Climate change and human health: Spatial modeling of water availability, malnutrition, and livelihoods in Mali, Africa

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\textbf{ABSTRACT}

This study develops a novel approach for projecting climate trends in the Sahel in relation to shifting livelihood zones and health outcomes. Focusing on Mali, we explore baseline relationships between temperature, precipitation, livelihood, and malnutrition in 407 Demographic and Health Survey (DHS) clusters with a total of 14,238 children, resulting in a thorough spatial analysis of coupled climate-health dynamics. Results suggest links between livelihoods and each measure of malnutrition, as well as a link between climate and stunting. A ‘front-line’ of vulnerability, related to the transition between agricultural and pastoral livelihoods, is identified as an area where mitigation efforts might be usefully targeted. Additionally, climate is projected to 2025 for the Sahel, and demographic trends are introduced to explore how the intersection of climate and demographics may shift the vulnerability ‘front-line’, potentially exposing an additional 6 million people in Mali, up to a million of them children, to heightened risk of malnutrition from climate and livelihood changes. Results indicate that, holding constant morbidity levels, approximately one quarter of a million children will suffer stunting, nearly two hundred thousand will be malnourished, and over one hundred thousand will become anemic in this expanding arid zone by 2025. Climate and health research conducted at finer spatial scales and within shorter projected time lines can identify vulnerability hot spots that are of the highest priority for adaptation interventions; such an analysis can also identify areas with similar characteristics that may be at heightened risk. Such meso-scale coupled human-environment research may facilitate appropriate policy interventions strategically located beyond today’s vulnerability front-line.

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\textbf{Introduction: climate and child malnutrition}

Human well-being is linked to the environment through a complex web of relationships. The vicious circle model describes feedback relationships among population growth, poverty, health, and environmental degradation (such as climate change), which can lead to a downward spiral for poor households (Bremner, Lopez-Carr, Suter, & Davis, 2010). The Intergovernmental Panel on Climate Change (IPCC) has declared with “very high confidence” that climate change already contributes to the global burden of disease (Confalonieri et al., 2007). Mounting evidence suggests that this health burden will continue to extend to malnutrition as agriculture and food security becomes increasingly impacted by climatic events (Legg, 2008; McMichael, 2001; Otorstein, Stafford-Smith, Hiepe, Brklacich, & Rudder, 2010; Patz, Campbell-Lendrum, Holloway, & Foley, 2005; WHO, 2002). The 2004 Comparative Risk Assessment (CRA), part of the larger Global Burden of Disease Project, estimated that in the year 2000 17,000 deaths and 616,000 disability-adjusted life years could be attributed to malnutrition caused by climate change in Africa (McMichael et al., 2004). More than 200 million people remain malnourished in sub-Saharan Africa countries and this number could grow by 12 million as temperatures rise and crop yields fall (McMichael, Friel, Nyong, & Corvalan, 2008).

Because of their physical, physiological, and cognitive immaturity, children are particularly vulnerable to the health effects of environmental hazards, including those that are climate related.
At present, trend estimates are typically presented without accounting for the spatial accuracy of the estimation procedures, producing unreliable results. Our method attempts to rectify this inadequacy by using an approach supported by the US Agency for International Development's (USAID) Famine Early Warning System Network (FEWS NET). We therefore refer to a derived gridded trend product as FEWS NET Trend Analyses (FTA), and a long term mean field as FEWS NET Climatology (FCLIM). These observed trends are then used to project future climatic changes. While any climate projection is fraught with uncertainty, for short term (~20 year) projections, this approach may be the best available given the current state of climate science. The ability of climate models to recreate rainfall over the Sahel is extremely limited, with seasonal correlations remaining below 0.3 (Funk & Brown, 2009). Moreover, the climate change simulations differ substantially from model to model, providing no clear basis for prediction (Christensen et al., 2007).

**Adaptation and livelihoods**

Climate change is expected to have an overwhelmingly negative impact on health in sub-Saharan African countries (Ramin & McMichael, 2008). Speculating the future, the number of malnourished individuals by crops' contribution to average per capita calorie consumption in the Sahel, Lobell et al. (2008) confirmed that sorghum and millet were important for averting hunger in the region. Rainfed cereals including millet, maize, and sorghum are particularly important for Mali, constituting 85% of consumed cereal calories (Moseley, Carney, & Becker, 2010). Yet under some climate scenarios, cereal productivity in Africa is projected to decrease by about 10% by 2080, with the consequent risk of hunger in the region increasing by 20% (Rosenzweig, Iglesias, Yang, Epstein, & Chivian, 2001).

Malnutrition is already a significant problem for Mali, and projected increases of hunger risks could have catastrophic impacts on the population's health and economic productivity. The 2006 Demographic and Health Survey (DHS) found that 60% of children aged 6–59 months are moderately or severely anemic, while 50% of children 18–23 months are stunted and 25% are underweight (DHS, 2007). Overall, acute malnutrition affects 15% of children less than five years old as measured by World Health Organization standards. In the only extensive study on climate and health in Mali, Butt, McCarr, Angerer, Dyke, and Stuth (2005) found crop yield changes by 2050 will range from minus 17 to plus 6% at the national level, forage yields will fall by 5–36%, and livestock animal weights will be reduced by 14–16%. In terms of health, they project that climate change will increase the proportion of the country's population at risk of hunger from 34% in 2005 to 64–72% in the 2050s, unless adaptation measures are successfully implemented (Butt et al., 2005).

A key to reducing nutrition related deleterious effects of climate change lies in human adaptation. Food access and availability are the poor's primary interface between nutrition and climate change (Bloem, Semb, & Kraemer, 2010). Unstable agricultural systems drive food insecurity, and societies with insecure food supplies are more susceptible to shocks in agricultural productivity (Alderman, 2010; Darnton-Hill & Cogill, 2010; Haines & McMichael, 1997). These shocks degrade income and livelihoods, because many farmers in food insecure regions grow crops to consume and sell, decreasing yield impacts both household incomes as well as nutritional well being (Brown & Funk, 2008). The inability to protect the household against shocks has adverse consequences across generations through reduced investment in nutrition, health, and schooling (Alderman, 2010). A conceptual understanding of livelihoods, interfaced with climate-based variables to...
analyze the potential for exposure to particular hazards, permits the assessment of both risk and adaptation potential by livelihood zone (Verdin et al., 2005). Demographic processes, particularly migration, are alternative or additional adaptation strategies. A decline in crop yields across climate vulnerable regions of sub-Saharan Africa results in considerable numbers of environmentally-induced migrants (Adepoju, 2003; Swain, 1996). Little research exists on migration promoted by gradual environmental change (Findlay & Hoy, 2000; Mortreux & Barnett, 2009), nor on the exposures these migrants face in their new homes. Based on the importance of livelihoods for food security, governments and development organizations that are serious about alleviating future malnutrition need to strategically invest beyond areas of current vulnerability, to areas where climate change is projected to shift livelihood zones – in other words, a focus on the moving ‘front-line’ of vulnerability is necessary to mitigate future food insecurity as places transition from one livelihood to another. This requires a more spatially detailed approach to examining climate and malnutrition than has been previously utilized. Woodward and Scheraga (2003) propose using population epidemiology to develop a baseline relationship between climate and malnutrition at a finer scale than previously observed. Our approach of examining DHS clusters in Mali with livelihood and climate data provides fine spatial detail of the interplay between climate and malnutrition, representing a novel contribution to the climate and malnutrition literature. We then project our climate data to 2025 and incorporate demographic changes to further explore baseline trends and discuss potential compounding impacts of climate and demographics on future malnutrition. While long-term projections are vital for understanding possible overall changes in a region, the focus on the short term may uncover immediate areas of vulnerability with relatively high levels of probability, and therefore we purposefully focus on the next fifteen years.

Data

Climate data

Mali was selected as the study site due to its wide range of land cover and agricultural livelihoods. As a part of the Sahel, Mali’s climate and related nutritional situation can be generalized to countries throughout sub-Saharan Africa with similar climate and agricultural characteristics. The method used to generate the FCLIM long term mean rainfall fields incorporates climate, satellite, and physiographic data using a total of ten specific input variables listed in Table 1. Below is a brief description of each variable.

Two dense rainfall station datasets were provided for the Sahel by the Ethiopian NMA (~100 stations) and the Centre Régional Agrhymet (~700 stations). These stations were augmented by rainfall records from the GHCN archive and United Nations’ Food and Agriculture Organization’s FAOCLIM database. Overall, records of 1339 rainfall stations and 178 temperature stations were examined.

Four satellite fields were used to improve the spatial resolution and precision of the gridded temperature and precipitation data. The high correlations between our in situ data and these fields supported regression models to interpolate among sparse station observations guiding the rainfall and temperature FCLIM and the rainfall FTA modeling2. Land Surface Temperature (LST) maps at 1-km resolution were produced by the LST group at University California Santa Barbara using thermal infrared (TIR) data collected by the Moderate Resolution Imaging Spectroradiometer (MODIS). In addition to LST, thermal near infrared (TIR, 11 um) brightness temperatures from geostationary Meteosat weather satellites were also used in our regression modeling to guide estimates of rainfall and air temperature. Multi-satellite rainfall estimates (RFE2) from NOAA CPC (Xie & Arkin, 1997) were also used as potential guides to the FCLIM and FTA estimates for rainfall data.

Four physiographic indicators were used as potential predictor variables for precipitation and temperature: latitude, longitude, elevation and slope. Mean elevation and slope fields were derived from GTOP030 data on a 0.05° grid. The four satellite fields (LST, IR10, IR90, and RFE2) were re-sampled to the same grid.

Livelihood zones, health, and population

Livelihoods are a way of understanding food economies as represented by a typical rural household’s everyday circumstances and ability to obtain access to food (Boudreau, 1998). This study will utilize the FEWS NET livelihood zones, which attempt to define how households obtain and maintain access to critical resources (http://www.fews.net/pages/livelihoods-learning.aspx?en). FEWS NET delineates 13 livelihood zones for Mali. Similar zones were aggregated, resulting in 8 dummy coded regions.

Health data was drawn from the 2006 DHS IV for Mali (DHS, 2007). Increasingly, health researchers are taking advantage of global positioning systems (GPS), which during recent rounds of DHS surveys have provided location attributes of clustered households (Tanser & De Sueur, 2002). DHS data have been analyzed in hundreds of studies in the public health literature, including those examining human—environmental interactions (De Sherbinin et al., 2008; Sutherland, Carr, & Curtis, 2005). However the use of DHS cluster data to examine climate effects on humans has not been attempted to our knowledge.

The survey sample of 410 clusters was stratified, weighted, and representative at the national, regional (8 regions plus Bamako, Mali’s capital), and residential (urban/rural) levels. The analysis for this study revolved around the national and residential levels. 407 clusters were successfully surveyed including 14,238 children. Three commonly utilized measures of nutrition were selected from the DHS for analysis: the child’s level of anemia (the amount of iron in the blood), the child’s measure of stunting (height divided by age indicative of chronic malnutrition), and the child’s measure of underweight status (weight divided by age indicative of short-term malnutrition). The DHS measures anemia through hemoglobin levels adjusted by altitude, and assigns children to one of four categories: severely anemic, moderately anemic, mildly anemic, and not anemic. Stunting and underweight are assessed by number of standard deviations from the World Health Organization (WHO) child growth standards, with measures of −2 standard deviations from the guideline considered malnourished (WHO & UNICEF, 2009).

Population data is derived from the Gridded Population of the World data set (CIESIN, 2005). Population values for 2025 were projected based on the 1990 to 2010 population changes, and are only meant to be broadly indicative of demographic inertia.

Methods

The FEWS NET Climatology FCLIM method

The FCLIM uses satellite mean fields and environmental predictors (Table 1) to guide the spatial interpolation of station data for point estimates of long term means and decadal trends. This procedure has been used to guide trend analyses of Kenyan and Ethiopian rainfall (Funk et al., 2008; Funk & Verdin, 2010). The

\footnote{The temperature gauge density was not sufficient to support the use of satellite & topographic data in the derivation of the FTA.}
The FCLIM approach involves exploratory analysis and selection of a relatively small number (typically 4–6) of predictors, and the identification of a characteristic scale determined primarily by station density. Instead of focusing on the ability of datasets to represent temporal variations in weather, the FCLIM approach focuses on the ability of these variables to represent spatial gradients of temperature and precipitation. Core to the FCLIM model fitting are the local spatial correlations between station data and satellite and environmental predictors. At a local scale, satellite fields typically exhibit a strong spatial covariance with in situ observations, and this can be used to make accurate long term mean and trend maps. Satellite fields also typically exhibit local spatial correlations that are much stronger and more consistent than physiographic fields.

The FCLIM methodology was developed using a multivariate set of predictors including physiographic variables (latitude, longitude, elevation, and slope), and satellite observations of rainfall, infrared brightness temperatures, and LST. The first step used moving window regressions to create a ‘first cut’ estimate of the gridded field estimated at each target grid cell (i.e., each 0.1° cell across the maps). Each station value was then paired with the closest grid cell, and the regression model errors (residuals) were estimated. A model of the spatial structure of these errors was then used to produce another grid of values. Because the model of the spatial structure explicitly quantifies the spatial de-correlation with increasing distance, the interpolation produces spatial maps of standard error, contingent on the spatial distribution of the observation network. The moving window regression and residual fields were summed, creating an estimate that combines correlated exogenous predictors and the spatial covariance of the in situ observations. At each grid location, the final FCLIM estimate combines the local regression estimate with the interpolated residuals.

One advantage of the approach taken here, which calculates at-station changes and then interpolates the results, is that it supports the explicit estimation of interpolation errors. This allows us to address the following question: does the density of the observed stations truly support the mapped trends? This degree of certainty can be represented as ‘sigma fields’, calculated by dividing the interpolated trends by the interpolation standard errors; these provide a means of visualizing the statistical significance of the observed climate trends, vis-à-vis the spatial uncertainty field.

Trend surfaces

As in many semi-arid regions of the tropics, both long term mean fields and trend maps provide critical information for the Sahel where, burgeoning populations literally find themselves ‘up against a wall’ of the environmental limit capable of sustaining even low-yield rainfed agriculture. Across these semi-arid drylands, the high temperatures of arid regions largely arise due to little soil moisture. Lack of moisture limits evaporation and it’s associated cooling, hence the land surface transmits energy back to the atmosphere as a flux of heat. Meanwhile, the atmosphere’s ability to absorb moisture from the surface, or atmospheric demand, increases with increasing temperatures and is represented by potential evapotranspiration (PET). Relatively simple temperature-based PET estimates are proven to be robust relative indicators of atmospheric moisture demand (Mavromatis, 2007; Vicente-Serrano, Beguería, & López- Moreno, 2010). This study uses Thornthwaite’s original (1948) formulation to estimate the JJAS total PET in millimeters, for each 0.1° FCLIM pixel, using that pixels’ average air temperature resulting in a simple ‘water balance’ index (which we label PPET) where positive values represent wet areas where soils remain moist for most of the rainy season, and negative values are regions where atmospheric water demand exceeds the rainfall supply.

\[ PPET = \text{Rainfall} - PET \quad (1) \]

The temperature and precipitation trends derived from the FCLIM process are combined to create PPET for the study as an input variable for the malnutrition modeling by assigning a PPET value to each DHS cluster based on latitude, longitude coordinates. Because the PPET maps for Mali express a strong southwest-to-northeast gradient, this study examines 1990–2009 and 2010–39 southwest-to-northeast transects of Mali rainfall, air temperature, PET and population. These transects extend from −8°E, 12.9°N and end at −0.9°E, 15.7°N.

**Modeling malnutrition**

The goal of modeling malnutrition for Mali was to assess how it is influenced by livelihoods and climate, and in this sense we focus not on individual outcomes, but rather on cluster outcomes. We assume that malnutrition as influenced by climate and livelihood zones will be similar for individuals living close together (for example a village), but differences may emerge at a larger scale, in this case between clusters. For this reason we chose to aggregate individual child data to the cluster level, and run a simpler regression rather than a multi-level model. The latter would focus on differences of individuals and households within clusters rather than between the clusters themselves, where climate and livelihood effects are more saliently observed. Therefore conclusions about climatic and livelihood impacts on health will be drawn at the cluster level, and will provide a novel spatial richness.
We examined relationships between PPET, livelihood zones, and three measures of childhood malnutrition — anemia, underweight, and stunting. The measures were calculated as mean cluster values (Table 2), and treated as continuous variables in the regression models. Individual or household predictor variables considered important for malnutrition were selected from the DHS and aggregated to the cluster level including: number of durable goods, age of household head, years of mother’s education, children ever born to mother, wealth index of household, the use of an unprotected well by the household, and the child’s age in months. High Pearson’s correlation values (above 0.56) resulted in the removal from the model of durable goods and education of the mother. All remaining variables were utilized as controls in the multivariate model (Table 2).

We used Predictive Analytics Software (PASW) Statistics 18 for multivariate linear regression analysis. Two regression sets were run, the first on all clusters representing the national level, and the second on clusters classified by the DHS as rural, representing the residential level. Within each set, an iteration of three regressions was performed for each malnutrition measure as the dependent variable. Iteration 1 focused on climatic effects on malnutrition. Iteration 2 focused on the influence of livelihood zones. Finally, to better understand the effects of climate and livelihood zones, iteration 3 was run with both climate and significant livelihood zones.

Results

Observed warming trends

Averages of station data for selected countries are shown in Fig. 1. The time-series were smoothed with seven-year running means. The Sudan-Niger-Mali arc has experienced a 1960–2009 increase of more than 1.0 °C, while Kenya-Ethiopia has experienced an increase of about 0.7 °C. The magnitude of the temperature increases is equal to or greater than the inter-annual standard deviations (0.5 °C for Kenya-Ethiopia, 0.65 °C for Sudan-Niger-Mali). This warming can disrupt the seasonal cycle of crops, draw additional water from soil and plants, and reduce the amount of grain produced. By the year 2025, a temperature trend of 0.2 °C per decade would be associated with a warming of 1 °C since 1975.

Trend analysis with sigma fields

During JJAS, the inter-tropical front establishes itself north of the equator, and the Sahel receives the bulk of its rains. A strong north-south temperature gradient appears during the JJAS period, with the southern edges of the Sahelian countries receiving the most rainfall and coolest air temperatures. Fig. 2 shows the FEWS NET trend analysis maps for JJAS rainfall and air temperatures. Pockets of rainfall reduction appear near the border of Senegal and Mali, as well as southern Chad and Sudan. This drying is likely linked to desiccation in southwestern Ethiopia. The JJAS temperature shows values ranging from near zero to more than 0.4 °C per decade. Warming is generally greater in Senegal-Mali and southern Sudan-Ethiopia than in Niger and northern Sudan and Ethiopia. The warming patterns tend to mirror the inverse of the rainfall trends. In some of the areas, the magnitude of the decadal temperature trends (up to 0.4 °C per decade) approaches the inter-annual air temperature standard deviation, and thus indicates large climate changes.

When evaluating climate trends, two primary factors should be considered: 1) how large are the observed trends, and 2) how large are the estimated trends vis-à-vis the underlying uncertainty of the interpolated fields. The latter factor is rarely considered, and can often be obfuscated by the analysis of interpolated monthly or seasonal data. One simple way to evaluate these two components is to divide the interpolated trend fields by the standard error in the interpolation. The resulting unitless ‘sigma’ images retain the sign of the underlying trend fields, but are now expressed in units of

![Fig. 1. Time-series (smoothed with a seven-year running mean) of air temperature anomalies for three countries in the Sahel (Sudan, Niger, Mali) and two countries in the Greater Horn of Africa (Kenya and Ethiopia).](image)
standard errors (Fig. 3). Values of 1, 2, and 3 correspond to the 85%, 98% and 99.9% confidence levels respectively. Most regions covered in this analysis had sigma values with absolute values of greater than 2; thus the signal-to-noise ratio for the trend analysis is high, and our confidence in the spatial accuracy of the results high. This is surprising considering that the associated station densities were on the order of ~1 rainfall station every 5000 km², and 1 temperature observing site every 40,000 km². The appropriate use of satellite fields helped achieve this result, reducing the geo-spatial random error and improving the signal-to-noise ratios. The sigma fields shown in Fig. 3 suggest that the resulting trend analyses can be accepted with a high degree of confidence, either because of the high density of observations and reasonable levels of predictability in the rainfall trends, or that the trend signal is coherent (everywhere positive) and the spatial covariance pattern of the warming trends is relatively simple.

**PPET and livelihoods**

We can visualize climate and climate change across Mali by examining southwest-to-northeast PPET (the combined temperature and precipitation index) transects across the country (Fig. 4). These transects, created by rotating the coordinate system by 45° and averaging, show the spatial transition from the wet-cool southwest to hot-dry northeast; a climate transition that broadly corresponds to a spectrum of livelihoods that range from agricultural, agro-pastoral and pastoral modalities (Table 3). The transition across the country is dramatic, with main season rainfall varying from >700 mm to less than 300 mm, across a distance of approximately 250 km, marking one of the worlds steepest rainfall gradient. Air temperature variations are similarly marked, transitioning from 27 °C to ~31 °C. The ~100 PPET lines for the 1990–2009 and 2010–2039 periods are marked, designating
(imprecisely) a transition point between agricultural and pastoral livelihoods. Note that this –100 line shifts southwestward, suggesting that the area of the country suitable for farming is diminishing with time.

Examining the observed 1990–2009 transects and the 2010–2025 projected transects, we observe a pattern of decreasing rainfall in the west and increasing rainfall in the east. This dichotomous pattern, with the inflection point centered just north of the –100 PPET lines (Fig. 4) contrasts with the anticipated pattern warming, which remains broadly uniform across the country.

The 8 livelihood zone groupings are displayed in Fig. 5, and mean health values for livelihoods of particular interest are in Table 3. The pastoral livelihood is characterized by having rainfall less than 200 mm, being sparsely populated, and relying on livestock and limited agriculture. People are particularly susceptible to threats to their herds, with limited activities to serve as secondary response strategies. The rice livelihood is dependent on rice production for food, but also includes livestock rearing, as well as some farming. For all of these livelihoods, there is a reliance on water from the Niger River, and its inland delta for water. Coping mechanisms typically involve additional sales of livestock to increase income.

The plateau, millet, and rainfed millet livelihoods highlight the transitional nature of this region from pastoral semi-arid to agricultural livelihoods, as well as from sparse to moderate population density. The PPET = –100 contour runs directly between the millet and rainfed millet livelihoods (Fig. 5), highlighting the importance of climate in shaping these livelihoods. This contour is particularly important as a driver of the transition from rainfed crops to semi-arid subsistence, and carves a front-line of potential vulnerability of climate in shaping these livelihoods. This contour is particularly important as a driver of the transition from rainfed crops to semi-arid subsistence, and carves a front-line of potential vulnerability of climate in shaping these livelihoods.

Malnutrition modeling

Results for the climate models are reported in Table 4. The PPET < –100 zone was significant for all health measures when including all clusters, and significant for stunting when including only rural clusters. For all clusters, the standardized β coefficients for stunting and underweight were –0.165 and –0.159 respectively, both highly significant. Therefore, a cluster’s location within the PPET < –100 zone significantly predicts malnutrition severity for both stunting and underweight measures, likely due to the climate-driven livelihoods in these areas that fail to support cereal crops. The standardized β coefficient for anemia was –0.149 at α = .01, indicating that a cluster’s location within the PPET < –100 zone significantly predicts lower cluster anemia measures. This is likely due to the practice of livestock rearing in these areas, and accompanying meat and thus iron consumption.

When excluding urban clusters from the analysis, the PPET < –100 zone remained significant only for the stunting measure with a β value of –0.138 at α = .05. Comparison of adjusted R² values between all cluster and rural only cluster models indicate that more variability is explained when including all clusters in the analysis. The overall stunting and underweight results are consistent with Legg’s (2008) findings across sub-Saharan Africa, where more arid regions were correlated with worse nutritional measures, and less densely populated areas (rural) did not show higher prevalence of malnourishment than high density areas (urban). Legg’s study did not include anemia however, which this study suggests is diminished when clusters are located in arid climates, likely due to livelihoods that rely largely on meat rather than grain consumption.

Multiple models with different combinations of livelihoods were run, and resulted in three significant livelihood zones: pastoral, rice, and plateau (Table 5). The pastoral livelihood was

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Table 3
Livelihood zones, arid climate zone, and health variable means.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Description</th>
<th># Clusters</th>
<th>Anemia β</th>
<th>Stunting β</th>
<th>Underweight β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arid Climate</td>
<td>Clusters with PPET values less than –100</td>
<td>144</td>
<td>2.287</td>
<td>–1.576</td>
<td>–1.335</td>
</tr>
<tr>
<td>Pastoral</td>
<td>Nomadism, trans-Saharan trade, transhumant pastoralism</td>
<td>38</td>
<td>1.903</td>
<td>–1.454</td>
<td>–1.229</td>
</tr>
<tr>
<td>Rice</td>
<td>Fluvial rice, Niger Delta rice, irrigated rice, livestock rearing</td>
<td>50</td>
<td>2.272</td>
<td>–1.612</td>
<td>–1.453</td>
</tr>
<tr>
<td>Plateau</td>
<td>Millet, shallots, wild foods, tourism</td>
<td>27</td>
<td>2.469</td>
<td>–1.715</td>
<td>–1.277</td>
</tr>
<tr>
<td>Millet</td>
<td>Millet and transhumant livestock rearing</td>
<td>33</td>
<td>2.469</td>
<td>–1.492</td>
<td>–1.320</td>
</tr>
<tr>
<td>Rainfed millet</td>
<td>West and central millet/sorghum</td>
<td>68</td>
<td>2.570</td>
<td>–1.402</td>
<td>–1.255</td>
</tr>
<tr>
<td>South crops</td>
<td>Sorghum, millet, cotton, maize, fruit</td>
<td>120</td>
<td>2.535</td>
<td>–1.492</td>
<td>–1.214</td>
</tr>
</tbody>
</table>

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Fig. 4. Southwest to northeast transects of average JJAS precipitation (left) and air temperature (right). Transect begins at –8°E, 12.9°N and ends at –0.9°E, 15.7°N.
highly significant for both the all cluster and rural only cluster anemia models, with standardized $\beta$ coefficients at $-0.276$ and $-0.272$ respectively. However, more variability was explained by the all cluster model as indicated by improved $R^2$ values. The rice livelihood zone was significant at $\alpha = .05$ with $\beta = -0.098$, indicating a slight positive impact on anemia. This may be due to livestock rearing activities within the rice livelihood zones. The coefficient is notably smaller and less significant than the pastoral

**Table 4**
Multivariate regression results with PPET < $-100$ zone variable for all cluster ($n = 407$) and rural cluster ($n = 358$) models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Adjusted R²</th>
<th>Beta</th>
<th>Std Error</th>
<th>Beta</th>
<th>Std Error</th>
<th>Beta</th>
<th>Std Error</th>
<th>Beta</th>
<th>Std Error</th>
<th>Beta</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Anemia All Clusters</td>
<td>0.139</td>
<td></td>
<td>Anemia Rural Clusters</td>
<td>0.120</td>
<td></td>
<td>Stunting All Clusters</td>
<td>0.322</td>
<td></td>
<td>Stunting Rural Clusters</td>
<td>0.148</td>
</tr>
<tr>
<td>Age of Child</td>
<td>-0.102* 0.009</td>
<td>-0.148** 0.011</td>
<td>-0.196*** 0.011</td>
<td>-0.290*** 0.014</td>
<td>-0.097* 0.008</td>
<td>-0.191** 0.010</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CEB</td>
<td>0.106 0.034</td>
<td>-0.127 0.041</td>
<td>-0.190*** 0.042</td>
<td>-0.133* 0.053</td>
<td>-0.082 0.031</td>
<td>-0.002 0.039</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age of Head</td>
<td>-0.025 0.006</td>
<td>-0.124* 0.007</td>
<td>0.231*** 0.008</td>
<td>0.205*** 0.010</td>
<td>0.120** 0.006</td>
<td>0.117 0.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unprotected Well</td>
<td>-0.008 0.001</td>
<td>-0.015 0.001</td>
<td>0.096* 0.001</td>
<td>0.072 0.001</td>
<td>0.075 0.001</td>
<td>0.025 0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wealth</td>
<td>-0.277*** 0.029</td>
<td>-0.211*** 0.048</td>
<td>0.365*** 0.036</td>
<td>0.094 0.062</td>
<td>0.378*** 0.026</td>
<td>0.056 0.046</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPET &lt; -100 zone</td>
<td>-0.149** 0.052</td>
<td>-0.111 0.064</td>
<td>-0.165*** 0.063</td>
<td>-0.138* 0.083</td>
<td>-0.159*** 0.047</td>
<td>-0.126 0.061</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* $p < .05$, ** $p < .01$, *** $p < .001$. 

Fig. 5. Mali livelihood zones with DHS cluster locations and PPET gradients (above). The $-100$ PPET contour lines in year 2000 and 2025 situated between the millet and rainfed millet livelihoods (below).
livelihood, and becomes insignificant in the rural only model. The pastoral livelihood is located in the most northern area of Mali, and the significance of this livelihood for reduced anemia measures is consistent with the climate model results. However, other livelihoods north of the PPET < −100 contour are not significant for anemia. These livelihoods have little livestock rearing, emphasizing the importance of livestock rearing decreasing anemia prevalence.

The rice livelihood zone is significant at α = .001 for the all cluster stunting and underweight models, as well as the rural underweight model. It is also significant at α = .01 for the rural stunting model. In these models, a cluster’s location within a rice livelihood zone has negative consequences for health, with the largest standardized β coefficients of all models emerging in the livelihood and climate analyses, accompanied by higher R² values when compared to stunting and underweight all and rural climate models. Two large areas within this zone are arid regions that rely heavily on livestock as a predominant livelihood, but because of their access to pooling water on the Niger River and within the Niger Delta, they are also able to cultivate rice. In all regards other than rice cultivation, these areas remain similar to the pastoral livelihood zones, explaining their negative impacts on stunting and underweight.

There is less difference observed between all cluster and rural only cluster models within the livelihood models as compared to the climate models. One exception to this is the plateau livelihood, which is significant at α = .05 for stunting in both the all and rural only cluster models, however the standardized β is equal to −0.135 for rural clusters as opposed to −0.099 for all clusters. This suggests that rural plateau livelihood clusters experience a larger negative impact on stunting than rural and urban areas combined. All adjusted R² values were higher for the livelihood models than for the climate models, indicating that livelihoods explain more variability of the malnutrition measures than climate. However, both sets of models highlight the complex pathways through which malnutrition is influenced by climate.

To test if the climatic health effects found in the first set of models was entirely explained by livelihoods, the model (including all clusters) was re-run to include both PPET and livelihood results. Climate becomes insignificant for anemia and underweight when considering livelihoods. However, climate remains significant for stunting, and the adjusted R² increases when compared to the other stunting models. This finding is particularly important when interpreting malnutrition measures. Anemia and underweight are short-term measures of malnutrition that may be responses to climatic seasonal flux and shocks. Based on the insufficiency of PPET when accounting for livelihoods, these short-term shocks are becoming absorbed by livelihood vulnerabilities and adaptation capabilities. Nevertheless, livelihoods are a product of climate and environmental conditions, and significant changes in climate may lower a livelihood’s adaptive capacity to seasonal effects that cause underweight and anemia. Stunting is a comparatively chronic measure of malnutrition. Our results indicate that climate in Mali influences stunting beyond the significant effect of livelihoods, underscoring a component of malnutrition that may not be easily mitigated at the local livelihood level.

### Discussion

The vulnerability front-line is moving

The results of the study demonstrate that the arid and semi-arid climate of Mali as defined by PPET < −100 negatively influences underweight and stunting, and positively influences anemia; in the case of anemia and underweight this effect can be explained by livelihoods shaped by climate. However, in the case of stunting, arid climate trends influence malnutrition even when controlling for livelihood effects, suggesting a climatic effect on malnutrition beyond the adaptability and coping mechanisms of livelihoods. Furthermore, the PPET < −100 contour is demonstrably shifting southward, enveloping more land, and consequently, as it moves towards the more densely populated southern region of the country, more Malians.

Our results suggest that quantitative assessments of interpolation errors can be combined with at-station climate trends to produce rigorous assessments of the uncertainty associated with the interpolated surfaces. For both temperature and rainfall, the interpolated changes were significant, suggesting that drying and warming have shifted semi-arid climate zones southward, and that this claim can be statistically demonstrated with the distribution of station networks. This front-line, as demonstrated by the FCLIM method results, may be extending east and westward throughout the Sahel, and the land located between the 2000 and 2025 contours is extensive at 18,285 km². Children living within the

### Table 5

<table>
<thead>
<tr>
<th>Variable</th>
<th>Anemia All Clusters</th>
<th>Stunting All Clusters</th>
<th>Underweight All Clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adjusted R²</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.205</td>
<td>0.326</td>
<td>0.220</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>Std Error</td>
<td>Beta</td>
</tr>
<tr>
<td>Age of Child</td>
<td>−0.078</td>
<td>0.009</td>
<td>−0.201***</td>
</tr>
<tr>
<td>CEB</td>
<td>0.066</td>
<td>0.033</td>
<td>0.040</td>
</tr>
<tr>
<td>Age of Head</td>
<td>−0.027</td>
<td>0.006</td>
<td>−0.120*</td>
</tr>
<tr>
<td>Unprotected Well</td>
<td>−0.068</td>
<td>0.001</td>
<td>0.081</td>
</tr>
<tr>
<td>Wealth</td>
<td>−0.269***</td>
<td>0.028</td>
<td>0.048</td>
</tr>
<tr>
<td>Pastoral</td>
<td>−0.276***</td>
<td>0.084</td>
<td>−0.164***</td>
</tr>
<tr>
<td>Rice</td>
<td>−0.098</td>
<td>0.073</td>
<td>−0.099*</td>
</tr>
<tr>
<td>Plateau</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* − p < .05, ** − p < .01, *** − p < .001.

### Table 6

<table>
<thead>
<tr>
<th>Variable</th>
<th>Anemia all clusters</th>
<th>Stunting all clusters</th>
<th>Underweight all clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj. R²</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.189</td>
<td>0.332</td>
<td>0.224</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>Std Error</td>
<td>Beta</td>
</tr>
<tr>
<td>PPET &lt; −100</td>
<td>0.011</td>
<td>0.065</td>
<td>−0.099*</td>
</tr>
<tr>
<td>Pastoral</td>
<td>−0.282***</td>
<td>0.098</td>
<td>−0.121**</td>
</tr>
<tr>
<td>Rice</td>
<td>−0.104</td>
<td>0.086</td>
<td>−0.121**</td>
</tr>
<tr>
<td>Plateau</td>
<td>−0.074</td>
<td>0.124</td>
<td></td>
</tr>
</tbody>
</table>

* − p < .05, ** − p < .01, *** − p < .001.
2000 and 2025 PPET -100 contours will become more vulnerable to underweight and stunting as climatic effects on livelihoods impact their nutrition.

Dynamic demographics and shifting climate and livelihood zones increase vulnerability

While our findings indicate that climatic factors in addition to livelihoods are influencing stunting, livelihoods are important factors for each of the malnutrition measures. The shifting of the PPET < −100 front-line directly translates to a change from rainfed millet and sorghum production to more vulnerable non-rainfed livelihoods. As only 3% of Mali’s arable land is irrigated, the shifting of PPET into the southern agricultural areas of the country would have significant impact not only on those living within this region, but also on Mali’s ability to sustain its food needs and export cash crops (Butt, McCarl, & Kergna, 2006). Furthermore, a household’s resilience is directly related to their current food and income source (Moseley & Logan, 2001). For those currently living with pastoral livelihoods, shifting PPET will likely have less of an influence on their way of life than those with rainfed livelihoods transitioning to non-rainfed crops or even to pastoral livelihoods. Therefore understanding future malnutrition due to the shifting vulnerability front-line may emerge as a policy priority.

Incorporating demographic trends into this scenario from the Gridded Population of the World estimates pushes more people into the vulnerable arid zone. Transects are used to visualize the climatic distribution of Mali’s population (Fig. 6). The population tends to be much denser towards the climatically favorable southwest, and this is also where we anticipate to see the most demographic change by 2025, with the population increasing by ~50%–66 million (Table 7). At the same time, population across the agriculturally vital southwest will decrease, and air temperatures will rise, increasing PET (Fig. 4), reducing PPET values and shifting associated contours (Fig. 5). If climate remains constant (the same as the 1990–2009 mean), population growth estimates suggest that an additional ~4.4 million people will live northeast of the −100 PPET contour by 2025. If both expanding population and the southwestward shift of the −100 contour are taken into account, the increase in exposed population increases to 6 million, of which three quarters of a million to one million are projected to be children. Holding constant observed morbidity levels, by 2025 approximately one quarter of a million children will suffer stunting and nearly two hundred thousand will be malnourished in this expanding arid zone (Fig. 7). Our regression results suggest that we can isolate climate change as the cause of a statistically significant number of these children suffering from stunting.

Conclusion

We developed in this article a novel approach to examine and project climate and health trends in the African Sahel through the spatial coupling of FEWS NET climate data and DHS health data in Mali. Results suggest that cluster measures of underweight and anemia appear influenced by livelihoods and mitigation efforts should therefore focus on livelihood adaptation strategies. However, chronic outcomes of malnutrition, are influenced by climate in addition to livelihood, presenting a more complicated picture for mitigation, and underscoring the need for future research to identify aspects of this climate-stunting pathway. The moving vulnerability front-line is projected to subject 6 million additional Malians, three-quarters to one million of them being children, to malnutrition from climate, livelihood, and demographic changes in the near future.

There are two primary limitations for the study and areas for future work: variables included in modeling and the type of statistical model utilized. FEWS NET Livelihoods take into account numerous factors that dictate food economics including agroecology (what people can grow or produce and where), assets, expenditures, income, and coping capacities to various vulnerabilities. After accounting for major factors such as average village child age and mothers’ education, livelihoods, or how a village

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Table 7
Mali population totals for 2010 and 2025.

<table>
<thead>
<tr>
<th>Total [millions]</th>
<th>PPET -100 position based on 1990–2009 climatology</th>
<th>PPET -100 position based on 2010–2039 climatology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PPET &gt; −100</td>
<td>PPET ≤ −100</td>
</tr>
<tr>
<td>2010 44.8</td>
<td>32.4</td>
<td>12.4</td>
</tr>
<tr>
<td>2025 65.8</td>
<td>49</td>
<td>16.8</td>
</tr>
</tbody>
</table>

3 Based on numbers for low, medium, and high variant 2025 population projections by the United Nations for Mali.
produces, sells, and acquires food, should account for much of the variability of measured malnutrition. However, as per the FEWS NET Household Ecology Approach (HEA), the risk of food insecurity and malnutrition is also based on hazards such as climate, production, policy, and market fluctuations. Our model only takes into account the hazard of climate. Previous studies have shown policy, production, and market fluctuation to impact malnutrition in Mali (Butt et al., 2005), yet it is important to remember that climate is a large driver of production and market fluctuation, and that livelihoods also can be proxies for resilience. While local variations in soils, the locations of rivers and streams, and the impact of transportation and market networks all influence livelihoods, Mali’s strong north-south climatic gradient also plays a critical role in determining which livelihoods remain viable. While climate shapes livelihoods, our study contributes a novel finding in demonstrating that for the measure of stunting, dry climate negatively impacts chronic malnutrition when also considering livelihoods; in other words climate is impacting malnutrition beyond the livelihoods that climate largely dictates. An important next step would be to find a way to include local and national food policies in the model and to understand the interplay of climate, policy, and livelihoods on malnutrition. Another step would be conducting a multi-level model for clusters to better understand local level drivers of malnutrition while also taking into account climate and livelihoods.

This research responds to a call over recent years for meso-scale research of coupled natural and human systems to link to local and global-scale analyses, where the vast majority of human-environment work is done (Marston et al., 2005; Turner et al., 1990). The adaptation literature is largely focused on small village-level case studies, and implies climate change as a cause when it remains unproven or insufficiently referenced as the true source of adaptation (Bremner et al., 2010; Butt et al., 2005). Further, institutional and household adaptation is highlighted while place adaptation remains insufficiently recognized as a critical human and physical geographical context for describing resilience (Alderman, 2010; Confalonieri et al., 2007). Perhaps most importantly, adaptation studies have yet to fully consider how climate change will transform geographies, and the places of adaptation. In other words, case studies of adaptation may take place in villages or regions that twenty years hence will hold relatively little or relatively great promise for future adaptation (Lobell et al., 2008). Future research may consider the concept of shifting places of vulnerability and climate front-lines.

Policy makers may interpret our results for Mali to concentrate on devising adaptation efforts in our designated current and projected future front-line zone. Butt et al. (2006) highlight adaptation measures that could significantly decrease the economic and health impacts of climate change for Mali. We propose that these strategies be intensely applied in our designated current and projected front-line zone to assist the current and near future transition from rainfed to non-rainfed crops. By translating ‘global climate change’ into estimates of local climate velocity, and intersecting climate and health, specific at-risk populations may be identified. Our methodology may be extended to other nations facing similar potential human health consequences of changing climate, particularly neighboring nations where climate and health data are available. Future research might continue to push the spatial boundaries of analysis to finer spatial and temporal scales, while still achieving geographic spread. Investments in such research efforts would undoubtedly pay high dividends in advancing the identification of climate vulnerability hot spots. Only by advancing such research can the scientific community provide increasingly informed policy prescriptions towards spatially targeted and temporally preventative adaptation measures.

**Acknowledgments**

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**References**


