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Original Contribution

Do Deviations From Historical Precipitation Trends Influence Child Nutrition? An Analysis From Uganda

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Changes in precipitation patterns might have deleterious effects on population health. We used data from the Uganda National Panel Survey from 2009 to 2012 ($n = 3{,}223$ children contributing 5,013 assessments) to evaluate the link between rainfall and undernutrition in children under age 5 years. We considered 3 outcomes (underweight, wasting, and stunting) and measured precipitation using household-reported drought and deviations from long-term precipitation trends measured by satellite. We specified multilevel logistic regression models with random effects for the community, village, and individual. Underweight (13%), wasting (4%), and stunting (33%) were common. Reported drought was associated with underweight (marginal risk ratio (RR) = 1.18, 95% confidence interval (CI): 1.04, 1.35) in adjusted analyses. Positive annual deviations (greater rainfall) from long-term precipitation trends were protective against underweight (marginal RR per 50-mm increase = 0.94, 95% CI: 0.92, 0.97) and wasting (marginal RR per 50-mm increase = 0.93, 95% CI: 0.87, 0.98) but not stunting (marginal RR per 50-mm increase = 1.00, 95% CI: 0.98, 1.01). Precipitation was associated with measures of acute but not chronic malnutrition using both objective and subjective measures of exposure. Sudden reductions in rainfall are likely to have acute adverse effects on child nutritional status.

child health; droughts; Uganda; undernutrition

Abbreviations: CHIRPS, Climate Hazards Group InfraRed Precipitation with Stations; CI, confidence interval; RR, risk ratio.

Child undernutrition poses a threat to planetary health and productivity and is responsible for an estimated 3.1 million child deaths each year (1, 2). Acute undernutrition is associated with greater susceptibility to infectious diseases in early life and delayed development (3), and chronic undernutrition can lead to cognitive deficits and low school achievement (4, 5).

Evidence suggests that insufficient or erratic precipitation can increase the risk of child undernutrition (6–13). Studies have reported associations between low levels of precipitation and stunting (6, 10), underweight (8, 10), and anemia (8). Unfortunately, none of these studies have evaluated potential nonlinearities in the relationship between precipitation and nutritional status. This is important because there might be a threshold of rainfall at which undernutrition is affected, information that is vital for projections of health impacts under potential climate change scenarios.

East Africa is particularly vulnerable to changes in rainfall regimes (14, 15). Uganda demonstrates a high potential for reduced rainfall and a shorter growing season. The country has experienced annual reduction in rainfall at a rate of 3.5% per decade since 1960 (15, 16). The burden of undernutrition in Uganda is high; in 2011, the prevalence of stunting among children under 5 years of age was 33%, of underweight 14%, and of wasting 5% (17). A recent study in nearby Ethiopia found no impact of rainfall shocks on acute undernutrition, contrasting with previous findings in East Africa (7). There is no empirical evidence on how changes in rainfall affect child undernutrition in Uganda.

The present analyses use nationally representative survey and satellite data to examine the impacts of rainfall deviations on the nutritional status of Ugandan children under the age of 5 years. This study extends previous literature by evaluating nonlinear relationships between rainfall deviations and undernutrition. In addition, we utilize both household-reported drought and absolute deviations from historical trends of precipitation measured via interpolation of satellite and ground station data as exposures. This is important because previous studies have used only rainfall estimated via satellite without addressing respondents' perceptions of drought. Using a self-reported measure, we can model the relationship between perceived drought and objective measures of rainfall deviations and capture drought at a finer resolution than what is measured via satellite. Furthermore, we aim to substantiate the link between precipitation and nutritional outcomes using multiple measures of exposure. This is important because there is conflicting evidence as to the relationship between weather patterns and acute undernutrition (7, 18); combining subjective and objective measures enhances our elucidation of this relationship.

METHODS

Data source

Data from the nationally representative Uganda National Panel Survey, Living Standards Measurement Study, were used to investigate the relationship between rainfall deviations and child undernutrition. These data were collected in 4 waves: 2009–2010, 2010–2011, 2011–2012, and 2013–2014. We make use of the first 3 waves, excluding the final wave due to a different sampling methodology.

Across 5 administrative regions, 3,123 households were selected for the 2005 Uganda National Household Survey using a 2-stage sampling design. First (within urban/rural and regional strata) 322 out of 783 enumeration areas were selected at random. Households were then selected at random from these enumeration areas. The Uganda National Panel Survey attempted to track and survey each of these 3,123 households during its first 3 waves. A random subset of the households, representing 20% of the sample (2 households from each enumeration area), was selected for individual tracking (i.e., if any individual in the household who was related to the head of household moved away, they were tracked and, if located in person, their household was added to the Uganda National Panel Survey—considered as "split-off" households). This was done to account for losses to follow-up. Split-off households were included in our analyses. See Web Table 1 (available at https://academic.oup.com/aje) for information on the number of households sampled at each wave.

At each wave, respondents from the same sample households provided information on demographic factors, assets, expenditures, employment, health status, agricultural practices, and contraception, among other variables. Households were geolocated. Although the analytical sample is based on a longitudinal cohort, new children aged into cohort eligibility, and some children either aged out or were not successfully followed; thus, the average number of observations per child was 1.6. Children were eligible for the study if they were aged 6–59 months at each time of survey; they were added to the study sample as they were born into survey households and excluded from subsequent waves as they surpassed 59 months of age. They were excluded from analyses if the household did not respond to the self-reported drought question, if the household was not geolocated, or if they were missing covariate data. Finally, children were excluded from primary analyses if their anthropometric measurements were not taken.

Measures

Exposure. We considered 2 exposure measures: a self-reported measure of drought or irregular rainfall and an indicator of deviations from cumulative rainfall measured with satellite and ground stations. The self-reported measure represents the respondent's perception of precipitation deviations in the previous year. Survey enumerators asked each head of household (or other adult member, in their absence), "Did you experience drought/irregular rains during the past 12 months?" (yes/no response).

We also obtained cumulative rainfall for the Global Positioning System (GPS) location of the household. Monthly rainfall raster data were acquired at a resolution of 0.05 decimal degrees from Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) data; CHIRPS uses a validated algorithm to measure atmospheric precipitation (19). We extracted a continuous value for monthly rainfall in millimeters at the GPS location of each household and summed over the prior 12 months, and we then subtracted an average of annual precipitation from 1999 to 2008 (10 years) from this value, such that negative values reflected lower rainfall than average and positive values reflected higher.

Neither measure represents a gold standard; each measure has flaws. The self-reported measure might be subject to inaccurate recall and reporting bias, while the satellite-measured precipitation's resolution might not reflect rainfall levels within pixels and might not reflect how rainfall variations were experienced by individual households.

Outcome. We determined child nutritional status using the World Health Organization 2006 Child Growth Standards (20), which include 3 nutritional indicators: underweight, wasting, and stunting. These dichotomous measures are combined with information on a child's age in addition to anthropometric measurements (weight and height/length), taken in the present study by enumerators for all children aged 6–59 months during the Uganda National Panel Survey. During each household survey, 2 trained enumerators with measuring boards and solar-charging digital scales (UNICEF Electronic Scale or Uniscale, manufactured by Seca, Birmingham, United Kingdom) recorded child anthropometry. Length was measured for children aged 6–23 months, while height was measured for children 24 months or older. Using these anthropometric data, we computed a weight-for-age z score (used to assess underweight), defined as the difference between the child's weight-for-age z score and the mean for all children of the same sex and age of a World Health Organization standard group normalized by the standard deviation, a weight-for-height z score (assessing wasting), and a height-for-age z score (assessing stunting). For each outcome, if a child's measure was more than 2 standard deviations below the average measure for the World Health Organization standard group, they were considered to have the adverse nutritional outcome. We separately specified models with continuous nutritional indicators as outcomes (weight-for-age, weight-for-height, and height-for-age z scores) and models with dichotomous outcomes (underweight, wasting, and stunting).

Covariates. The directed acyclic graph representing assumptions that guided covariate selection can be found in Web Figure 1. In models using household-reported drought/irregular rains as the primary exposure of interest, we included child and household-level sociodemographic characteristics selected due to their theoretical association with both household-reported drought and undernutrition. Child characteristics included sex and age in months. Household characteristics included a binary indicator of urban versus rural residence and the numbers of female and male adults and of children under age 5 years in the household. Household socioeconomic status was defined using an asset index modeled off the asset index used by Demographic and Health Surveys (21). The asset index included questions regarding materials for flooring and roof, ownership of consumer products, and type of drinking source and toilet facilities, among others. We assigned households a wealth score based on a principal component analysis of these assets, which was then used to assign households to wealth quintiles. We included fixed effects (i.e., indicator variables) for the month of survey collection to account for season.

Models that used the deviations from rainfall measured with satellite as an exposure included only the fixed effect term for month of survey collection, because deviations from long-term trends should be independent of the other potential confounding variables. Because deviations are relative to a location's long-term precipitation history, we have removed variation representing sociodemographic factors that might be associated with historically dryer or wetter places and might affect child nutritional status.

Statistical analysis

We evaluated the relationship between rainfall deviations in millimeters and household-reported drought/irregular rains graphically using locally weighted scatterplot smoothing. In addition, we estimated the pairwise correlation between continuous satellite-derived rainfall deviations and self-reported drought.

Subsequently, we specified mixed-effect ordinary-least-squares regression models for each continuous outcome (weight-for-age, weight-for-height, and height-for-age z scores) and mixed-effect logistic regression models for each dichotomous outcome (underweight, wasting, and stunting) using self-reported and CHIRPS rainfall exposures separately. Models included 3 random effects simultaneously: community ($n = 316$), household ($n = 1{,}809$), and individual child ($n = 3{,}223$). These were included as random intercepts; random slopes were also considered but were not included in the final models due to results from likelihood ratio tests comparing models with and without random slopes suggesting that random intercepts were sufficient. We first estimated models with fixed effects for calendar month only to control for confounding by season. Additional covariates were then added for those models that evaluated the household-reported exposure; these additional covariates were not included in the models with precipitation measured via satellite. All effect estimates were computed as marginal risk ratios using Stata's *margins* command, which estimates effects by first computing predicted potential outcomes for each observation in the sample under each possible level of the exposure, using both the fixed and random effects estimated in the regression equation. The potential outcomes under drought were then averaged across all individuals in the sample and divided by the average of the potential outcomes under no drought condition to estimate the marginal effect of drought on the ratio scale.

To assess whether continuous rainfall variability influenced undernutrition in a nonlinear fashion, we used restricted cubic splines and tested for deviations from nonlinearities using Stata's *testparm* command, which compares models that have spline terms with those having only a linear predictor. The number of knots was determined using Akaike's information criterion.

As a sensitivity analysis, we generated inverse-probability weights for the probability of not being measured at baseline to account for potential bias due to missingness in the outcome variable. Models used to generate weights included all covariates and both satellite-derived and self-reported exposure measures. We truncated the weights, replacing all values above the 99th percentile with the value of the 99th percentile weight (22). We then repeated primary analyses with weights. All analyses were carried out in R-Cran, version 3.4 (R Foundation for Statistical Computing, Vienna, Austria) (23), and Stata, version 14.2 (StataCorp LP, College Station, Texas) (24).

RESULTS

Participant characteristics

A total of 4,138 individual children in 2,115 households between the ages of 6 months and 5 years at the time of survey were living in sample households; 5,013 observations of 3,223 unique children were included in the final sample (Figure 1). These children resided in in 1,809 households. Baseline characteristics of children included in the sample at each wave can be found in Table 1, which reflects data for each child the first time they were observed. Characteristics of all observations at each wave can be found in Web Table 2. Approximately 16%–18% of the sample resided in urban areas. Households had an average range of 1.9–2.1 children under 5 (standard deviations, 0.8–0.9). In the first wave of data collection, over half of households (51%) reported drought/irregular rains; in 2010–2011 and 2011–2012, the proportion reporting drought dropped to 36% and 25%, respectively. At baseline, 13%–16% of children were considered underweight, 5%–6% were afflicted with wasting, and 32%–34% with stunting. Average annual rainfall ranged from 483.5 mm to 2,246.6 mm (mean = 1,284.6) across the 3 waves. Mean deviation from long-term annual precipitation across the 3 waves was +37.6 mm (standard deviation, 115.5).

Rainfall and undernutrition

A graphical depiction of the relationship between self-reported drought/irregular rains and annual rainfall deviations using locally weighted scatterplot smoothing demonstrated a threshold of approximately 100-mm lower-than-average trends of annual rainfall during the year immediately prior to the survey, after which the proportion of respondents reporting drought/irregular rains decreased in almost a linear fashion (Figure 2). Households reporting drought/irregular rains were more likely to be located within a pixel with negative precipitation deviations: The median rainfall deviation among those endorsing self-reported drought/irregular rains was +6.3 mm (interquartile range, −76.0 to +102.3), and among those not endorsing self-reported drought/irregular rains, the median rainfall deviation was +47.9 (interquartile range, −33.0 to +134.7).

In models controlling for all covariates, children living in households that reported drought demonstrated 1.18 times the

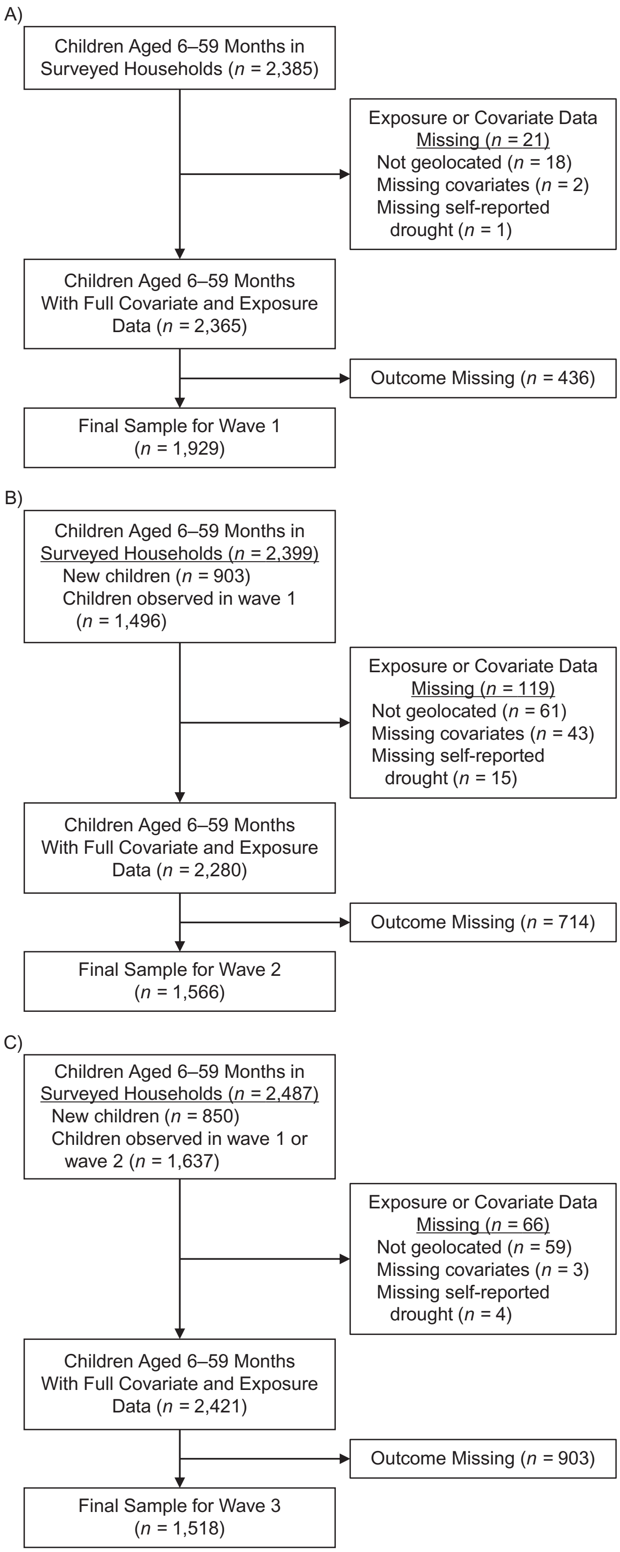

Figure 1. Flow diagram of study subjects between 6 and 59 months of age included in the Uganda National Panel Survey, Uganda, 2009–2012. A) Wave 1, B) wave 2, and C) wave 3 (total n = 5,013 observations of 3,223 unique children aged 6–59 months; mean number of observations per child = 1.6). The primary reason cited for missing outcome at each wave was that the child was not present at the time of survey (28.0%, 50.0%, and 63.9% at waves 1, 2, and 3 respectively).

risk of underweight (95% confidence interval (CI): 1.04, 1.35) and 1.27 times the risk of wasting (95% CI: 0.98, 1.68) compared with those living in households that did not report drought (Table 2). We did not find evidence for an association between reported drought and stunting in adjusted models (marginal risk ratio (RR) = 1.02, 95% CI: 0.94, 1.11). We observed similar relationships in mixed effect linear regression models with z scores as outcomes (Web Table 3).

Increased deviations, meaning higher than average rainfall in the 12 months prior to survey, had a protective association with underweight (marginal RR per 50-mm increase in rainfall = 0.94, 95% CI: 0.92, 0.97) and wasting (marginal RR per-50 mm increase in rainfall = 0.93, 95% CI: 0.87, 0.98) (Table 3). This equates to a 17.6% predicted marginal probability of underweight for children under the lowest rainfall deviation (less precipitation than long-term averages; −232.7 mm/year), compared with an 8.3% predicted probability for children under the highest rainfall deviation (more precipitation than long-term averages; +404.6 mm/year). Predicted probabilities for wasting were 6.3% under the low-precipitation scenario and 2.3% in the high-precipitation scenario. Rainfall deviations were not associated with stunting (marginal RR per 50-mm increase in rainfall = 1.00, 95% CI: 0.98, 1.01). Mixed-effect linear models with z scores as outcomes demonstrated a similar pattern (Web Table 4).

When we modeled the rainfall deviation exposure nonlinearly with restricted cubic splines and compared models with and without splines, we found evidence for a nonlinear association with wasting but not underweight or stunting (Figure 3). This nonlinear relationship represented a steep decline in the predicted marginal probability of wasting at the lowest levels of 12-month rainfall deviations, as well as a flattening of the relationship at approximately −100 mm.

The inclusion of inverse-probability weights to account for potential bias due to missingness in the outcome variable did not notably affect primary results (Web Tables 5 and 6).

DISCUSSION

The goal of this analysis was to assess the relationship between rainfall and undernutrition among children in Uganda using 2 different measures of exposure. Exposures measured via household report and via satellite demonstrated similar results: Both household-reported drought and remotely sensed estimates of lower levels of rainfall over the 12 months prior to the survey were positively associated with underweight and wasting but not stunting. Projections of climate change state that precipitation in Uganda might decline by as much as 7% by 2030 (16). This decline could have severe implications.

Our findings contrast with those from a recent study using similar measures, which concluded that deviations from precipitation averages were not associated with wasting in Ethiopia (18). One hypothesized reason for these different findings is that Ethiopia is a more arid country than Uganda; households in the Ethiopian sample might have developed more adaptive strategies than those in the present study. Importantly, nutrient-, fat-, and protein-dense livestock represents a larger portion of the livelihood strategy of Ethiopian farmers, which allows for herd mobility strategies, including transhumance, that are not available to rain-fed agriculturalists. Another possibility is that

Table 1. Baseline Characteristics of Children[a] Aged 6–59 Months Added to the Analytical Sample at Each Wave From the Uganda National Panel Survey (n = 3,223), Uganda, 2009–2012

Characteristic	2009–2010 (n = 1,929)			2010–2011 (n = 663)			2011–2012 (n = 631)		
	No.	%	Mean (SD)	No.	%	Mean (SD)	No.	%	Mean (SD)
Demographic									
Number of children aged <5 years			1.9 (0.8)			2.1 (0.9)			2.0 (0.9)
Number of male adults in household			1.2 (0.9)			1.3 (1.0)			1.3 (1.1)
Number of female adults in household			1.4 (0.9)			1.6 (1.0)			1.7 (1.1)
Environmental									
Urban	360	18.7		107	16.1		111	17.6	
Household self-reported drought/irregular rains in previous 12 months	975	50.5		236	35.6		158	25.0	
Cumulative precipitation in previous 12 months, mm			1,236.2 (222.7)			1,375.0 (218.6)			1,252.7 (246.0)
Deviation from 10-year annual precipitation, mm			−12.7 (101.2)			123.3 (90.9)			13.2 (105.5)
Among children aged 6–59 months									
Age, months			31.8 (15.3)			26.0 (15.6)			22.3 (14.0)
Male sex	983	50.1		359	54.1		303	48.0	
Weight-for-age z score			−0.8 (1.3)			−0.8 (1.4)			−0.7 (1.3)
Underweight	290	15.0		85	12.8		99	15.7	
Weight-for-height z score			−0.0 (1.3)			0.0 (1.6)			0.0 (1.5)
Wasting	98	5.1		40	6.0		36	5.7	
Height-for-age z score			−1.4 (1.7)			−1.4 (1.6)			−1.4 (1.7)
Stunting	620	32.1		223	33.6		199	31.5	

Abbreviation: SD, standard deviation.

[a] Children were included the first time they were observed. In the first wave, this included all children aged 6–59 months. In subsequent waves, this included only children who were born into or moved to survey households.

the 13-year period the authors used to calculate a long-term mean of precipitation was already characterized by drought; therefore, children living in dry areas and already at risk of wasting might not have been further affected by reductions in precipitation.

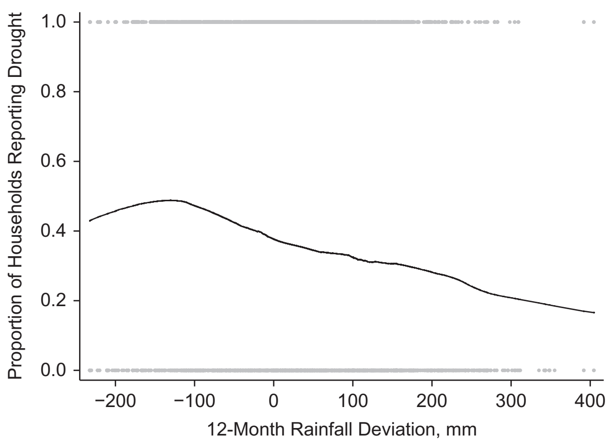

Figure 2. Locally weighted scatterplot-smoothed representation of the relationship between self-reported drought and annual rainfall deviation prior to survey date, Uganda National Panel Survey, Uganda, 2009–2012. They gray dots represent individual observations.

The lack of association between rainfall and stunting in the present study could be explained by differences in the underlying constructs captured by underweight and wasting compared with stunting. Wasting is a measure of acute undernutrition, caused by episodic reductions in caloric intake or infections such as diarrheal diseases—factors that might be more strongly influenced by reduced rainfall. Underweight, in addition, is a composite measure of acute and chronic malnutrition. Stunting, in contrast, measures only chronic malnutrition, which might be influenced by recurrent infections or poor diets and is less responsive to acute environmental episodes. The relationship between rainfall, underweight, and wasting is consistent with previous findings (7, 8, 25). However, some previous research has found an association between reduced rainfall and stunting (6, 8, 25, 26); a recent systematic review found associations in 12 of 15 articles assessing the relationship between weather events and stunting (27). More work should evaluate this potential relationship, including assessments of rainfall prior to the child's birth and during pregnancy, because a mother's nutrition before conception and before delivery can affect a child's likelihood of undernutrition (28).

Finally, we observed a nonlinear relationship between rainfall deviations and acute undernutrition. This is suggestive of a threshold level of precipitation at which children are at higher risk for undernutrition. There remain challenges in operationalizing a definition of "drought," with a lack of consensus among

Table 2. Multilevel Logistic Regression Analysis Between Household-Reported Exposure and Nutritional Indicators (n = 5,013 Observations of 3,223 Individuals)[a], Uganda National Panel Survey, Uganda, 2009–2012

Exposure	Underweight				Wasting				Stunting			
	Crude		Adjusted[b]		Crude		Adjusted		Crude		Adjusted	
	Marginal RR	95% CI	Marginal RR	95% CI	Marginal RR	95% CI	Marginal RR	95% CI	Marginal RR	95% CI	Marginal RR	95% CI
Self-reported drought/irregular rains	1.26	1.11, 1.44	1.18	1.04, 1.35	1.49	1.08, 1.86	1.27	0.98, 1.68	1.05	0.97, 1.14	1.02	0.94, 1.11

Abbreviations: CI, confidence interval; RR, risk ratio.

[a] Random effects were included for community (n = 316), household (n = 1,809), and individual (n = 3,223). Models included fixed effects for month of outcome measurement.

[b] Model adjustments included child sex and age in months, number of children under age 5 years in the household, number of male adults in the household, number of female adults in the household, urban location, and quintile of socioeconomic status.

experts (29). Previous studies have identified drought-stricken areas using food production indices (9), z scores of vegetation indices to measure deviations from the historical norms of agricultural capacity (30), and records of areas receiving emergency food aid (31). Instead of imposing a definition of drought, this analysis took advantage of continuous precipitation data to compare annual precipitation with long-term trends, thereby modeling the threshold of the impact of precipitation on undernutrition. It should also be noted that we did not find evidence for an increase in undernutrition at higher levels of precipitation relative to long-term trends. This is in contrast with previous findings that have linked higher levels of precipitation and flooding with stunting (10), underweight (32), and wasting (33). Consistent with the tropical savannah climate covering most of the country (Köppen classification *Aw*), the lack of association between positive deviations and undernutrition could be because rainfall did not reach a level at which major flooding occurred and agricultural yields were affected (34).

This study has several limitations. First, we were unable to evaluate mechanisms through which undernutrition was affected by rainfall. Second, there might be residual confounding in models using the household-reported exposure. However, satellite exposure data corroborated results from household reports. Third, there might be inadequacies with the quality of anthropometric measurements due to human error. However, enumerators undertook extensive training and were given measuring boards and solar-charging scales (35). In addition, we expect this mismeasurement to have occurred randomly with respect to exposure, and therefore on average it would bias our findings towards the null (36). Fourth, caution must be taken when interpreting the results from models with the household-reported exposure, because "drought/irregular rains" could be interpreted as excessive rain rather than drought. However, plotting the relationship between the household-report and deviations revealed a negative trend, without an increase in the relationship at extremely high levels of positive deviations, implying that households most likely referred to drought in their responses. Finally, we acknowledge the potential for misclassification of both exposures. The self-reported measure might be prone to recall or reporting bias. In addition, the CHIRPS data might have inaccuracies in regions with low ground station coverage. However, we do not expect the misclassification of these 2 variables to be correlated, and results were consistent across models using each exposure.

Climate change projections point unequivocally towards shifting rainfall patterns across East Africa. Our findings suggest that these changes augur negative impacts for child growth and well-being. Impacts could differ among ecoregions characterized by diverse climate change patterns, requiring interventions tailored to regional and local contexts. Despite uncertainties inherent in climate change projections, this study implies that sudden reductions in rainfall might have increasingly adverse effects on the acute nutrition of children under the age of 5 years.

Table 3. Multilevel Logistic Regression Analysis Between Deviations in Precipitation and Nutritional Indicators (n = 5,013 Observations of 3,223 Individuals)[a], Uganda National Panel Survey, Uganda, 2009–2012

Exposure	Underweight		Wasting		Stunting	
	Marginal RR	95% CI	Marginal RR	95% CI	Marginal RR	95% CI
Rainfall deviation, per 50-mm increase	0.94	0.92, 0.97	0.93	0.87, 0.98	1.00	0.98, 1.01

Abbreviations: CI, confidence interval; RR, risk ratio.

[a] Random effects were included for community (n = 316), household (n = 1,809), and individual (n = 3,223). Models include fixed effects for month of outcome measurement.

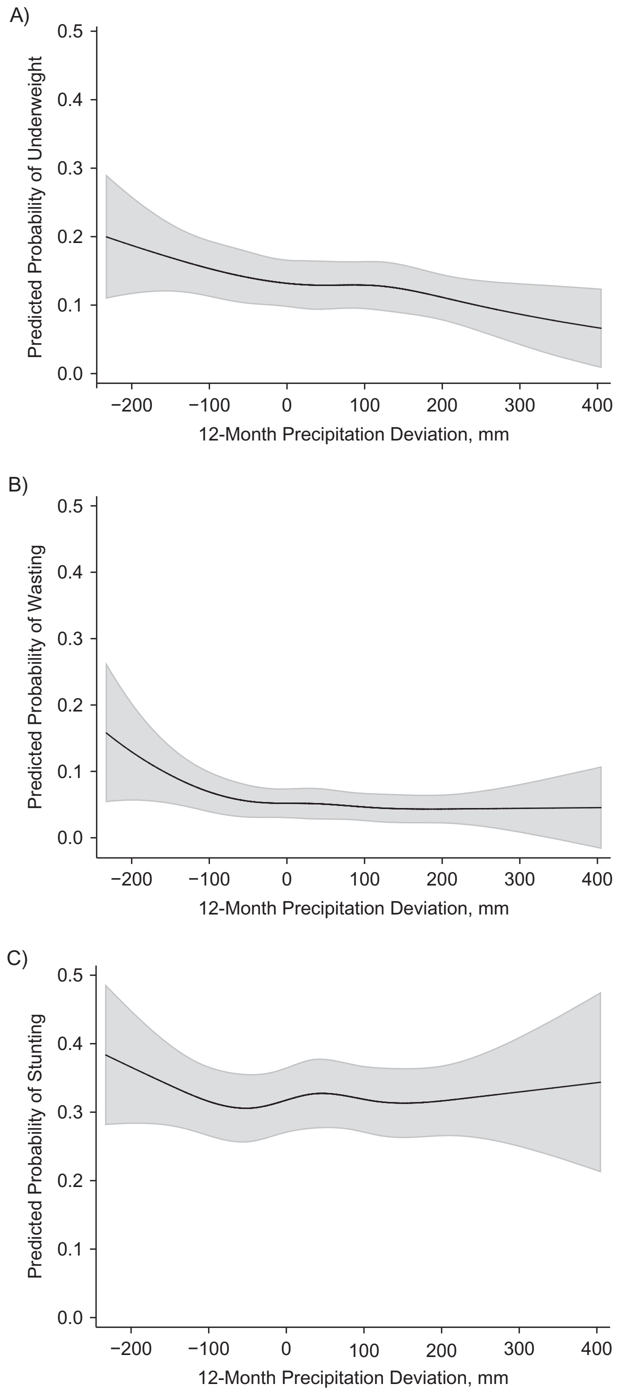

Figure 3. Predicted probabilities of underweight (A), wasting (B), and stunting (C) with deviations modeled as restricted cubic splines, Uganda National Panel Survey, Uganda, 2009–2012.

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