Climate, Birth Weight, and Agricultural Livelihoods in Kenya and Mali

Maryia Bakhtsiyarava, BS, Kathryn Grace, PhD, MSPH, and Raphael J. Nawrotzki, PhD

Objectives. To examine an association between climate variability and birth weight in Mali and Kenya in relation to the local agricultural specialization.

Methods. We combined health and sociodemographic data from the Demographic Health Surveys for Kenya (2008 and 2014) and Mali (2006 and 2012) with detailed data on precipitation, temperature, and vegetation. We analyzed the association between climate variability and birth weight by using multilevel regression models for the most common agricultural specializations: food cropping, cash cropping, and pastoralism.

Results. There are differences in sensitivity to climate among different agricultural communities. An additional 100 millimeters of rainfall during the 12-month period before birth was associated with a 47-gram (P=.001) and 89-gram (P=.10) increase in birth weight for food croppers in Kenya and Mali, respectively. Every additional hot month in food-cropping communities in Kenya was associated with a 71-gram decrease in birth weight (P=.030), likely because of food croppers' limited use of modern agricultural techniques. Overall, cash croppers are least sensitive to climate variability in both countries.

Conclusions. Effective climate change adaptation strategies are essential for protecting and improving health outcomes and should be tailored to local households' livelihood strategies. (*Am J Public Health.* 2018;108:S144–S150. doi:10.2105/AJPH. 2017.304128)

limate change manifests itself differently depending on the location: for example, North Africa is predicted to experience a decrease in rainfall by the end of the 21st century, whereas increased rainfall is predicted for the mountainous areas of East Africa.¹ As a consequence, the effects of climate change are not uniform and depend on the local geographic and socioeconomic context.² Although most of the studies of the climate change-health nexus are conducted at specific sites or at the level of entire countries, it is important to use a spatially detailed approach and consider how the observed effects vary depending on the local economic and demographic backgrounds.^{3,4}

Sub-Saharan Africa (SSA) is particularly vulnerable to the adverse effects of climate change because of its low adaptive capacity and geographic characteristics. The combined burden of climate change and poor health outcomes potentially hinder the ability of African nations to foster human and

Bakhtsiyarava et al.

Research Peer Reviewed

economic development. Undernutrition and poor child growth account for 11% of annual gross domestic product losses in Africa.⁵ In 2016, one third of children younger than 5 years in Africa experienced stunted growth.⁵ Within SSA, Kenya and Mali have demonstrated stalled progress in improving child health as the percentage of children with low birth weight (LBW; < 2.5 kg World Health Organization standard)⁶ has risen in recent years.^{7,8} Poverty and rapid population growth^{9,10} coupled with climate variability suggest that a large number of children are and will continue to be born into households with undermined food and economic security, having an impact on both immediate and later-life health and well-being.

This study builds on previous research of climate, food insecurity, and infant health and adds a unique perspective by investigating the responses to variable rainfall and temperature —short-term consequences of climate change —among communities specializing in distinct types of agricultural production in Kenya and Mali. We combined cross-sectional health surveys and environmental and agricultural specialization data, and employed a multilevel analytic framework to investigate associations among climate change, agricultural specialization, and birth weight in these 2 climatically vulnerable countries.

LINK BETWEEN CLIMATE CHANGE AND HEALTH

Climate change has been shown to affect human health through the changing patterns of disease seasonality, physical injuries from extreme weather events, and thermal stress.² Food availability is another important link between climate change and health, but its investigation has received less attention because of data constraints and the difficulty of quantifying the impacts of both the changing climate and food availability on health.¹¹

In this study, we hypothesized that climate variability affects human health through its impact on food availability, mothers' diets, and, consequently, birth weight. Changing patterns of rainfall and temperature, indications of a changing climate, affect

ABOUT THE AUTHORS

Maryia Bakhtsiyarava is a PhD student with the Department of Geography, Environment, and Society, University of Minnesota, and Minnesota Population Center, Minneapolis. Kathryn Grace is also with the Department of Geography, Environment, and Society, University of Minnesota, and Minnesota Population Center. At the time of study, Raphael J. Nawrotzki was with the University of Minnesota and Minnesota Population Center, Minneapolis.

Correspondence should be sent to Maryia Bakhtsiyarava, 225 19th Ave S, 50 Willey Hall, University of Minnesota, Minneapolis, MN 55455 (e-mail: bakht013@umn.edu). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link. This article was accepted September 6, 2017.

doi: 10.2105/AJPH.2017.304128

crop-growing conditions and can cause yield losses. Birth weight is an indicator of a mother's diet and health during pregnancy: undernourished mothers are at risk for delivering LBW babies.¹² Because birth weight is affected by food availability, which in turn is affected by climate characteristics, birth weight serves as a potential measure of the impact of climate change on human health.^{13,14}

FOCUS ON AGRICULTURAL SPECIALIZATION

Agricultural production is the main livelihood strategy in SSA, providing both income and food.15 Most agricultural production in Mali and Kenya is rainfed and characterized by limited use of machinery, irrigation, and fertilizers,16 rendering agriculturalists susceptible to droughts and heat waves. In Kenya and Mali, food cropping, cash cropping, and pastoralism represent the 3 most common agricultural production strategies: food croppers mostly grow food for household consumption whereas cash croppers sell their crops for money; pastoralists rear livestock for sale or trade. Because of the different ways in which cash croppers, food croppers, and pastoralists earn their livelihoods, they may face different food-security concerns when threatened by climate variability. For example, a cash cropper may have an advantage of having available cash to purchase food from the markets. A food cropper, on the other hand, may experience a situation in which there are no food reserves left from last year and this season's yield is at risk. Agriculture as a general economic activity has been linked to nutritional outcomes because it determines food availability, quality, and quantity.¹⁷

METHODS

The health and sociodemographic data came from the Demographic Health Surveys (DHS) Program funded by the US Agency on International Development. The DHS collects and disseminates data on demographic, health, and nutrition characteristics for most of the poorest

Supplement 2, 2018, Vol 108, No. S2 AJPH

countries in the world.^{7,8} We based the analysis on the 2 most recent samples of birth records for Kenya and Mali: Kenya 2014 and 2008 (n = 9584) and Mali 2012 to 2013 and 2006 (n = 3416). These individual-level birth records can be linked to mothers' data files. The surveys have a 2-stage cluster sampling design, with a subset of households within a cluster selected into the sample.^{7,8} These data are nationally representative and spatially referenced at the cluster level. The DHS displaces rural clusters up to 5 kilometers (with an additional 1% of rural clusters displaced up to 10 km) and urban clusters up to 2 kilometers to preserve respondents' confidentiality.¹⁸ Consistent with recommendations, we created 5-kilometerradius buffers surrounding DHS clusters to account for the displacement.¹⁸

The analysis only included births for which the continuous measure of weight at birth was available: 9584 out of 16 127 records for Kenya and 7148 out of 17 322 cases for Mali had birth weight data (see Appendix A, available as a supplement to the online version of this article at http://www.ajph.org, for detailed information about missing birth weight records).

Health and Sociodemographic Variables

The dependent variable is a continuous measure of weight at birth in grams. Weight at birth depends on a combination of biological and socioeconomic conditions in which a pregnancy developed. Important biological factors that have an impact on weight at birth are mother's age, height, and weight; birth order; and baby's sex,¹³ and these are controlled for in this study. We controlled the source of birth weight (mother's recall or written card) to account for reporting bias. Other control variables affecting birth weight are mother's employment, education, and marital status, and household's floor material and residence in an urban area. Maternal employment, education, marital status, and household floor material relate to household wealth and access to resources. Those living in urban areas may have greater access to medical services and rely on different livelihood strategies or strategies for coping with climate change. Table 1 contains descriptive information for the variables used in the analysis.

Agricultural Specialization

Livelihood is defined as the strategy by which people secure income or food.¹⁹ In Kenya and Mali, agriculture represents the main livelihood strategy. The focus of this study is on birth weight outcomes according to specific agricultural specializationsfood cropping, cash cropping, or pastoralism. Data on livelihoods come from the US Agency on International Development's Famine Early Warning System Network (FEWS NET), which relies on local experts, climate patterns, market trends, and geophysical data to identify general areas dominated by a specific strategy to procure income or food. These livelihood zones provide insight into how individuals interact with their environment and therefore allow researchers to observe differential vulnerabilities according to how people produce their food or income.¹² FEWS NET's livelihood reports contain data on markets, hazards, prevailing livelihood strategies, and sources of income within each livelihood zone. We qualitatively assessed livelihood zone descriptions to assign zones into 1 of 3 agricultural specializations (food cropping, cash cropping, pastoralism) on the basis of the prevailing sources of income and food (see Figure A, available as a supplement to the online version of this article at http://www.ajph.org, for an example of a livelihood zone description).

Figure B (available as a supplement to the online version of this article at http://www. ajph.org) represents the location of DHS cluster points within cash cropping, food cropping, and pastoralist livelihood zones in Kenya and Mali.

Environmental Data

Temperature and rainfall may negatively affect crop yields, which may have an impact on food availability, putting diets and health at risk.¹⁷ The climate measures represent detailed (0.5×0.5 degrees) monthly temperature and precipitation data available through the Integrated Public Use Microdata Series (IPUMS)-Terra.²⁰ IPUMS-Terra integrates population and environmental data such as climate, land cover or use, crop yields, and population censuses from more than 160 countries.^{20,21} Monthly climate data in IPUMS-Terra are available TABLE 1—Summary Statistics for the Variables Used in the Analysis: Demographic Health Surveys for Kenya (2008 and 2014) and Mali (2006 and 2012)

| Variables | Kenya | Mali 3238.4 (861.58) | |
|--|------------------|-------------------------|--|
| Dependent variable: birth weight, g, mean (SD) | 3302.52 (654.26) | | |
| Climate variables, ^a mean (SD) | | | |
| No. of months above 35 °C | 0.19 (0.81) | 5.92 (1.78) | |
| Average precipitation, mm | 1000 (750) | 660 (840) | |
| NDVI | 0.53 (0.42) | 0.77 (0.16) | |
| Control variables | | | |
| Mother's age, y, mean (SD) | 28.25 (6.38) | 28.58 (7.17) | |
| Baby female, % | 49 | 47 | |
| Birth order | 2.94 | 3.93 | |
| Mother's weight, kg, mean (SD) | 60.75 (12.8) | 59.34 (10.97) | |
| Mother's height, cm, mean (SD) | 159.74 (6.77) | 161.72 (6.62) | |
| Married, % | 84 | 97 | |
| Birth weight recall, % | 50 | 75 | |
| Mother's education (none), % | 10 | 77 | |
| Mother's education (primary), % | 53 | 13 | |
| Mother's education (at least secondary), % | 37 | 10 | |
| Mother's employment status (employed), % | 62 | 58 | |
| Floor (finished), % | 49 | 29 | |
| Urban residence, % | 43 | 34 | |
| Cash croppers, % | 33 | 34 | |
| Food croppers, % | 56 | 49 | |
| Pastoralists, % | 11 | 17 | |
| Total births, no. | 9584 | 3416 | |
| Mothers, no. | 6333 | 2551 | |

Note. NDVI = Normalized Difference Vegetation Index.

^aNumber of months above 35 °C refers to the number of months during the 12 months preceding birth when the average maximum temperature exceeded 35 °C; average monthly precipitation refers to the average monthly precipitation during the 12 months preceding birth.

from 1900 through 2014 and were developed by the Climate Research Unit of the University of East Anglia.²² The resolution of climate data is appropriate to approximate community-level environmental conditions.

We obtained the Normalized Difference Vegetation Index (NDVI) from Moderate Resolution Imaging Spectroradiometer (MODIS) remotely sensed satellite images.²³ The MODIS NDVI product has a 250-meter spatial resolution and is provided every 16 days, enabling the assessment of the state of vegetation during a growing season. The NDVI is constructed from land cover's reflectance in red and near-infrared spectral regions, enables the assessment of the effect of temperature and rainfall on plant health, and has been widely used by researchers.²⁴ Higher NDVI indicates more healthy and dense

vegetation.²³ The NDVI serves as indicator of

Research

Bakhtsiyarava et al.

a yield's success and crop-growing conditions, which can have an impact on women's diets and child's weight at birth.

Environmental Measures

We relied on the following climate measures to account for the environmental conditions that shaped food availability and mothers' diets during pregnancy and affected weight at birth: average monthly precipitation during the 12-month period preceding birth and the number of months during the 12-month period when the average maximum temperature exceeded 35 °C, a threshold commonly used for defining heat waves.

Vegetation conditions during a growing season affect food security for births given the following year. Maximum NDVI values reflect plant productivity during the growing season. As such, this study relied on maximum NDVI for the growing season in Mali (June–September) for 2000 to 2012 and for the growing season in Kenya (April–mid– September) for 2002 to 2013.¹⁹ We constructed a measure of maximum NDVI values for the growing season months and temporally matched them to the birth records to approximate food availability, and investigated their impact on birth weight.

Data Linking

We utilized publicly available data from 4 sources: sociodemographic and health data from DHS, agricultural specialization (livelihood zone) data from FEWS NET, climate data from IPUMS-Terra, and NDVI data from MODIS. These data come in different formats and scales and must be properly linked for the analysis. First, we overlaid spatially referenced DHS cluster points by polygons of livelihood zones to link agricultural specialization to birth records (i.e., if a cluster point fell within a pastoral zone boundary, agricultural specialization for the birth records in this cluster was considered pastoralism). Second, we overlaid DHS cluster points and gridded climate data to derive monthly climate measures for the 5-kilometer buffers surrounding DHS clusters. Then, on the basis of every child's month of birth, we temporally matched climate data to represent climatic conditions for 12 months preceding birth. Finally, we computed maximum NDVI summaries for the 5-kilometer buffers around DHS clusters during the growing season months. We linked the NDVI values to birth records assuming that growing conditions in the current year affect food availability for the next year (i.e., if a child was born in 2008, the child was assigned NDVI values for the 2007 growing season).

Estimation Strategy

We used multilevel models with the dependent variable representing a continuous measure of weight at birth in grams. As described previously, the DHS has a hierarchical structure with births nested within mothers, and mothers nested within clusters. Clusters are then grouped according to coarser scale measures of climate characteristics and agricultural specialization. A random effect for the clusters accounts for the hierarchical nature of the DHS data.¹² A random "mother effect" is added to account for multiple births by 1 mother. Fixed effects for the year and month of birth account for the unobserved characteristics that could have an impact on birth weight.

As a first step, we investigated the importance of agricultural specialization for birth weight by including specialization as a category into multilevel models with sociodemographic and then with sociodemographic and climate predictors (details on modeling strategy are in Appendix B and Tables A and B, available as supplements to the online version of this article at http:// www.ajph.org). These models, the results from t test for group mean differences (Tables C and D, available as supplements to the online version of this article at http://www. ajph.org), and interactions between agricultural specializations and climate measures revealed significant differences in the observed effects on birth weight among the 3 agricultural specializations, which warranted our interest to analyze the specializations separately. Fitting separate models to each dominant agricultural specialization provides a way to obtain separate coefficients for each climate effect.¹³ We performed all analyses in the R environment for statistical computing (R Foundation for Statistical Computing, Vienna, Austria).

Our modeling approach can be represented as follows:

- (1) $\gamma_{ijks} = b_0 + \beta_c x_n + u_k + w_j + \varepsilon_{ijk}$
- (2) $\gamma_{ijks} = b_0 + \beta_c x_n + \beta_c lim_k + u_k + w_j + \varepsilon_{ijk}$

In Equation 1, γ_{ijks} represents a birth weight of baby *i* of mother *j* in cluster *k* for agricultural specialization *s*; $\beta_c x_n$ is a vector of *c* socioeconomic and biological variables associated with birth weight; u_k represents a DHS cluster random effect term, which accounts for the nesting of birth records within DHS clusters; w_j is a mother random effect to account for multiple children by 1 mother; and ε_{ijk} is an error term. Equation 2 adds $\beta clim_k$, a vector of climate variables for cluster *k*, to Equation 1. To ensure the results are not biased by multicollinearity, we checked all the variables for correlation.

Supplement 2, 2018, Vol 108, No. S2 AJPH

RESULTS

The main research question this study attempted to answer is the following: In the face of climate variability, is agricultural specialization in food cropping, cash cropping, or pastoralism differentially associated with birth weight outcomes?

We found significant differences in children's average birth weight by agricultural specialization. Children born in foodcropping communities in Kenya (n = 4785) were heavier than those born in cashcropping (n = 3874) and pastoralist communities (n = 1015; 3380 g vs 3204 g and 3205 g). In Mali, babies born by food croppers (n = 1143) and cash croppers (n = 1698) had similar average birth weights (3245 g and 3285 g), while children born in pastoralist (n = 575) communities weighed on average 3123 grams. In the DHS data sample, about 6% of births in Kenya were LBW compared with 15% in Mali. Among food and cash croppers, the majority of LBW births in Kenya and Mali occurred in cash-cropping zones-7% and 14%, respectively. However, pastoralists in both countries were characterized by a high prevalence of LBW: 7% in Kenya and 20% in Mali. Such a high prevalence of LBW among pastoralists in Mali might be indicative of socioeconomic disparities existing in pastoralist communities at the family level.

Table 2 presents results from a regression of birth weight on biological and socioeconomic variables. Mother's weight, height, education, employment, marital status, and birth parity were positively associated with weight at birth. Factors negatively associated with birth weight were mother's age and baby's sex (female). These results are consistent with previous studies: maternal height and weight serve as proxy to assess a woman's overall health and food security status.¹² Education, employment, and marital status are indicative of a socioeconomic status and access to shared resources.¹² In the next step, we added climate measures to the models specified in Table 2. The first 3 models added temperature, precipitation, and NDVI measures separately, followed by a model with all 3 climate measures.

As can be seen from Table 3, cash croppers in both countries did not appear to be sensitive to climate variability. Although negative, the associations between temperature and birth weight for cash croppers in both countries were not significant. Similarly, we observed no significant effects for precipitation and NDVI among cash croppers.

Food croppers exhibited different patterns of sensitivity to climate variability compared with cash croppers. An increase in the number of months with average maximum temperature above 35 °C in a year preceding birth was associated with a small negative effect on birth weight for food croppers in Kenya. We observed a positive significant association between birth weight and precipitation for food croppers in both Kenya and Mali (Table 3). The positive effect of precipitation is consistent with previous work.^{12,25,26} As can be seen from Table 3, NDVI during the growing season was positively associated with birth weights for food croppers in Mali. This relationship was not reflected in the Kenyan case, however. Findings from the full models in Table 3 indicate that precipitation maintained a positive association with birth weight on food croppers in Kenya even in conjunction with increased temperatures.

Even though the directionality of climate effects for pastoralists resembles that for the other agricultural groups, the only positive association with birth weight was observed for precipitation in Kenya. The positive effect of precipitation for pastoralists held in conjunction with increased temperatures.

Beyond differences among agricultural specializations, we also observed differences in climate effects between Mali and Kenya. For example, NDVI provides a fine-spatial scale measure of vegetation capable of reflecting community-level variation in agriculture. In Mali, as in many West African communities, rainfall can be highly variable over relatively short distances,²⁷ affecting agricultural output at a relatively fine scale. In the Malian case, NDVI is particularly useful because it is capable of capturing this finescale spatial variation. Kenya's different topographical and landscape features do not seem to require the fine-scale vegetation information that is useful in the West African context.²⁸

TABLE 2—Results From Multilevel Models Investigating Associations Between Sociodemographic Variables and Children's Birth Weight in Kenya (2008 and 2014) and Mali (2006 and 2012) by Agricultural Specialization

| | Kenya | | | Mali | | |
|--------------------------------|------------------------------|------------------------------|-----------------------------|------------------------------|------------------------------|-----------------------------|
| Variables | Cash Croppers, b (95% CI) | Food Croppers, b (95% CI) | Pastoralists, b (95% CI) | Cash Croppers, b (95% CI) | Food Croppers, b (95% CI) | Pastoralists, b (95% CI) |
| Child's characteristics | | | | | | |
| Baby female | -95.72 (-131.0, -60.4) | -117.84 (-153.6, -82.1) | -96.95 (-166.0, -27.9) | -206.13 (-303.0, -109.3) | -158.76 (-233.9, -83.6) | -48.75 (-186.9, 89.4) |
| Birth order | 24.19 (7.1, 41.3) | 46.99 (32.0, 62.0) | 33.77 (5.4, 62.1) | 14.96 (-19.3, 49.2) | 5.21 (-22.6, 33.0) | -38.21 (-84.6, 8.2) |
| Mother's characteristics | | | | | | |
| Age, y | -7.33 (-12.5, -2.2) | -10.67 (-15.6, -5.8) | -6.99 (-17.6, 3.6) | 1.13 (-11.3, 13.6) | -1.55 (-11.3, 8.2) | 9.78 (-6.1, 25.6) |
| Weight, kg | 3.37 (1.3, 5.4) | 4.65 (2.7, 6.6) | 1.08 (-2.7, 4.8) | 0.41 (-6.2, 7.0) | 3.73 (-0.8, 8.2) | 5.96 (-1.8, 13.7) |
| Height, cm | 9.23 (5.1, 13.3) | 7.46 (4.2, 10.7) | 6.41 (-0.5, 13.4) | 8.94 (-0.4, 18.3) | 3.78 (-3.3, 10.9) | 4.08 (-8.3, 16.5) |
| Married | -6.91 (-71.3, 57.5) | 73.3 (17.6, 129.0) | 1.66 (-137.0, 140.4) | -158.38 (-511.1, 194.4) | 80.13 (-177.7, 337.9) | 236.85 (-346.8, 820.5) |
| Recalled birth weight | -3.87 (-46.7, 38.9) | 27.88 (-11.8, 67.5) | -156.14 (-238.4, -73.9) | -21.98 (-161.9, 118.0) | -0.67 (-106.0, 104.6) | 80.31 (-90.5, 251.1) |
| Employed | -8.46 (-61.5, 44.6) | 51.47 (6.4, 96.5) | 100.59 (-7.4, 208.5) | -41.99 (-157.0, 73.0) | 69.45 (-28.3, 167.2) | -97.28 (-272,1, 77.6) |
| Education (primary) | 31.69 (-71.1, 134.5) | 84.19 (-20.2, 188.6) | -37.98 (-152.3, 76.4) | -79.49 (-240.2, 81.2) | 12.55 (-118.9, 144.0) | -128.79 (-388.5, 130.9) |
| Education (at least secondary) | 4.97 (-105.9, 115.8) | 51.51 (-57.3, 160.3) | -0.33 (-158.3, 157.6) | 51.46 (-142.5, 245.4) | -9.35 (-160.8, 142.1) | -96.09 (-447.1, 254.9) |
| Household's characteristics | | | | | | |
| Finished floor | 4.48 (-58.4, 67.3) | -59.16 (-108.3, -10.0) | 112.57 (-13.5, 238.6) | 89.53 (-52.1, 231.2) | 38.84 (-76.4, 154.0) | 2.35 (-203.9, 208.6) |
| Urban residence | -12.46 (-72.3, 47.3) | -34.07 (-86.0, 17.9) | -93.21 (-209.1, 22.7) | -79.39 (-250.1, 91.3) | -94.54 (-230.5, 41.4) | 23.87 (–223.6, 271.4) |
| Model statistics | | | | | | |
| Random intercept (cluster) | 6 602.951 | 25 712.47 | 15 160.41 | 61 090.25 | 55 374.71 | 115 776.5 |
| BIC | 57 718 | 75 283 | 15 605 | 18 605 | 27 521 | 9 2 9 2 |
| Total cases, no. | 3 784 | 4 785 | 1 015 | 1 143 | 1 698 | 575 |
| Mothers, no. | 2 155 | 3 560 | 618 | 879 | 1 255 | 417 |
| DHS clusters, no. | 586 | 1 015 | 203 | 191 | 231 | 83 |

Notes. BIC = Bayesian information criterion; CI = confidence interval; DHS = Demographic Health Survey. Models are stratified by agricultural specialization and represent changes in birth weight in grams. Unless specified, the following unit changes or levels are associated with the explanatory variables: baby female—baby male; birth order—every following birth; married—nonmarried or nonpartnered; birth weight recalled—information about birth weight was obtained from a written card; employed—mother is unemployed; education primary—no education; education (at least secondary)—no education; finished floor—dirt floor; urban residence—rural residence.

DISCUSSION

We investigated how climate variability, by affecting food availability, affects child health in communities with different agricultural production strategies. Food croppers in both countries appear to be more sensitive to both negative (increased temperature) and positive (precipitation and NDVI) effects of climate. Compared with cash croppers, food croppers have smaller plot sizes; have less access to fertilizers, irrigation, and machinery; and have smaller incomes.²⁹ These factors expose their crops to heat stress and droughts and put yields and diets at risk, contributing to the increased possibility of giving birth to a lower-weight infant.^{29,30} When one does not consider climate factors, cash cropping has been shown to be beneficial for children's nutrition outcomes,³¹ but our

Research Peer Reviewed

Bakhtsivarava et al.

results did not demonstrate that advantage when we accounted for climate measures. In terms of climate change, it is possible that increased use of agricultural technologies cannot completely reduce the negative impacts on agriculture associated with increased temperatures. Reduced yields may ultimately have an impact on the household resources of cash croppers, which has a negative impact on household food security. Pastoralists are typically more mobile and can move to find land with enough forage for livestock during hot months-this mobility may explain the absence of the association between temperature and birth weight. This study also reveals a positive relationship between precipitation and birth weight for food cropping and pastoralist communities. Irrigation, modern machinery, and fertilizers are generally out of

reach for small-scale subsistence farmers, which is why they may experience notable beneficial effects of increased rainfall.¹⁶

A causal relationship between climate change and children's health outcomes is difficult to establish because of 2 main factors. First, health effects of climate change are potentially small and challenging to detect because climate and weather affect individuals through both direct and indirect pathways.^{4,26} Therefore, public health interventions should consider these multiple pathways and should be based on the expansion of food aid, efforts to promote efficient and technological agriculture among African farmers, and sanitation improvement efforts.

A second factor complicating climate change-health research has to do with data quality and availability because such research TABLE 3—Results From Multilevel Models Investigating Associations Between Sociodemographic and Climate Variables and Children's Birth Weight in Kenya (2008 and 2014) and Mali (2006 and 2012) by Agricultural Specialization

| | Kenya | | | Mali | | |
|--|------------------------------|------------------------------|-----------------------------|------------------------------|------------------------------|-----------------------------|
| Variables | Cash Croppers, b (95% CI) | Food Croppers, b (95% CI) | Pastoralists, b (95% CI) | Cash Croppers, b (95% CI) | Food Croppers, b (95% CI) | Pastoralists, b (95% CI) |
| Temperature | | | | | | |
| No. of months above 35 °C ^a | -11.66 (-45.2, 21.8) | -70.58 (-170.7, -105.9) | -2.75 (-34.4, 28.9) | -12.27 (-74.1, 49.6) | -23.52 (-53.9, 6.9) | 0.62 (-48.7, 51.1) |
| BIC | 57 659 | 75 207 | 15 559 | 16 001 | 23 336 | 7 899 |
| Precipitation | | | | | | |
| Average precipitation (100 mm) ^b | -16.83 (-51.9, 18.2) | 47.09 (77.7, 106.9) | 109.61 (38.1, 181.2) | 22.23 (-188.5, 233.0) | 88.75 (16.7, 194.2) | 81.26 (29.6, 288.9) |
| BIC | 57 658 | 75 203 | 15 548 | 15 999 | 23 333 | 7 897 |
| NDVI | | | | | | |
| NDVI ^c | -28.86 (-92.7, 35.0) | -1.93 (-30.7, 23.1) | 11.02 (-108.6, 130.7) | -131.24 (-924.6, 662.1) | 397.26 (70.7, 723.8) | -34.85 (-456.0, 319.4) |
| BIC | 57 657 | 75 212 | 15 556 | 15 851 | 23 121 | 7 895 |
| Temperature, precipitation, NDVI | | | | | | |
| No. of months above 35 °Cª | -15.11 (-48.9, 18.7) | -62.87 (-155.6, -90.8) | 9.24 (-23.4, 41.9) | -14.59 (-77.4, 48.2) | -0.38 (-38.4, 37.6) | 0.62 (-51.0, 53.5) |
| Average precipitation (100 mm) ^b | -18.26 (-53.5, 17.0) | 45.16 (73.8, 103.2) | 115.19 (41.4, 189.09) | 11.95 (-203.2, 227.1) | 46.06 (-69.3, 161.4) | 88.11 (40.9, 304.4) |
| NDVI ^c | -31.19 (-95.3, 32.9) | 7.11 (-12.9, 40.7) | 23.09 (-96.9, 143.0) | -160.83 (-969.7, 648.1) | 340.82 (-76.5, 758.2) | -83.68 (-575.3, 247.2) |
| BIC | 57 657 | 75 199 | 15 544 | 15 844 | 23 118 | 7 886 |
| Total cases, no. | 3 784 | 4 785 | 1 015 | 1 143 | 1 698 | 575 |

Notes. BIC = Bayesian information criterion; CI = confidence interval; NDVI = Normalized Difference Vegetation Index. Models are stratified by agricultural specialization and represent changes in birth weight in grams. Adjusted for mother's age, weight, height, education, marital and employment status; baby's sex and birth order; household's floor type and urban or rural residence; and source of birth weight data (recall or written card).

^aNumber of months during the 12 months preceding birth when the average maximum temperature exceeded 35 °C. Unit change—every additional month with maximum monthly temperature above 35 °C.

^bAverage monthly precipitation in millimeters during the 12 months preceding birth. Unit change—a 100-mm increase in precipitation. ^cMaximum value of NDVI. Unit change—every additional increase of index value by 0.01.

requires collaboration and data from varied disciplines such as climate science, public health, and agronomy. Birth weight research in developing countries is especially complicated by data availability-65% of births in SSA are not weighed.⁶ In addition, the DHS temporarily stopped including information about the length of time at current residence, which hinders researchers' ability to correctly link a pregnancy to the weather conditions in which it developed. As such, although children in developing countries potentially face important health challenges related to weather and climate variability, data constraints limit research of these issues.

Although the study relied on the most spatially refined temperature data available (at 50 km), ideally, finer spatial resolution should be used to investigate the effect of climate change on health. In addition, unexplained variation remains in the multilevel models that investigate the association be tween anthropometric and

lement 2, 2018, Vol 108, No, S2 AJPI

sociodemographic and environmental factors.²⁶ Moreover, in this study, we explored the important relationships among biological, economic, and environmental factors on birth weight with cross-sectional data, but it would be informative to conduct longitudinal surveys and analyses to track the causal effect of climate change on health.¹⁴ We conducted multiple robustness tests (Appendix C, available as a supplement to the online version of this article at http://www.ajph.org) that indicated the robustness of our results.

Our study faced the difficulties described here, but nonetheless represents an important step in linking climate change and birth outcomes. Future research on the impacts of climate change on health would benefit from the expansion of health surveillance and reporting.32 Future research should also explore possible nonlinear effects of climate variability on health. Such nonlinearities have been observed in the effect of climate change on such human processes as migration, for

example,³³ and remain largely unexplored in public health research. AJPH

CONTRIBUTORS

M. Bakhtsiyarava and K. Grace designed the study and drafted the article. M. Bakhtsiyarava and R. J. Nawrotzki performed statistical analyses. All authors participated in revising the article.

ACKNOWLEDGMENTS

The authors acknowledge support from the Minnesota Population Center (R24 HD041023), funded through grants from the Eunice Kennedy Shriver National Institute for Child Health and Human Development. This work also received support from the National Science Foundation-funded Terra Populus project (NSF award ACI-0940818). M. Bakhtsiyarava and K. Grace received additional support for this study from the Minnesota Population Center Research Collaboration Award.

The authors wish to acknowledge the Demographic and Health Surveys (DHS) Program for providing publicly available DHS data. The authors are also thankful to the anonymous reviewers for their helpful comments

HUMAN PARTICIPANT PROTECTION

Institutional review board approval was not needed for this study because it relied on publicly available data.

REFERENCES

1. Niang I, Ruppel OC, Abdrabo MA, et al. Africa. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK, and New York, NY: Cambridge University Press; 2014: 1199–1265.

 McMichael AJ, Woodruff RE, Hales S. Climate change and human health: present and future risks. *Lancet*. 2006; 367(9513):859–869.

 Deschenes O, Greenstone M, Guryan J. Climate change and birth weight. *Am Econ Rev.* 2009;99(2): 211–217.

4. Strand LB, Barnett AG, Tong SL. The influence of season and ambient temperature on birth outcomes: a review of the epidemiological literature. *Environ Res.* 2011;111(3):451–462.

5. Global Nutrition Report 2016: From Promise to Impact: Ending Malnutrition by 2030. Washington, DC: International Food Policy Research Institute; 2016.

6. Wardlaw T. Low Birthweight: Country, Regional and Global Estimates. New York, NY: United Nations Children's Fund; 2004.

7. Mali Demographic and Health Survey. Washington, DC: The Demographic and Health Surveys Program; 2017.

8. Kenya Demographic and Health Survey. Washington, DC: The Demographic and Health Surveys Program; 2017.

 Bongaarts J, Casterline J. Fertility transition: is sub-Saharan Africa different? *Popul Dev Rev.* 2013;38(suppl 1): 153–168.

10. Cleland J, Machiyama K. The challenges posed by demographic change in sub-Saharan Africa: a concise overview. *Popul Dev Rev.* 2017;43:264–286.

11. Myers SS, Patz JA. Emerging threats to human health from global environmental change. *Annu Rev Environ Resour.* 2009;34:223–252.

12. Grace K, Davenport F, Funk C, Lerner AM. Child malnutrition and climate in sub-Saharan Africa: an analysis of recent trends in Kenya. *Appl Geogr.* 2012;35(1-2):405–413.

13. Grace K, Davenport F, Hanson H, Funk C, Shukla S. Linking climate change and health outcomes: examining the relationship between temperature, precipitation and birth weight in Africa. *Glob Environ Change*. 2015;35: 125–137.

14. Grace K. Considering climate in studies of fertility and reproductive health in poor countries. *Nat Clim Chang.* 2017;7(7):479–485.

15. *The World Factbook*. Washington, DC: Central Intelligence Agency; 2016.

16. Brown ME, Hintermann B, Higgins N. Markets, climate change, and food security in West Africa. *Environ Sci Technol.* 2009;43(21):8016–8020.

17. Lloyd SJ, Kovats RS, Chalabi Z. Climate change, crop yields, and undernutrition: development of a model to quantify the impact of climate scenarios on child undernutrition. *Environ Health Perspect.* 2011; 119(12):1817–1823.

18. Burgert C, Colston J, Roy T, Zachary B. Geographic displacement procedure and georeferenced data release policy for the Demographic and Health Surveys. Calverton, MD: ICF International; 2013.

19. Famine Early Warning Systems Network. 2016. Available at: http://www.fews.net/east-africa/ethiopia. Accessed September 27, 2017.

Peer Reviewed

S150 Research

Bakhtsivarava et al.

20. Kugler T, Van Riper D, Manson S, Haynes DI, Donato J, Stinebaugh K. Terra Populus: workflows for integrating and harmonizing geospatial population and environmental data. *J Map Geogr Libr.* 2015;11(2):180– 206.

21. Nawrotzki RJ, Schlak AM, Kugler TA. Climate, migration, and the local food security context: in-troducing Terra Populus. *Popul Environ*. 2016;38(2): 164–184.

22. Harris I, Jones PD, Osborn TJ, Lister DH. Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 dataset. *Int J Climatol.* 2014;34(3): 623–642.

23. MODIS MOD13Q1 Normalized Difference Vegetation Index. Version 5. Sioux Falls, SD: NASA EOSDIS Land Processes DAAC, USGS Earth Resources Observation and Science Center; 2017. Available at: https:// lpdaac.usgs.gov/dataset_discovery/modis/modis_ products_table. Accessed September 27, 2017.

24. Grace K, Brown M, McNally A. Examining the link between food prices and food insecurity: a multi-level analysis of maize price and birthweight in Kenya. *Food Policy*. 2014;46:56–65.

25. Dos Santos S, Henry S. Rainfall variation as a factor in child survival in rural Burkina Faso: the benefit of an event-history analysis. *Popul Space Place*. 2008;14(1):1–20.

26. Shively GE. Infrastructure mitigates the sensitivity of child growth to local agriculture and rainfall in Nepal and Uganda. *Proc Natl Acad Sci U S A*. 2017;114(5):903–908.

 Hulme M. Climatic perspectives on Sahelian desiccation: 1973–1998. *Glob Environ Change*. 2001;11(1): 19–29.

28. Husak G, Grace K. In search of a global model of cultivation: using remote sensing to examine the characteristics and constraints of agricultural production in the developing world. *Food Secur.* 2016;8(1):167–177.

 Govereh J, Jayne TS. Cash cropping and food crop productivity: synergies or trade-offs? *Agric Econ.* 2003; 28(1):39–50.

 Maxwell S, Fernando A. Cash crops in developingcountries—the issues, the facts, the policies. *World Dev.* 1989;17(11):1677–1708.

31. Braun JV, Kennedy E. Agricultural commercialization, economic development, and nutrition. Baltimore, MD; London, UK: International Food Policy Research Institute; The Johns Hopkins University Press; 1994.

 Shea KM, American Academy of Pediatrics Committee on Environmental Health. Global climate change and children's health. *Pediatrics*. 2007;120(5):e1359– e1367.

 Nawrotzki RJ, DeWaard J, Bakhtsiyarava M, Ha JT. Climate shocks and rural–urban migration in Mexico: exploring nonlinearities and thresholds. *Clim Change*. 2017;140(2):243–258. Copyright of American Journal of Public Health is the property of American Public Health Association and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.

