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Climate-Related Child Undernutrition in the Lake Victoria Basin: An Integrated Spatial Analysis of Health Surveys, NDVI, and Precipitation Data

David López-Carr, Kevin M. Mwenda, Narcisa G. Pricope, Phaedon C. Kyriakidis, Marta M. Jankowska, John Weeks, Chris Funk, Gregory Husak, and Joel Michaelsen

***Abstract*—Despite growing research into the socio-economic aspects of vulnerability [1]–[4], relatively little work has linked population dynamics with climate change beyond the complex relationship between migration and climate change [5]. It is likely, however, that most people experience climate change *in situ*, so understanding the role of population dynamics remains critical. How a given number of people, in a given location and with varying population characteristics may exacerbate or mitigate the impacts of climate change or how, conversely, they may be vulnerable to climate change impacts are basic questions that remain largely unresolved [6]. This paper explores where and to what extent population dynamics intersect with high exposure to climate change. Specifically, in Eastern Africa's Lake Victoria Basin (LVB), a climate change/health vulnerability hotspot we have identified in prior research [7], we model child undernutrition vulnerability indices based on climate variables, including proxy measures (NDVI) derived from satellite imagery, at a 5-km spatial resolution. Results suggest that vegetation changes associated with precipitation decline in rural areas of sub-Saharan Africa can help predict deteriorating child health.**

***Index Terms*—Climate, Lake Victoria Basin (LVB), NDVI, stunting, undernutrition, vulnerability.**

I. Introduction

THE impact of climate change on humans varies geographically. The risks from warming, in particular, depend upon where one lives. Coastal communities are at risk of sea level rise. Inland populations, especially those depending upon subsistence agriculture, are at risk of rising temperatures and lower levels of precipitation that can reduce the productivity of the land and alter the habitats of disease vectors. Some of these environmental changes can be assessed through the analysis of satellite imagery. Hay, Guerra, Tatem, Atkinson, and Snow, for example, have utilized imagery to identify zones at high risk of malaria in sub-Saharan Africa [8]–[10]. In a more general way, Weeks, Getis, Hill, Gadalla, and Rashed [11], Getis, Stow, Hill, Rain, Engstrom, Stoler, Lippitt, Jankowska, Lopez-Carr, Coulter, and Ofiesh [12] have found that health in urban areas is associated with the amount of vegetation (observed from high-resolution satellite imagery). It is not the vegetation per se that is affecting health. Rather, levels of vegetation serve as a proxy for the overall well being of the population. However, in rural areas of the developing world, rain-fed subsistence agriculture represents much of a region's photosynthetic output, especially in relatively arid areas where virtually all rural inhabitants depend on agro-pastoralist livelihoods for survival. Perhaps in no place is this truer than in sub-Saharan Africa. Given this intimate population-crop viability relation in the region, and the high proportion of infant and child deaths related to undernutrition, it seems that remotely sensed measures of photosynthetic production coupled with local precipitation measures might be important predictors of child undernutrition. Following the recent tradition of linking pixels to people in human–environment systems, this study explores how vegetation changes associated with climate change in rural areas of sub-Saharan Africa might help predict health status among children.

Where and to what magnitude is child undernutrition related to climate change? Research points to the devastating health effects of climate change, especially in places already experiencing significant health burdens [13]–[15]. The diverse pathways linking climate change and disease ultimately operate through vulnerability mechanisms. We define vulnerability as a function of the sensitivity and adaptive capacity of socio-ecological systems when exposed to environmental and climate changes [16]–[18]. Climate change in sensitive environments can result in increased vulnerability at a number of nested scales from individuals to political states, with a consequent negative effect on human health [19], [20]. In this paper, we move beyond generalized regional models to better understand how climate variation affects child undernutrition at the smallest nested scale, the location of the child. While all individuals may become increasingly exposed to climate-related diseases in the world's most climate-vulnerable parts of developing countries, children are particularly vulnerable due to their physiological and cognitive immaturity (sensitivity) and limited ability to change their situation (adaptive capacity) [21], [22]. Moreover, the World Health Organization asserts that "the major diseases most sensitive to climate change—diarrhea, vector-borne disease like malaria,

Manuscript received September 30, 2015; revised February 24, 2016 and April 15, 2016; accepted May 11, 2016. *(Corresponding authors: David López-Carr and Kevin M. Mwenda.)*

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Digital Object Identifier 10.1109/JSTARS.2016.2569411

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and infections associated with under-nutrition—are most serious in children living in poverty" [23]. Childhood diseases have a life-long impact, resulting in a higher probability of decreased overall wellness and diminished human capital later in life [24]–[26].

Research has grown sharply in the area of socio-economic aspects of vulnerability [27], [28], yet little work to date has empirically tested population dynamics linked to climate change at meaningful spatial scales. How Number, density, and spatial distribution of a population may exacerbate or mitigate the impacts of climate change or the magnitude of these impacts are questions that remain far from resolved [6]. Similarly, there is already a growing literature on remotely sensed measurements of infectious disease dynamics, but relatively little work to date in the area of climate change links to child undernutrition vis a vis spatially varying and temporally changing indicators of food production potential. This is both a critical gap and a research opportunity, as well as an area of attention in the future as climate change and vulnerability will continue to pose human health challenges. Population dynamics and distribution may exacerbate or mitigate the impacts of climate change and may be varyingly vulnerable to climate change impacts [6]. Where and to what extent do population dynamics intersect with high exposure to climate change? We explore this question in Eastern Africa's Lake Victoria Basin (LVB), a climate change vulnerability hotspot [7]. Specifically, we model child undernutrition probability estimates based on climate variability and landscape vigor at a 5-km resolution. This paper has two main objectives: first, we develop a spatially and temporally integrative dataset of climate exposure components related to children's vulnerability to undernutrition. Second, we develop and map measures of climate-related vulnerability to undernutrition among children under 5 in Eastern Africa's LVB.

II. Data and Methods

To achieve our objectives, we employ a unique combination of datasets including vegetation data coupled with the introduction of a new multidecadal remotely sensed precipitation dataset integrated with cluster level data from the Demographic and Health Surveys (DHS). While the benefits of using data from multiple satellite sensors over several decades to perform analyses at the human–environment interface is fairly well known and has been recently implemented for this study area by Pricope, Michaelsen, Lopez-Carr, Funk, and Husak [29], the inclusion of DHS data to test the relevance of incorporating remotely sensed data into health studies is relatively novel. Thus, we combine precipitation and vegetation trends from 1982 to 2012 with DHS cluster level data for the countries within the LVB (Burundi, Kenya, Rwanda, Tanzania, and Uganda) to perform grid-level modeling of stunted children under five years of age at the 5-km spatial resolution.

Trends in precipitation result from analysis of the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset, a blend of available stations, geostationary satellite information and a long-term climatology [30], [31]. The CHIRPS dataset is a near-real-time, quasi-global rainfall at 0.05° (approximately 5 km) resolution available at five-day time steps back to 1981. NDVI data provided by the NASA Global Inventory Monitoring and Modeling System (GIMMS) dataset estimates surface greenness based on satellite estimated reflectance back to 1981. This dataset uses homogenized data from multiple satellites to create a best estimate of vegetation vigor, and is used to capture changes in land cover and vegetation stress [32]–[34].

TABLE I
Climate-Related Independent Variables, Spatio-Temporal Resolution, Reference Year, and Data Sources

Indicator Name	Resolution	Temporal Scale	Data Source
Child Stunting	Cluster	2008-2012	MeasureDHS.org
Monthly Rainfall	5km	1981-2012	CHIRPS
NDVI	8km	1982-2012	GIMMS

Next, we examine climate exposure, or the degree to which a population experiences climate change impacts in their environment, as a function of precipitation and greenness/vigor change in the LVB, with the latter data being derived from performing a Theil–Sen regression analysis on the Advanced Very High Resolution Radiometer GIMMS normalized difference vegetation index (NDVI) third generation (NDVI3g) dataset. The Theil–Sen method is preferred mainly because it is insensitive to extreme values in the dataset, and the start and end time of the time series. It is a nonparametric method so it does not have to assume a particular distribution in the dataset [35]. While we recognize that a variety of socio-political, economic and cultural factors play important roles in determining vulnerability to climate change [36], [37], this study is exploratory in nature, and therefore the scope is limited to focusing on demographic and land-use pressures.

We create an integrative framework that uses weighted and standardized climate exposure variables to map climate-related chronic childhood undernutrition, as measured by extremely low height for age, commonly referred to as stunting. Before selection of the climate exposure variables, we eliminated temperature as a prospective climate variable, since it manifests itself through the change in vegetation as measured by the NDVI. NDVI is a well-known remotely sensed proxy for the amount of standing biomass in a given area. NDVI is based on a ratio of red and near-infrared wavelengths [(NIR-Red)/(NIR+Red)] due to the different reflectance and absorption properties of chlorophyll, a pigment found in the leaves of plants. It is well correlated with the amount and seasonality of above-ground net primary production and vegetation biophysical parameters [38], [39]. We then performed spatially explicit vulnerability mapping of climate-driven childhood stunting at the 5-km resolution. Fig. 1 illustrates a flowchart for the methodology.

The data used are either publicly available or created by the Climate Hazards Group at UCSB (see Table I).

A. Data Preprocessing

The number of DHS-sampled malnourished (stunted) children under 5 in the LVB was aggregated from the household to

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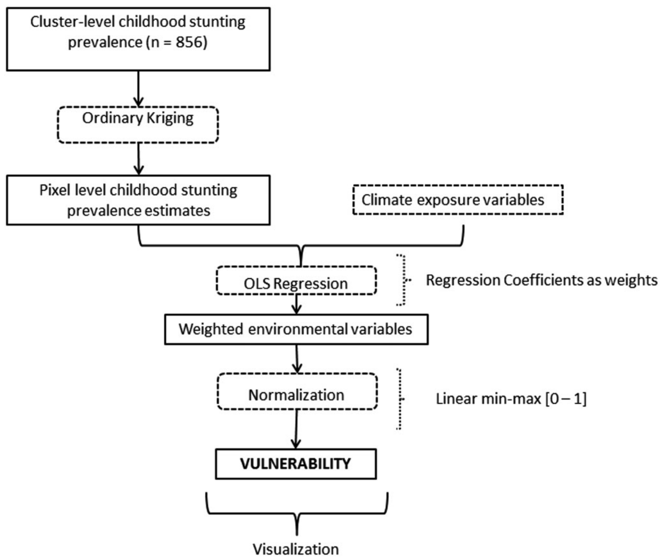

Fig. 1. Flowchart for methodology.

TABLE II
CLIMATE-RELATED INDEPENDENT VARIABLES, OBSERVED RELATIONSHIP WITH CHILD STUNTING AND REGRESSION COEFFICIENT AS WEIGHTS

Indicator Name	Observed Relationship	Weights
Monthly Rainfall	+	13
NDVI	−	0.73

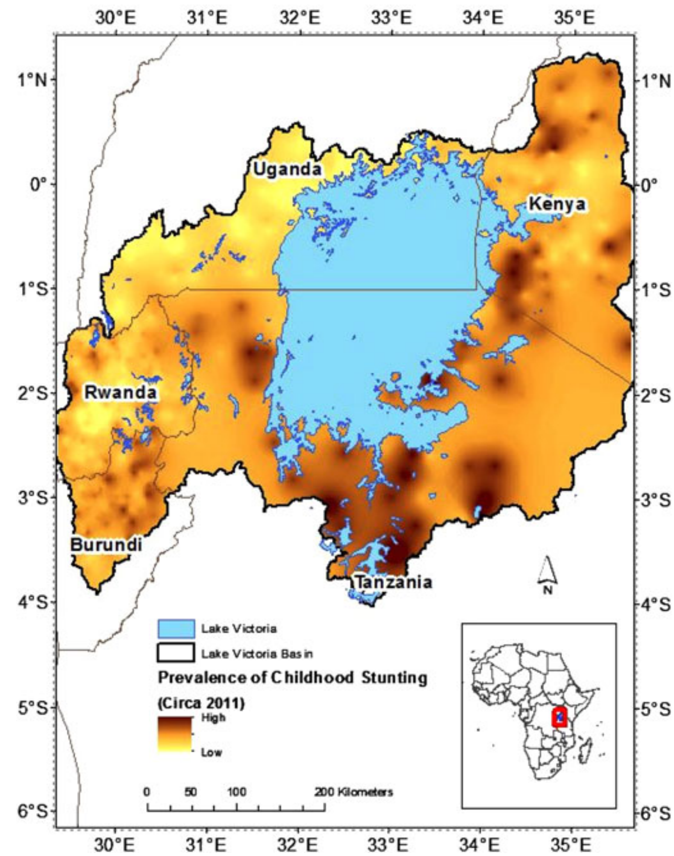

Fig. 2. Ordinary kriging map of childhood stunting prevalence (5-km resolution).

the cluster level (DHS 2008–2012; 95,500 households; $n = 856$ DHS household clusters) after which the prevalence was calculated as a percentage of children under 5 in each cluster. NDVI change from 1982 to 2012 was calculated using Theil–Sen estimators and was consequently resampled to 5-km resolution using the nearest neighbor approach. The 5-km resolution is appropriate given the 5-km uncertainty of the location of rural DHS clusters. Change in precipitation was measured as rainfall change in millimeters from 1981 to 2012.

B. Mapping of Childhood Stunting Prevalence

The cluster-level childhood stunting prevalence was converted into a continuous surface using ordinary kriging, assuming an unknown mean prevalence with a trend across the LVB and a search radius equivalent to 5 km. Kriging was employed as the interpolation method of choice since it contains parameters for expressing uncertainty that is inherent in the location of the DHS clusters.

C. Regression

We applied ordinary least squares (OLS) regression using the 5-km grid as the unit of analysis to estimate the parameters of a linear model between child undernutrition and the set of two climate exposure variables, namely NDVI and precipitation change (see Table I). Regression analyses with DHS data at the cluster level and adjacent pixels representing NDVI and rainfall were run initially with only modest significance for rainfall and low R^2's. A total of 10 241 pixels (5×5 km) were available for the regression analysis and the model is represented by the following equation: $y_i = b_0 + b_1 x_{1,i} + b_2 x_{2,i} + e_i$, where y_i is the expected value of the dependent variable y at pixel i, x pertains to the two independent climate-related variables, b refers to the estimated regression coefficients, and e_i is the residuals at each pixel *i*.

D. Calculating Standardized Measures of Vulnerability

In order to render them comparable, the independent climate-related indicators were each weighted by the coefficients from the OLS regression analysis (see Table II). The two domains were combined and the final vulnerability surface was normalized within a range of 0–1 using linear min–max normalization, where 0 indicates little to no climate-related childhood stunting prevalence and 1 represents the highest vulnerability.

III. RESULTS

OLS regression analysis suggested that both climate-exposure variables were significantly related to child undernutrition in the LVB. A significantly positive association (p-value < 0.05) was found between increase in rainfall and child stunting. A significantly negative association (p-value < 0.05) was found

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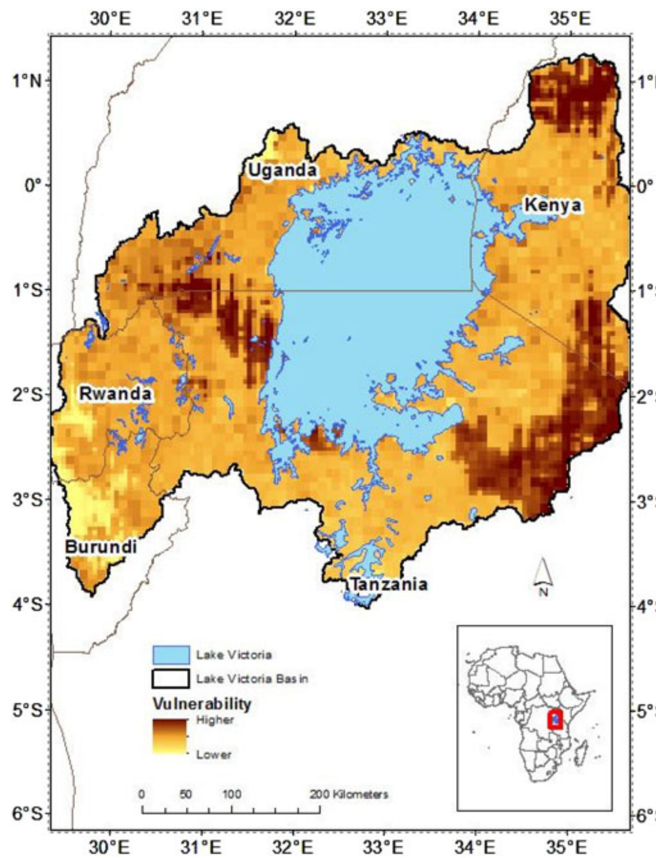

Fig. 3. Map of standardized measures of vulnerability of child stunting due to change in climate exposure variables (both precipitation and NDVI).

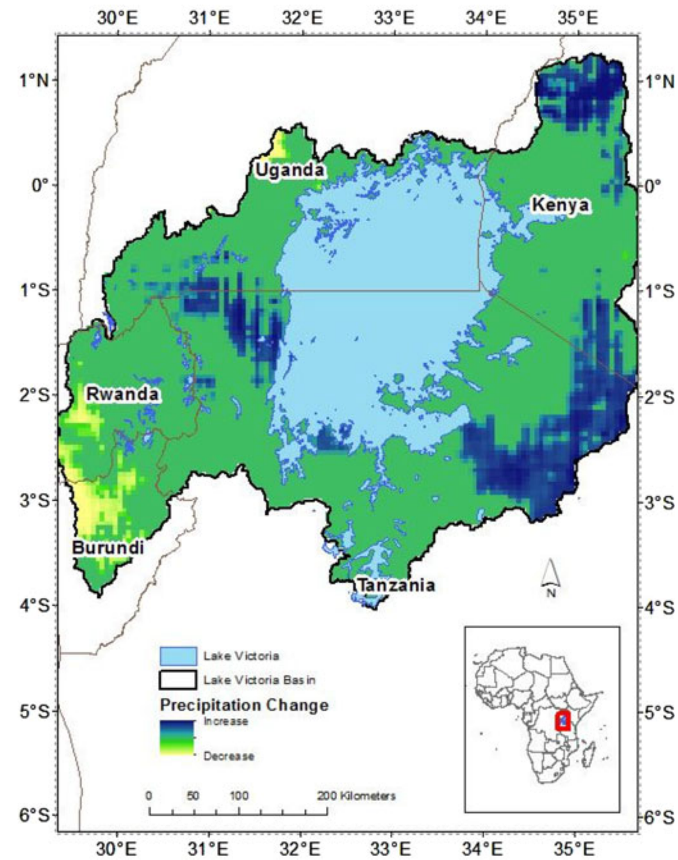

Fig. 4. Map of standardized measures of change in precipitation in the LVB (1981–2012).

between increase in vegetation index and child stunting (see Table II).

A map of childhood stunting prevalence is shown in Fig. 2. Child stunting vulnerability is generally higher in regions with a greater increase in rainfall over the years, especially in the Northeastern and Southeastern parts of the LVB in Kenya and Tanzania (see Figs. 3 and 4). Conversely, vulnerability of child stunting is relatively lower in the LVB areas that experienced the least change in vegetation index. Overall, vulnerability of climate-related child stunting is higher in areas that experienced increase in rainfall coupled with negative change in vegetation index (see Figs. 3 and 5).

IV. Discussion

Exploratory work presented here notes that pockets of high stunting are salient in the southern portion of the LVB but other concentrations are evident in the eastern and southwestern portions of the LVB. Relatively lower stunting is observed in parts of the northeast. The finding that child stunting vulnerability is higher in areas that experience increase in rainfall coupled with negative change in vegetation index suggests the importance of human socio-political and agricultural factors. Specifically, in areas with increased rainfall and decreased NDVI, crop production may be waning despite potentially favorable climate change conditions. If this is the case, factors driving changing food demand and production, and other environmental variables not measured here, such as soil quality change, may explain food insecurity and its consequences more than climate change per se. This finding has implications for policy and agricultural assistance in the region. A highly dense rural population intensively cropping the land over time may be pushing local agricultural and ecological systems to become less resilient. By exploring the two domains of climate-related vulnerability to child stunting, this study does not necessarily imply that both domains have similar effects on overall vulnerability. While rainfall change generally has a greater effect on child stunting than change in NDVI, some areas with increase in rainfall and positive NDVI change may show a higher vulnerability of child stunting, such as the LVB area between Rwanda and Uganda. Such apparently inconsistent results point to the importance of spatial variation in human and political geography.

V. Conclusion

This paper begins to explore a crucial barrier to further progress in the field of climate-health interactions. Numerous studies have utilized remotely sensed imagery for developing measures of environment related to climate change and health [40]. However, few studies have merged such data with population and health data to obtain detailed and location-specific

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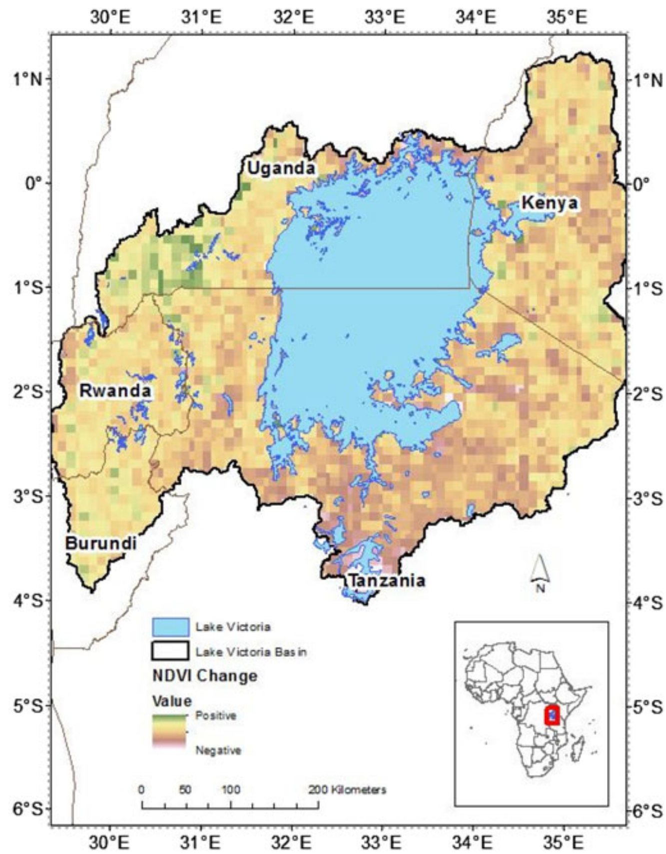

Fig. 5. Map of standardized measures of change in NDVI in the LVB (1982–2012).

maps of climate change impacts on children's undernutrition. By unraveling some of the statistical links between climate change and child health, projecting where African children most vulnerable to climate change reside now and possibly in the near future, our results have direct implications for adaptive response given demographic and land change policy.

This project has multiple potentially transformative and novel components including: 1) the first application of a 5-km precipitation and NDVI change grid for LVB, which will enhance our ability to analyze the minimum rainfall and maximum vegetation change thresholds necessary to support staple crops across different regions, 2) the first application of time-series NDVI data to climate-health vulnerability research, 3) the first application of under-five measure of vulnerability at the 5-km resolution, and 4) combining 1-3 above, the first integration of DHS cluster-level data on children's health with climate, land change, livelihood, and demographic data to model the location and magnitude of the relationships between climate and child undernutrition.

We note caveats in this exploratory research. One concern is theoretical. The extent to which undernutrition is expressed spatially has been inadequately explored and, therefore, we remain uncertain to what extent spatial interpolation as opposed to, for example, a clustering, regional, or threshold approach, appropriately describes the spatial distribution of child undernutrition. A second caveat is methodological. We believe that our statistics should be interpreted as indications rather than formal tests due to the likely presence of spatial autocorrelation. The interpolated child undernutrition prevalence surface in the model shown here led to significant results for NDVI and rainfall in predicting stunting. However, interpolation increases observations and reduces variance. Additional research is necessary to understand potential relationships through refining independent variables and adding additional explanatory variables. A third issue combines theory and methods. The existence of unmeasured variance suggests the addition of further human and physical variables.

In future research, we hope to address these concerns and, in doing so, expand our analysis to provide novel, uncertainty-aware estimates of children's nutritional vulnerability to climate change in the LVB. We hope to refine and expand our approach to the continental scale in future research and to develop a simulation framework to address the uncertainty inherent in interpolations. While this strand of integrative research remains in an early stage of development, with associated limitations, the opportunity for further refinement is great given the rapidly increasing availability of geo-reconciled human and physical data. Continued exploration of climate change interactions with local environments and implications for human populations and their health promises rich policy implications for enhancing rural resilience in the fastest growing, poorest, rural areas of the planet.

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