation over the last three months preceding the survey on child undernutrition, stratified by geographical parts. The results show that in the south, a 1 mm increase in monthly average precipitation over the last three months preceding the survey reduced the odds of a child being wasted by 0.012 (AOR = 0.988, $p = 0.045$). Similarly, in the north, the odds of wasting decreased by 0.023 (AOR = 0.977, $p = 0.012$). Conversely, temperature did not exhibit any significant effects on child undernutrition in either part.

Table 3 also details the estimates for covariates, highlighting specific associations. Girls were consistently

Table 3 Multivariable multilevel logistic regression for the effect of monthly average precipitation and temperature over the last three months on child undernutrition

	South			North		
	Stunting	**Underweight**	**Wasting**	**Stunting**	**Underweight**	**Wasting**
Average monthly precipitation (mm) (preceding the survey)						
Over the last 3 months	1.003	1.001	0.988	1.009	1.000	0.977
	(0.484)	(0.859)	(0.045)*	(0.208)	(0.953)	(0.012)*
Average temperature (°C) (preceding the survey)						
Over the last 3 months	0.998	1.067	0.794	1.383	1.229	0.717
	(0.987)	(0.568)	(0.166)	(0.086)	(0.237)	(0.184)
Covariates						
Child's gender						
Boy[a]						
Girl	0.886	0.953	0.839	1.044	0.917	0.663
	(0.046)*	(0.425)	(0.030)*	(0.702)	(0.431)	(0.011)*
Child's age						
0–11 months[a]						
12–23 months	6.273	5.428	2.501	6.720	7.654	3.705
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
24–35 months	5.165	3.822	0.788	7.724	6.620	1.156
	(0.000)*	(0.000)*	(0.069)	(0.000)*	(0.000)*	(0.565)
36–47 months	6.012	2.411	0.556	6.348	3.085	0.666
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.134)
48–59 months	4.567	1.868	0.485	5.483	2.229	0.560
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.038)*
Mother's age						
15–19 years[a]						
20–24 years	0.882	0.953	0.967	0.792	0.839	0.800
	(0.151)	(0.569)	(0.760)	(0.170)	(0.282)	(0.339)
25–29 years	0.842	0.836	1.022	0.632	0.805	0.856
	(0.067)	(0.052)	(0.854)	(0.012)*	(0.207)	(0.530)
30–49 years	0.869	0.899	0.985	0.770	0.728	0.914
	(0.133)	(0.242)	(0.901)	(0.135)	(0.062)	(0.708)
Mother's education						
No education[a]						
Primary	0.793	0.824	0.987	1.107	0.985	0.582
	(0.030)*	(0.062)	(0.924)	(0.638)	(0.943)	(0.097)
Secondary	0.547	0.502	0.872	0.560	0.804	0.874
	(0.000)*	(0.000)*	(0.361)	(0.040)*	(0.393)	(0.704)
Higher	0.329	0.232	0.586	0.394	0.462	1.423
	(0.010)*	(0.000)*	(0.220)	(0.465)	(0.525)	(0.797)
Religion of household's head						
Other[a]						
Muslim	1.117	1.111	1.282	0.874	0.944	1.523
	(0.402)	(0.422)	(0.170)	(0.718)	(0.874)	(0.482)
Ethnicity of household's head						
Other[a]						
Bambara	1.056	1.142	0.989	0.982	1.363	1.855
	(0.506)	(0.101)	(0.922)	(0.954)	(0.290)	(0.127)
Peulh	1.057	1.274	1.160	1.252	1.875	1.592
	(0.609)	(0.022)*	(0.288)	(0.287)	(0.002)*	(0.100)

Table 3 (continued)

	South			North		
	Stunting	**Underweight**	**Wasting**	**Stunting**	**Underweight**	**Wasting**
Sarakole/Soninke/Marka	1.131	1.173	0.897	0.909	1.893	2.623
	(0.320)	(0.192)	(0.513)	(0.847)	(0.152)	(0.102)
Household asset quintile						
Lowest[a]						
Lower middle	0.790	0.838	0.910	0.924	0.731	0.841
	(0.022)*	(0.085)	(0.479)	(0.625)	(0.044)*	(0.453)
Middle	0.792	0.727	0.746	0.759	0.551	0.680
	(0.023)*	(0.002)*	(0.035)*	(0.127)	(0.001)*	(0.138)
Upper middle	0.496	0.511	0.650	0.429	0.397	0.644
	(0.000)*	(0.000)*	(0.004)*	(0.000)*	(0.000)*	(0.149)
Highest	0.265	0.380	0.635	0.254	0.201	0.452
	(0.000)*	(0.000)*	(0.008)*	(0.000)*	(0.000)*	(0.050)*
DHS Round						
2012–2013[a]						
2018	0.442	0.516	0.757	0.350	0.879	2.963
	(0.032)*	(0.072)	(0.610)	(0.081)	(0.816)	(0.168)
DHS Survey month						
January[a]						
February	1.085	1.525	0.453	1.000	1.000	1.000
	(0.934)	(0.669)	(0.595)	(.)	(.)	(.)
August	0.866	1.071	6.838	0.359	0.366	1.167
	(0.836)	(0.920)	(0.057)	(0.075)	(0.057)	(0.840)
September	0.739	1.199	7.436	0.361	0.423	1.552
	(0.684)	(0.804)	(0.064)	(0.079)	(0.107)	(0.565)
October	0.699	1.489	10.62	0.524	0.450	1.468
	(0.622)	(0.577)	(0.026)*	(0.179)	(0.071)	(0.539)
November	0.605	1.327	5.435	1.000	1.000	1.000
	(0.358)	(0.600)	(0.034)*	(.)	(.)	(.)
December	1.085	1.136	1.606	1.000	1.000	1.000
	(0.752)	(0.620)	(0.210)	(.)	(.)	(.)
Observation	9645	9645	9645	2636	2636	2814

Adjusted odds ratios (AOR) are reported, p-values are in parentheses, *$p < 0.05$, [a]Reference

less likely to be wasted than boys across both parts, with an AOR of 0.839 ($p = 0.030$) in the south and 0.663 ($p = 0.011$) in the north. In the south, girls also exhibited a lower likelihood of stunting (AOR = 0.886, $p = 0.046$). Child age showed a strong positive association with stunting and being underweight in both regions. For instance, in the south, children aged 12–23 months had significantly higher odds of being stunted (AOR = 6.273, $p < 0.001$) compared to infants aged 0–11 months. Maternal education played a protective role against stunting and underweight in the south, with children of mothers having secondary education exhibiting an AOR of 0.547 ($p < 0.001$) for stunting and 0.502 ($p < 0.001$) for underweight. Additionally, household wealth was strongly associated with a reduced likelihood of undernutrition, for instance, children from the wealthiest households had an AOR of 0.265 ($p < 0.001$) for stunting in the south and 0.254 ($p < 0.001$) in the north. Regarding the survey months, the AOR for wasting in southern Mali was significantly higher in October (AOR = 10.62, $p = 0.026$) and November (AOR = 5.435, $p = 0.034$) compared to January.

Next, Table 4 presents the results of three multivariable multilevel logistic regression models (Models 4.1 to 4.3) examining the effects of precipitation and temperature on child undernutrition over different time frames (six months, one year, and two years) preceding the survey. In the north, increased precipitation over the last six months preceding the survey (Model 4.1) decreased

Table 4 Multivariable multilevel logistic regression model for the effect of average monthly precipitation and temperature on child undernutrition

	South			North		
	Stunting	**Underweight**	**Wasting**	**Stunting**	**Underweight**	**Wasting**
Model 4.1						
Average monthly precipitation (mm) (preceding the survey)						
Over the last 6 months	0.999	0.998	0.992	1.007	0.990	0.974
	(0.829)	(0.648)	(0.184)	(0.326)	(0.123)	(0.003)*
Average temperature (°C) (preceding the survey)						
Over the last 6 months	0.867	0.988	0.895	1.521	1.190	0.843
	(0.232)	(0.918)	(0.512)	(0.028)*	(0.320)	(0.483)
Model 4.2						
Average monthly precipitation (mm) (preceding the survey)						
Over the last year	0.998	0.996	0.990	1.001	0.985	0.968
	(0.696)	(0.350)	(0.122)	(0.891)	(0.010)*	(0.000)*
Average temperature (°C) (preceding the survey)						
Over the last year	0.812	0.939	0.883	1.351	1.144	0.738
	(0.090)	(0.605)	(0.479)	(0.102)	(0.430)	(0.196)
Model 4.3						
Average monthly precipitation (mm) (preceding the survey)						
Over the last two years	0.998	0.996	0.988	1.001	0.984	0.969
	(0.633)	(0.378)	(0.081)	(0.889)	(0.009)*	(0.000)*
Average temperature (°C) (preceding the survey)						
Over the last two years	0.805	0.947	0.848	1.388	1.187	0.779
	(0.078)	(0.657)	(0.352)	(0.074)	(0.312)	(0.285)

Adjusted odds ratios (AOR) are reported, p-values are in parentheses, *$p < 0.05$, Estimates of control variables are omitted from the table

the odds of wasting (AOR = 0.974, $p = 0.003$). Similarly, higher precipitation over the last year (Model 4.2) and two years (Model 4.3) were associated with reduced odds of being underweight (Model 4.2: AOR = 0.985, $p = 0.010$; Model 4.3: AOR = 0.984, $p = 0.009$, respectively) and wasting (Model 4.2: AOR = 0.968, $p < 0.001$; Model 4.3: AOR = 0.969, $p < 0.001$, respectively). Additionally, in the north, an increase in the average temperature over the last six months (Model 4.1) was significantly associated with higher odds of stunting (AOR = 1.521, $p = 0.028$). Aside from this association, no other significant relationships were observed for any climate-related indicators in either part.

Finally, Table 5 presents the results of six distinct multivariable multilevel logistic regression models examining the effects of rainfall deviations, dry climate conditions, and temperature on child undernutrition. Models 5.1 to 5.4 assess the impact of rainfall deviations and temperature over different time frames, while Models 5.5 and 5.6 focus on dry climate conditions.

In the north, deviations in rainfall over the last three months (Model 5.1: AOR = 0.978, $p = 0.039$) and six months (Model 5.2: AOR = 0.949, $p = 0.001$) preceding the survey were associated with lower odds of wasting. Additionally, rainfall deviations over the last year (Model 5.3: AOR = 0.940, $p = 0.04$) and two years (Model 5.4: AOR = 0.937, $p = 0.025$) were linked to reduced odds of underweight.

Table 5 also reports the effects of dry climate conditions, which are defined as areas with annual total precipitation below 200 mm. In the north, children exposed to dry climates over the last year (Model 5.5: AOR = 5.668, $p < 0.001$) and two years preceding the survey (Model 5.6: AOR = 2.654, $p = 0.024$), exhibited significantly higher odds of wasting. Since no regions in the south were classified as experiencing dry climate conditions, this variable was omitted from the models for these regions.

Regarding temperature, in the northern region, when dry climate conditions were used as an explanatory variable, an increase in average temperature over the last year (Model 5.5) was significantly associated with higher odds of stunting (AOR = 1.351, $p = 0.036$) and underweight (AOR = 1.565, $p = 0.001$). Similarly, an increase in average temperature over the last two years (Model 5.6) was associated with higher odds of stunting (AOR = 1.400, $p = 0.032$) and underweight (AOR = 1.598, $p = 0.002$). Conversely, in the southern region, when rainfall deviation was used as an explanatory variable, an increase in average temperature over the last year (Model 5.3: AOR = 0.853, $p = 0.012$) and two years (Model 5.4:

Table 5 Multivariable multilevel logistic regression model for the effect of rainfall deviation, dry climate and temperature on child undernutrition

	South			North		
	Stunting	**Underweight**	**Wasting**	**Stunting**	**Underweight**	**Wasting**
Model 5.1						
Rainfall deviation (preceding the survey)						
Over the last 3 months	1.001	1.002	0.995	1.008	1.002	0.978
	(0.709)	(0.637)	(0.367)	(0.344)	(0.759)	(0.039)*
Average temperature (°C) (preceding the survey)						
Over the last 3 months	0.942	1.071	1.023	1.256	1.289	0.894
	(0.331)	(0.265)	(0.798)	(0.132)	(0.072)	(0.577)
Model 5.2						
Rainfall deviation (preceding the survey)						
Over the last 6 months	1.005	1.002	0.995	1.001	0.981	0.949
	(0.358)	(0.715)	(0.518)	(0.950)	(0.105)	(0.001)*
Average temperature (°C) (preceding the survey)						
Over the last 6 months	0.933	1.059	1.047	1.312	1.195	0.846
	(0.330)	(0.417)	(0.648)	(0.138)	(0.288)	(0.473)
Model 5.3						
Rainfall deviation (preceding the survey)						
Over the last year	1.016	1.010	0.995	0.995	0.940	0.891
	(0.146)	(0.369)	(0.723)	(0.822)	(0.004)*	(0.000)*
Average temperature (°C) (preceding the survey)						
Over the last year	0.853	1.041	1.109	1.295	1.118	0.751
	(0.012)*	(0.523)	(0.265)	(0.158)	(0.503)	(0.208)
Model 5.4						
Rainfall deviation (preceding the survey)						
Over the last two years	1.033	1.024	0.992	1.008	0.937	0.878
	(0.052)	(0.155)	(0.743)	(0.793)	(0.025)*	(0.001)*
Average temperature (°C) (preceding the survey)						
Over the last two years	0.832	1.025	1.108	1.400	1.271	0.888
	(0.003)*	(0.690)	(0.263)	(0.055)	(0.139)	(0.596)
Over the last year	1.000	1.000	1.000	1.400	2.087	5.668
	(.)	(.)	(.)	(0.437)	(0.069)	(0.000)*
Average temperature (°C)						
Over the last year	0.846	1.035	1.112	1.351	1.565	1.390
	(0.008)*	(0.579)	(0.250)	(0.036)*	(0.001)*	(0.097)
Over the last two years	1.000	1.000	1.000	1.268	1.730	2.654
	(.)	(.)	(.)	(0.509)	(0.104)	(0.024)*
Average temperature (°C) (preceding the survey)						
Over the last two years	0.847	1.039	1.104	1.400	1.598	1.347
	(0.008)*	(0.535)	(0.279)	(0.032)*	(0.002)*	(0.178)

AOR = 0.832, $p = 0.003$) was associated with lower odds of stunting.

Discussion

This study examined the effects of precipitation and temperature on childhood undernutrition, including stunting, underweight, and wasting among children under five years of age in Mali. Our analysis used a nationally representative sample derived from the DHS, combined with survey-location-specific climatic data. Specifically, we utilized DHS data from 2012–2013 and 2018, with corresponding climate data covering 2010–2013 and 2016–2018. Overall, both precipitation and temperature, particularly the amount of rainfall in the northern part of Mali, exhibited statistically significant associations with the odds of child undernutrition. These findings align with previous studies conducted in Mali [35–37] and various other SSA countries [25, 26, 38], reinforcing the role of climate as a key determinant of child nutrition. Three key points warrant discussion, emphasizing the complex interactions between climate factors and child undernutrition.

First, our study showed that the amount of rainfall positively influenced the reduction of childhood underweight and wasting in northern Mali, which is primarily characterized as a warm desert area. Furthermore, exposure to a dry climate over the last year or two years preceding the surveys (DHS 2012–2013 and DHS 2018) was associated with increased odds of a child experiencing wasting in the north. These results resonate with findings from previous studies in Uganda [33] and other SSA countries [9, 26]. However, our study found that rainfall did not significantly affect childhood stunting, an indicator of chronic undernutrition. This suggests that while climatic variations are more likely to affect acute forms of undernutrition, such as wasting and underweight, the determinants of stunting may be more complex, involving long-term socioeconomic and dietary factors [39]. The minimal impact of rainfall on stunting is consistent with findings from a previous study in Uganda [33], while beneficial effects of rainfall on stunting have been documented in studies from Kenya [40], Uganda [10], Somalia [41], and Ethiopia [8].

Second, in northern Mali, analyses controlling for the arid climate revealed that an increase in average temperature over the last year or two years preceding the DHS surveys was significantly associated with higher odds of stunting and underweight, as shown in Table 5. This finding aligns with prior research in India, which demonstrated a strong correlation between temperatures exceeding 40 °C and an increased probability of stunting [42]. The adverse effects of rising temperatures on underweight observed in our study are also consistent with a study across 29 SSA countries involving 656,107 children under five, which showed that children in hotter regions were significantly more likely to be underweight than those in cooler areas [43]. These results highlight the role of heat stress in impairing child growth and increasing the risk of infection, both exacerbated by high temperatures [44].

In contrast, in southern Mali, an increase in average temperature was associated with lower odds of stunting (Table 5). This suggests that in the south, characterized by abundant vegetation and relatively cooler climate conditions, rising temperatures may reduce the likelihood of stunting. This may be attributed to resilience mechanisms in southern Mali, such as small-scale river irrigation, sustainable agricultural systems, and community-based nutrition and food security programs integrating satellite imagery and survey data [45–47]. Research indicates that southern Mali has benefited from long-term improvements in agricultural productivity on irrigated lands and comprehensive food security initiatives [45–47]. These measures help mitigate the negative impacts of climate change. Nonetheless, in southern Mali, the odds of wasting in October and November were significantly higher compared to January (Table 3). This suggests that while higher temperatures may reduce stunting, seasonal factors, particularly the post-rainy and early harvest periods, may still pose risks for wasting. These findings underscore the need for targeted policy approaches to enhance climate adaptation capacity in Mali.

Overall, the relationship between temperature and child undernutrition warrants further investigation, particularly considering regional climatic and ecological variations as well as socioeconomic conditions. A long-term, multidisciplinary approach is essential to gain deeper insights into the mechanisms through which temperature changes affect child growth and nutritional status.

Third, our findings suggest that children in northern Mali are more susceptible to fluctuations in precipitation and temperature than those in the south. The northern terrain, characterized by a desert area, experiences higher temperatures and lower rainfall than southern Mali, which increases the incidence of underweight and wasting among children. Climate data from our study covering 2010–2013 and 2016–2018 confirm this trend, reinforcing the vulnerability of northern Mali's population to climatic variations. These results align with broader findings in SSA countries, where frequent droughts and erratic rainfall patterns have been linked to declining food security [48]. Therefore, our study underscores the necessity of addressing child undernutrition in northern Mali through adaptation to adverse climatic conditions.

Our research has several limitations. In DHS 2012–2013, data from the northern regions were restricted to Mopti, the southernmost part of the north, raising concerns about whether they adequately represent the entire northern regions. The northern regions differ significantly from the south in climate and environment, making it challenging to generalize trends based on data from a single area. For instance, other areas in the north, such as Gao, Kidal, and Tombouctou, have distinct climatic conditions and terrains compared to Mopti. To address this limitation and assess the robustness of our findings, we conducted additional regression analyses using only DHS 2018 data, which covered the entire northern regions. These analyses yielded results nearly identical to those reported in Tables 3, 4 and 5, confirming that our estimates are not unduly influenced by data from Mopti. This additional analysis reinforces the reliability of our conclusions regarding northern Mali, despite the limited sample size in DHS 2012–13.

As a policy implication, integrating climate variability into relevant policies is crucial for enhancing the government's effectiveness in addressing the impacts of climate change. Particular attention should be given to children in the northern regions of Mali, who are especially vulnerable to the adverse effects of climate change. Targeted support can help alleviate both immediate and long-term challenges faced by these communities. Specifically, policies should focus on improving access to climate-resilient food systems, enhancing maternal and child healthcare, and strengthening social safety nets to mitigate the nutritional impacts of climate shocks. Furthermore, developing a better understanding of the link between climate change and child nutrition is essential. A comprehensive understanding of these connections will enable the design of effective interventions tailored to the specific needs of affected populations.

Conclusions

This study confirmed that precipitation and temperature significantly influence child undernutrition, notably in the northern regions of Mali. Nevertheless, due to certain data limitations, further research is recommended to validate the conclusions regarding the northern regions. Implementing effective strategies to address the impacts of climate change could significantly improve children's nutrition, especially in areas affected by extreme climatic conditions.

Abbreviations

AOR	Adjusted odds ratio
AReNA	Advancing research on nutrition and agriculture
CI	Confidence interval
DHS	Demographic and health survey
GIS	Geographic information system
HAZ	Height-for-age z-score
SSA	Sub-Saharan Africa
WAZ	Weight-for-age z-score
WHZ	Weight-for-height z-score

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Author contributions

MT was responsible for overall design, data analysis, and drafting of the paper. TK and YK provided critical comments on the draft and revised the manuscript.

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Availability of data and materials

The dataset used in the current study is in the public domain and can be obtained from the DHS Program (http://dhsprogram.com). The Advancing Research on Nutrition and Agriculture (AReNA)'s DHS-GIS dataset is publicly available at https://doi.org/10.7910/DVN/OQIPRW.

Declarations

Ethics approval and consent to participate

This study is a secondary analysis of anonymous data from the Demographic and Health Surveys of Mali. The survey was approved by the Mali's National Ethics Committee for Health and Life Sciences of the Ministry of Health and of Public Health and the ICF Institutional Review Board. Prior to the questionnaire survey, written informed consent was obtained from all adult respondents or from parents/guardian for minors. Permission to analyze the data was obtained from the DHS Program. All methods were performed in accordance with relevant guidelines and regulations.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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