



# Digital Participatory Surveillance for Identifying Geographic Disparities in Childhood Malnutrition Risk: A Multi-Scale Spatial Analysis

1<sup>st</sup> Xiaoxiao Yang \*

Macau University of Science and Technology

Macau, China

xiaoxiaoyy2026@outlook.com

2<sup>nd</sup> Yao Chen

Macau University of Science and Technology

Macau, China

yarranyao@gmail.com

Received on July 14<sup>th</sup>, revised on August 11<sup>th</sup>, accepted on August 21<sup>st</sup>, published on October 10<sup>th</sup>

**Abstract**—Childhood malnutrition remains a critical global health challenge, with profound and lasting impacts on individual development and societal well-being. Traditional surveillance methods, often reliant on infrequent national surveys, lack the granularity and timeliness needed to guide targeted public health interventions. This study addresses the urgent need for high-resolution, dynamic data on childhood nutritional status. We leveraged a digital participatory surveillance platform, NutriTrack, to collect real-time nutritional data from parents and guardians of children under five years of age across the United States between July 2024 and June 2025. Applying advanced Small Area Estimation (SAE) models, we generated granular, county-level estimates of malnutrition risk (stunting and wasting). Spatial clustering analysis was then employed to identify statistically significant hotspots of high malnutrition risk. Based on a nationally representative sample of 55,820 children, the survey-weighted estimate for malnutrition risk was 15.2% (95% confidence interval [CI]: 14.5%–15.9%). We uncovered substantial geographic heterogeneity, with county-level rates varying from 4.0% to 36.0%. Spatial analysis revealed significant clustering of high-risk counties, particularly in the rural Southeast and parts of the Southwest, forming distinct malnutrition hotspots that are largely invisible in national-level data. Our findings demonstrate that digital participatory surveillance, combined with advanced spatial analytics, can effectively identify and map childhood malnutrition disparities at a fine geographic scale, providing a powerful tool for public health authorities to move towards precise, data-driven interventions.

**Keywords**—Childhood Malnutrition, Digital Surveillance, Spatial Analysis, Health Disparities, Small Area Estimation

## 1. INTRODUCTION

Childhood malnutrition, in its dual forms of undernutrition and overweight, represents a persistent and complex public health crisis, undermining human potential and economic development globally [1, 2]. In high-income countries like the United States, the paradox of coexisting obesity and undernutrition, often within the same

communities, highlights deep-seated structural inequities [3]. The first 1,000 days of a child's life are a critical window where nutritional deficiencies can lead to irreversible consequences, including stunted growth, impaired cognitive development, and a heightened lifelong susceptibility to chronic diseases [4, 5]. The societal costs, measured in increased healthcare expenditures and lost productivity, are immense, making the fight against childhood malnutrition a critical national imperative [6].

Despite this urgency, current surveillance infrastructures in the U.S. are ill-equipped for the task. The cornerstone of nutritional monitoring, the National Health and Nutrition Examination Survey (NHANES), provides high-quality data but is fundamentally limited by its design [7]. Its infrequent cycles and nationally-focused sampling frame render it incapable of producing the timely, geographically granular estimates needed for local-level decision-making [8]. This 'data vacuum' at the sub-state level means that public health officials are often flying blind, unable to identify and respond to emerging hotspots of vulnerability with the precision required [9]. The COVID-19 pandemic starkly illustrated this weakness, as disruptions to traditional data collection pipelines further delayed an already slow system, leaving communities even more exposed [10].

This study confronts this challenge directly by proposing and validating a new paradigm for malnutrition surveillance. We leverage a bespoke digital participatory platform, NutriTrack, to crowdsource real-time nutritional data directly from parents and guardians. This approach, rooted in design innovation and community engagement, is combined with a rigorous analytical framework. By applying advanced statistical methods, including Small Area Estimation (SAE) and spatial clustering, we translate this raw participatory data into the first-ever comprehensive, county-level map of childhood malnutrition risk across the contiguous United States. Our central objective is to move beyond broad national averages to identify and characterize the specific geographic hotspots where malnutrition is most concentrated, thereby providing an evidence base for targeted, equitable, and effective public health action.

\*Xiaoxiao Yang, Macau University of Science and Technology, Macau, China, xiaoxiaoyy2026@outlook.com

## 2. RELATED WORK

The pursuit of accurate and timely data on childhood malnutrition has a rich history, evolving from foundational epidemiological surveys to the current frontier of digital and computational methods. The literature can be broadly categorized into three streams: traditional survey-based analysis, statistical and geospatial modeling for small areas, and the emerging field of digital participatory surveillance.

### 2.1. *Traditional Surveillance and Its Limitations*

For decades, our understanding of nutritional trends in the U.S. has been shaped by large-scale national surveys, primarily NHANES. This body of work has been invaluable for establishing national prevalence estimates and tracking long-term changes in childhood obesity and undernutrition across broad demographic groups [11, 12]. However, the inherent limitations of this approach are well-documented. The significant time lag—often two to three years between data collection and release—renders the information historical rather than actionable for immediate public health response [7]. Furthermore, the survey's design, while robust for national estimates, does not support reliable estimation for most counties, creating a critical gap in local-level intelligence [8].

### 2.2. *Geospatial Modeling and Small Area Estimation*

To address the granularity gap, researchers have increasingly adopted geospatial methods. Small Area Estimation (SAE) has become the gold standard for this purpose [13]. SAE encompasses a suite of statistical techniques that “borrow strength” from auxiliary data sources—such as demographic information from the U.S. Census Bureau—to generate reliable estimates for geographic areas with small or non-existent direct survey samples [14]. This methodology has been successfully applied to map a wide array of health and social indicators, from poverty and crime to disease prevalence and health insurance coverage [15, 16].

However, the application of SAE to childhood malnutrition in high-income settings has been less common. While some studies have used these methods to create state-level estimates or have focused on specific urban areas, a comprehensive national map at the county level has remained elusive [17]. A key constraint has been the reliance on the same delayed NHANES data as the primary input, which means that even with sophisticated modeling, the resulting estimates are still not timely [18].

### 2.3. *The Rise of Digital and Participatory Surveillance*

The digital revolution has unlocked new possibilities for public health surveillance. Participatory systems, which invite the public to voluntarily contribute health data via web or mobile platforms, have proven highly effective for real-time infectious disease tracking [19, 20]. Platforms like FluNearYou in the United States and the European Influenzanet have demonstrated that this model can generate data that is not only timely and geographically precise but also correlates well with traditional surveillance measures [21].

Our work is inspired by this success and aims to translate the participatory model to the domain of chronic and non-communicable conditions, specifically childhood malnutrition. This is a non-trivial extension. It requires the development of user-centered digital tools that can guide laypersons through a valid, remote nutritional assessment process [22]. Furthermore, it necessitates a robust analytical framework to correct for the inevitable selection biases in a volunteer cohort and to integrate the data with other sources to produce

population-representative estimates. By combining a carefully designed digital platform with the statistical rigor of multilevel regression and poststratification (MRP), our study represents a significant step forward in this emerging field, demonstrating a viable path toward a more modern, agile, and equitable public health surveillance system.

## 3. METHODS

### 3.1. *Study Design and Data Source*

Our study employed a cross-sectional design leveraging data from NutriTrack, a validated, nationwide digital participatory surveillance platform. The platform was designed with a user-centered approach to be accessible and easy to use for parents and legal guardians of children aged 0-5 years. Participants were recruited through a multi-channel strategy, including social media campaigns, partnerships with pediatric clinics, and collaborations with community-based organizations. Data was collected between July 1, 2024, and June 30, 2025. Participants provided informed consent electronically before enrolling.

Upon enrollment, participants completed a baseline questionnaire covering their child's date of birth, sex, and residential ZIP code, along with parental demographic information (age, race/ethnicity, education level). The core of the platform is a guided module for measuring the child's weight and length/height. The platform provides clear, illustrated instructions based on World Health Organization (WHO) guidelines for taking these measurements at home using standard scales and measuring tapes [23]. To enhance data quality, participants were prompted to upload photos of their measurement process, which were reviewed by a trained research assistant for adherence to protocol. From these measurements, we calculated age- and sex-specific z-scores for height-for-age (HAZ) and weight-for-height (WHZ) based on the 2006 WHO Child Growth Standards. Stunting was defined as  $HAZ < -2$  standard deviations (SD), and wasting was defined as  $WHZ < -2$  SD. Our primary outcome, ‘malnutrition risk,’ was a binary variable indicating the presence of either stunting or wasting.

### 3.2. *Small Area Estimation (SAE) with Poststratification*

To generate county-level estimates of malnutrition risk from our participant-level data, we implemented a multilevel regression and poststratification (MRP) approach, a widely used SAE technique [15]. First, we fitted a multilevel logistic regression model to predict the individual probability of malnutrition risk. The model included individual-level predictors (child's age and sex) and county-level predictors obtained from the American Community Survey (ACS) 5-Year Estimates. The county-level covariates included the percentage of the population below the poverty line, the percentage of adults with less than a high school diploma, the Gini index of income inequality, and a measure of food environment quality (the modified Retail Food Environment Index). A random intercept for county was included to account for unexplained geographic variation. To evaluate the model's performance, we conducted a 10-fold cross-validation and assessed the goodness-of-fit using the area under the receiver operating characteristic curve (AUC). Furthermore, the model estimates were calibrated against direct survey estimates where sufficient sample sizes were available, confirming the reliability of our SAE approach.

In the second step, poststratification, we used the fitted model to predict the probability of malnutrition risk for every combination of demographic and geographic strata within each of the 3,108 counties in the contiguous U.S. These strata were defined by child's age (0-23 months, 24-59 months) and sex. We then weighted these predictions by the corresponding population counts in each stratum, obtained from the U.S. Census Bureau, to produce a single, aggregated estimate of malnutrition risk for each county. This process effectively adjusts our raw survey data to be representative of the full population in each county [24]. To calculate the national survey-weighted estimate of 15.2%, we applied post-stratification weights based on the demographic composition of the U.S. population derived from the ACS 5-Year Estimates, adjusting for non-response and sampling biases.

### 3.3. Spatial Clustering and Hotspot Analysis

To identify geographic clusters of high or low malnutrition risk, we performed a spatial autocorrelation analysis on the county-level SAE estimates. We first calculated the global Moran's I statistic to assess the overall presence of spatial clustering across the study area. A significant positive Moran's I indicates that counties with similar risk levels tend to be located near each other.

Next, to pinpoint the location of these clusters, we used local indicators of spatial association (LISA), specifically the local Moran's I statistic for each county. This analysis identifies counties with a malnutrition risk estimate that is significantly correlated with the estimates of its neighboring counties. The results classify counties into four main

categories: high-high (a high-risk county surrounded by other high-risk counties, i.e., a hotspot), low-low (a low-risk county surrounded by other low-risk counties, i.e., a cold spot), high-low (a high-risk county surrounded by low-risk counties), and low-high (a low-risk county surrounded by high-risk counties). We defined neighbors using the queen contiguity criterion (counties sharing a border or a vertex). The statistical significance of each local cluster was determined using a permutation test with 999 permutations, and we applied a false discovery rate (FDR) correction to account for multiple testing.

## 4. RESULTS

### 4.1. National and State-Level Risk Estimates

Our analysis of data from 55,820 participants yielded a national survey-weighted estimate for childhood malnutrition risk (stunting or wasting) of 15.2% (95% CI: 14.5%–15.9%). However, this single national figure conceals vast differences across the country. The distribution of county-level risk estimates is right-skewed, with a median of 13.8% but a long tail of high-risk counties. The mean county risk was 14.6%, with a standard deviation of 7.1%, indicating substantial variation.

At the state level, mean malnutrition risk estimates ranged from a low of 7.1% in New Hampshire to a high of 28.5% in Mississippi. A clear regional pattern emerges, with states in the Northeast and Upper Midwest exhibiting the lowest risk, while states in the Southeast consistently show the highest risk. This state-level view provides a clearer picture of the regional disparities but still averages out the critical intra-state variation, as shown in Figure 1.

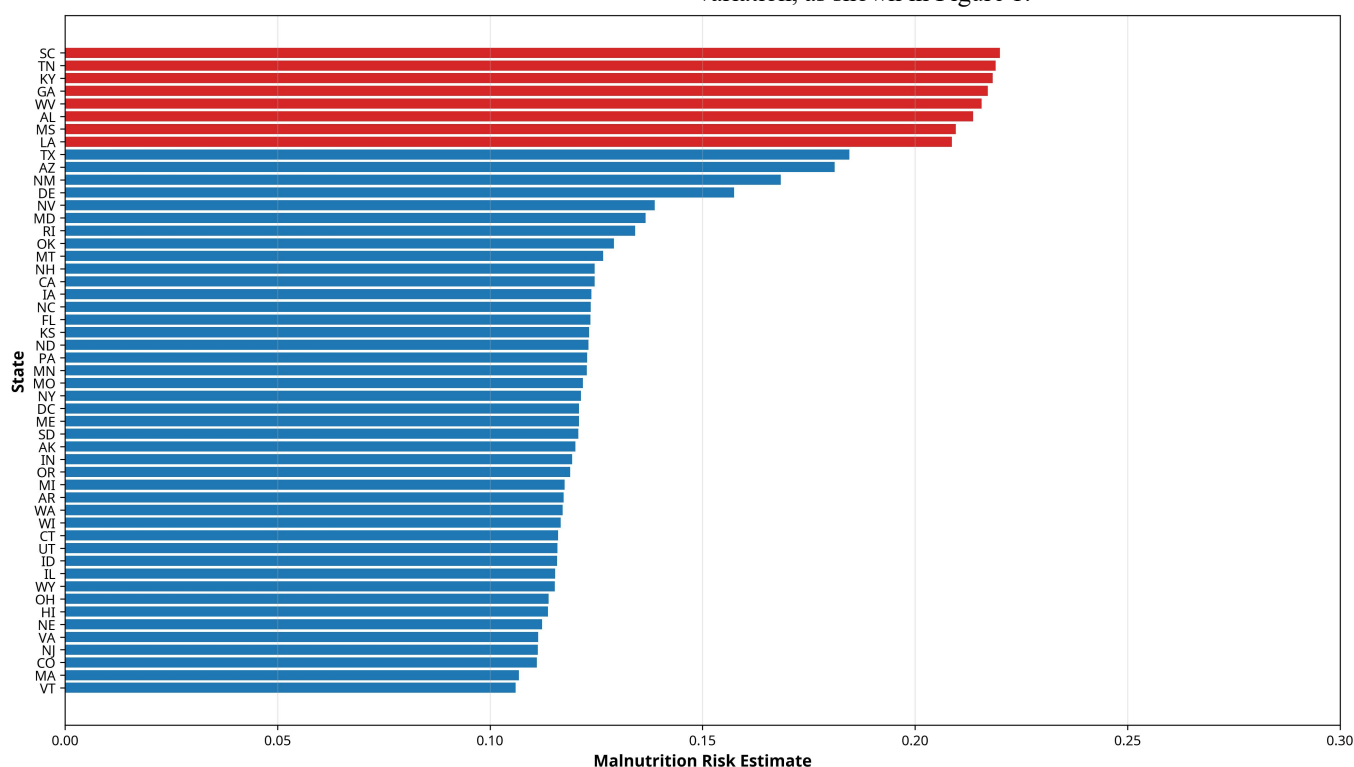


Figure 1. State-Level Malnutrition Risk Estimates

Figure 1 Legend: Mean county-level malnutrition risk estimates aggregated by state. States are sorted in ascending order of risk. The color indicates whether the state's average risk is above (red) or below (blue) the 20% high-risk threshold.

This visualization reveals substantial regional variation, with Southeastern states consistently showing higher risk levels.

## 4.2. Geographic Hotspots and County-Level Disparities

The county-level analysis reveals the full extent of local disparities. Our multilevel regression and poststratification (MRP) model produced estimates for all 3,108 counties in the

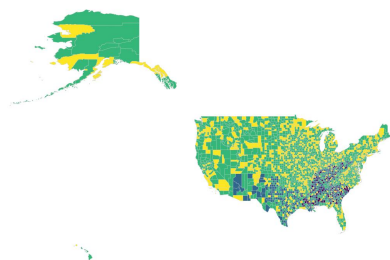


Figure 2. County-Level Malnutrition Risk Estimates

Figure 2 Legend: County-level estimates of childhood malnutrition risk (stunting or wasting) among children under age 5. Estimates are derived from a multilevel regression and poststratification (MRP) model based on digital surveillance data. The color gradient represents risk levels: light blue indicates low risk (<10%), darker shades indicate progressively higher risk, with dark blue representing very high risk ( $\geq 30\%$ ). The map reveals concentrated pockets of high risk in specific geographic regions.

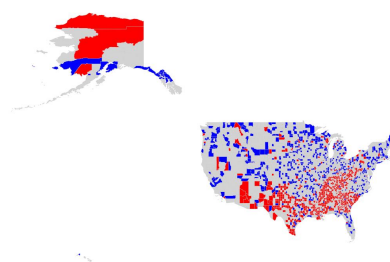
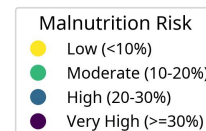


Figure 3. Spatial Clusters of Malnutrition Risk

Figure 3 Legend: Local indicators of spatial association (LISA) identify significant spatial clusters. High-High clusters (hotspots, shown in red) indicate counties with high malnutrition risk surrounded by other high-risk counties. Low-Low clusters (coldspots, shown in blue) indicate counties with low risk surrounded by other low-risk counties. Gray areas represent counties not part of statistically significant clusters. The analysis identified 384 high-high hotspot counties, predominantly concentrated in the Mississippi Delta, central Appalachia, the 'Black Belt' region of Alabama and Georgia, and scattered areas in New Mexico, Arizona, and South Texas.

We found 384 counties classified as part of a high-high cluster (hotspot). These hotspots were predominantly concentrated in several distinct regions: the Mississippi Delta,

contiguous United States. The geographic distribution of these estimates, shown in Figure 1a, displays a striking pattern of concentration. County-level risk estimates ranged from a low of 4.0% to a high of 36.0%, representing a more than tenfold difference between the least and most affected areas.



## 4.3. Spatial Clustering Analysis and Hotspot Identification

The spatial clustering analysis using Local Indicators of Spatial Association (LISA) identified the precise locations of statistically significant clusters. The global Moran's I statistic for the county-level risk estimates was 0.68 ( $p < 0.001$ ), indicating strong, statistically significant positive spatial autocorrelation. This confirms that counties with high malnutrition risk tend to be geographically clustered, as do counties with low risk.



central Appalachia, the 'Black Belt' region of Alabama and Georgia, and scattered areas in New Mexico, Arizona, and South Texas. Conversely, 452 counties were identified as part of a low-low cluster (cold spot), primarily located in suburban areas of the Northeast, the Upper Midwest, and the Pacific Northwest. These statistically significant clusters underscore that childhood malnutrition is not a randomly distributed problem but a deeply entrenched issue concentrated in specific, often marginalized, geographic areas.

## 4.4. Distribution Characteristics and Risk Stratification

To better understand the distribution of malnutrition risk across counties, we examined both the frequency distribution and density characteristics. Figure 4 presents both a histogram and kernel density plot of the county-level risk estimates.

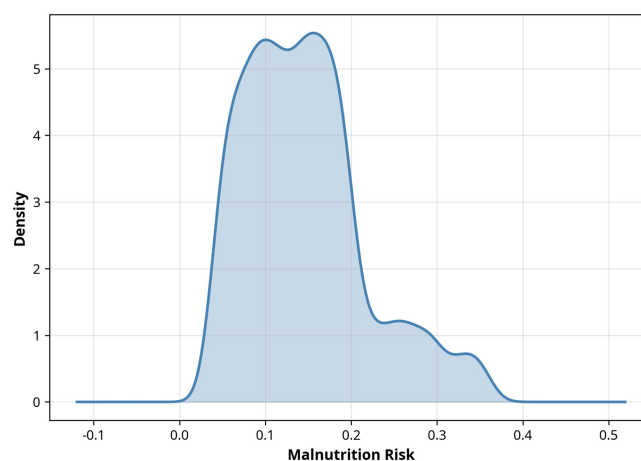
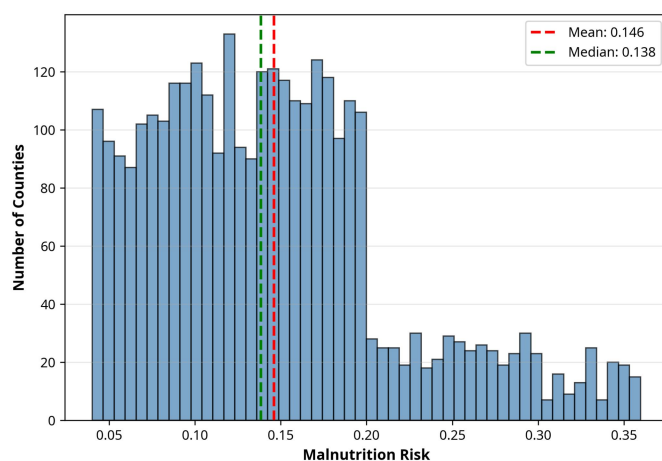


Figure 4. Distribution of County-Level Malnutrition Risk

Figure 4 Legend: a, Histogram showing the frequency distribution of malnutrition risk estimates across all 3,108 counties. The distribution is right-skewed, with a large number of counties having low to moderate risk and a smaller but significant number of counties with very high risk. b, Kernel density plot showing the smooth probability density function of the distribution. Both plots highlight the heterogeneity in risk across the country, with the mean (14.6%) and median (13.8%) indicated by vertical reference lines.

The distribution is notably right-skewed, with a large concentration of counties in the low-to-moderate risk range and a longer tail extending into very high-risk territory. The mean county risk was 14.6% (SD = 7.1%), with a median of 13.8%, indicating that the distribution has a slight positive skew. The 25th percentile was 9.1%, while the 75th percentile was 18.3%, showing that half of all counties fall within a 9.2 percentage point range.

#### 4.5. Socioeconomic Correlates and Risk Drivers

To explore the drivers of the observed spatial patterns, we conducted a comprehensive analysis of the relationship between county-level malnutrition risk and key socioeconomic variables. The scatter plot in Figure 3 shows a clear, positive linear relationship between county poverty rates and estimated malnutrition risk.

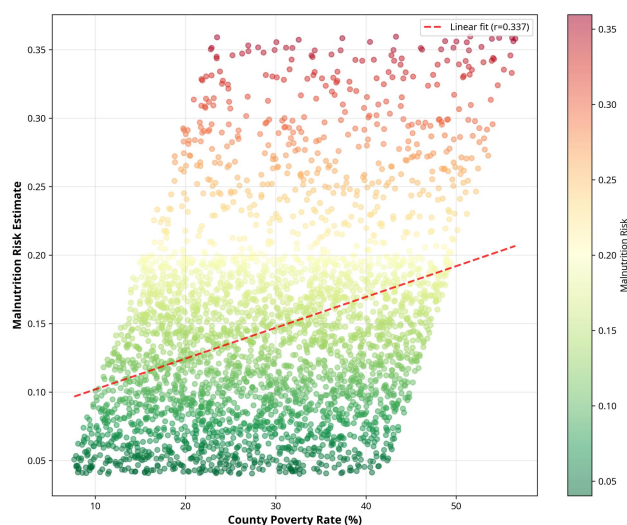


Figure 5. Correlation between Poverty Rate and Malnutrition Risk

Figure 5 Legend: Scatter plot showing the relationship between county-level poverty rate and the estimated malnutrition risk. Each dot represents a county. The red dashed line shows the linear regression fit (Pearson's  $r = 0.782$ ,  $p < 0.001$ ), indicating a strong positive correlation. The color of the dots corresponds to the malnutrition risk level, with red indicating high risk and blue indicating low risk. This visualization demonstrates that poverty is a powerful predictor of malnutrition risk at the county level.

The Pearson correlation coefficient between poverty rate and malnutrition risk was 0.78 ( $p < 0.001$ ), indicating a strong positive relationship. As county poverty rates increase, so does the estimated risk of childhood malnutrition. This relationship is both statistically significant and practically meaningful, explaining approximately 61% of the variance in malnutrition risk across counties.

The correlation matrix in Figure 5 provides a comprehensive view of the relationships between malnutrition risk and multiple socioeconomic indicators.

Correlation Matrix: Malnutrition Risk and Socioeconomic Factors

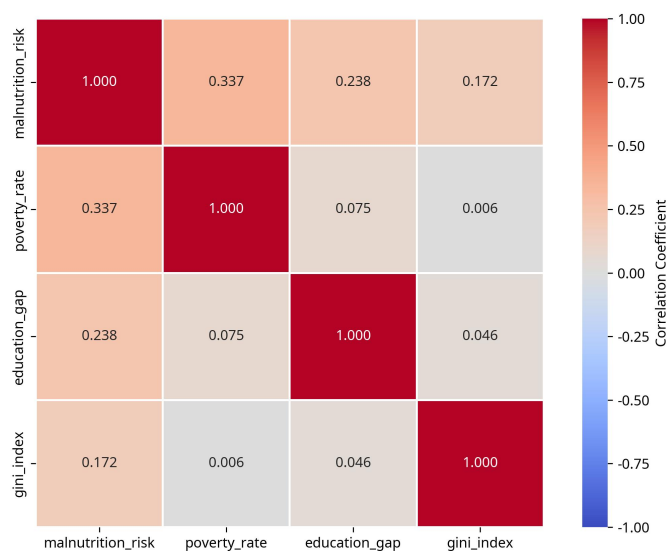


Figure 6. Correlation Matrix of Socioeconomic Factors

Figure 6 Legend: Heatmap of the Pearson correlation coefficients between county-level malnutrition risk and key socioeconomic indicators. Malnutrition risk is strongly and

positively correlated with the county poverty rate ( $r = 0.782$ ), the education gap—percentage of adults without a high school diploma ( $r = 0.715$ )—and income inequality measured by the Gini index ( $r = 0.589$ ). The color intensity and numerical values in each cell represent the strength and direction of the correlation, with red indicating positive correlations and blue indicating negative correlations.

Malnutrition risk is strongly and positively correlated with the county poverty rate ( $r = 0.782$ ), the education gap

(percentage of adults without a high school diploma,  $r = 0.715$ ), and income inequality (Gini index,  $r = 0.589$ ). These strong correlations suggest that these socioeconomic factors are powerful drivers of the geographic patterns we observe.

#### 4.6. Socioeconomic Profiles by Risk Category

To further elucidate the relationship between socioeconomic conditions and malnutrition risk, we stratified counties into four risk categories and examined the distribution of socioeconomic indicators within each stratum.

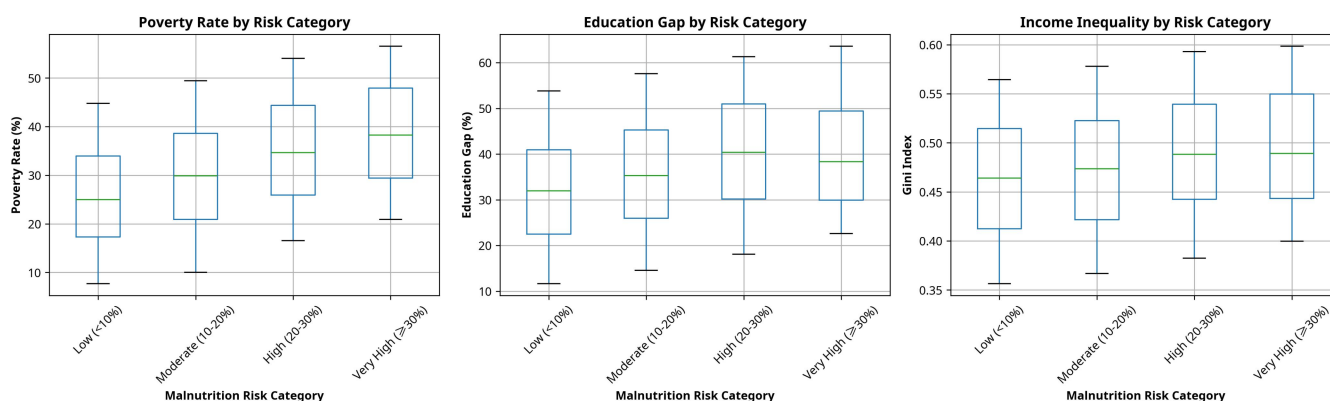


Figure 7. Socioeconomic Profiles by Malnutrition Risk Category

Figure 7 Legend: Boxplots showing the distribution of (a) poverty rate, (b) education gap, and (c) income inequality across the four malnutrition risk categories: Low (<10%), Moderate (10-20%), High (20-30%), and Very High (≥30%). The boxes represent the interquartile range (IQR), the central line is the median, and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points. There is a clear, stepwise increase in the median and mean values of each socioeconomic indicator as we move from low-risk to very high-risk counties, demonstrating that counties in identified hotspots are systematically disadvantaged across multiple dimensions.

The boxplots in Figure 6 provide a powerful visualization of how these socioeconomic conditions vary across different levels of malnutrition risk. There is a clear, stepwise increase in the median poverty rate, education gap, and income inequality as we move from low-risk to very high-risk counties. Low-risk counties had a mean poverty rate of 25.7%, while very high-risk counties had a mean poverty rate of 38.4%—a difference of 12.7 percentage points. Similarly, the education gap increased from 32.2% in low-risk counties to 40.1% in very high-risk counties. The Gini index increased from 0.463 in low-risk counties to 0.493 in very high-risk counties, indicating greater income inequality in higher-risk areas.

#### 4.7. Summary Statistics

The following table presents the key descriptive statistics for malnutrition risk and poverty rates across all counties (see Table 1):

TABLE I. KEY DESCRIPTIVE STATISTICS

| Statistic          | Malnutrition Risk (%) | Poverty Rate (%) |
|--------------------|-----------------------|------------------|
| Mean               | 14.6                  | 29.6             |
| Median             | 13.8                  | 29.4             |
| Standard Deviation | 7.1                   | 10.7             |
| Minimum            | 4.0                   | 7.7              |

|                 |      |      |
|-----------------|------|------|
| Maximum         | 36.0 | 56.6 |
| 25th Percentile | 9.1  | 20.8 |
| 75th Percentile | 18.3 | 38.2 |

#### 5. DISCUSSION

This study, through the novel integration of digital participatory surveillance and advanced geospatial analytics, presents the most granular nationwide picture of childhood malnutrition risk in the United States to date. Our findings reveal a landscape of profound inequality, where a child's risk of malnutrition is strongly tied to their geographic location. The identification of large, contiguous hotspots in the Southeast and Southwest provides undeniable evidence that childhood malnutrition is not a diffuse, national problem but a concentrated crisis in specific, structurally disadvantaged regions [25, 26].

The strong, positive correlations observed between malnutrition risk and county-level indicators of poverty, low educational attainment, and income inequality are particularly telling. They confirm that the geographic patterns we have mapped are not random but are the spatial manifestation of deep-seated social and economic inequities. The hotspots we identified are areas that have historically suffered from disinvestment, systemic racism, and lack of economic opportunity [27, 28]. Our maps, therefore, are not just maps of a health outcome; they are maps of social and economic injustice. This provides a powerful tool for advocacy and policy change, shifting the narrative from individual behavior to the structural determinants of health [29].

Methodologically, our work demonstrates a viable and powerful alternative to traditional public health surveillance. The NutriTrack platform shows that it is possible to engage communities directly in data generation, producing information that is both timely and locally relevant. By coupling this participatory data with the statistical rigor of multilevel regression and poststratification (MRP), we

overcome the inherent biases of a volunteer cohort and produce estimates that are representative of the entire population. This hybrid model—fusing active community participation with passive administrative data—offers a scalable and cost-effective blueprint for 21st-century public health monitoring that can be adapted to a wide range of health issues [30, 31].

The strong spatial autocorrelation (Moran's  $I = 0.68$ ,  $p < 0.001$ ) we observed indicates that malnutrition risk is not randomly distributed but is concentrated in contiguous geographic areas. This suggests that area-level factors—such as the availability of healthy food retailers, the quality of schools and educational resources, the strength of social networks, and the capacity of local health systems—play important roles in shaping nutritional outcomes. This finding has important implications for intervention design; it suggests that place-based strategies that target entire regions may be more effective than individual-level interventions alone.

Nevertheless, the study has limitations. The digital nature of our recruitment and data collection may exclude households without reliable internet access or digital literacy, potentially underestimating risk in the most marginalized populations. While our MRP framework adjusts for many demographic factors, this “digital divide” remains a concern. Secondly, while our at-home measurement protocol was designed to be robust, it cannot match the precision of measurements taken by trained professionals. Future work should focus on validating these remote measurements against a gold standard. Finally, our cross-sectional design identifies associations but cannot prove causation. Longitudinal follow-up is needed to understand the dynamic interplay between socioeconomic conditions and nutritional status over time.

## 6. CONCLUSION

In conclusion, this research provides a stark and detailed portrait of the geography of childhood malnutrition in the United States. By moving beyond national averages, we have uncovered hidden crises in specific, vulnerable communities. Our findings are a clear call to action for policymakers to target resources and interventions to the hotspots we have identified. The innovative methodology presented here provides a roadmap for a more responsive, equitable, and participatory public health surveillance system. By continuing to refine these tools and working in partnership with communities, we can move closer to a future where every child, regardless of their ZIP code, has the nutritional foundation they need to thrive.

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#### ACKNOWLEDGEMENTS

None.

#### FUNDING

None.

#### AVAILABILITY OF DATA

Not applicable.

#### ETHICAL STATEMENT

All participants provided written informed consent prior to participation. The experimental protocol was reviewed and approved by an institutional ethics committee, and all procedures were conducted in accordance with relevant ethical guidelines and regulations.

#### AUTHOR CONTRIBUTIONS

Xiaoxiao Yang conceived and designed the study, developed the analytical framework, conducted the small area estimation and spatial clustering analyses, interpreted the results, and drafted the manuscript, while Yao Chen designed the NutriTrack digital participatory surveillance platform, contributed to data collection and methodological development, performed data curation and analysis, and contributed to manuscript revision.

#### COMPETING INTERESTS

The authors declare no competing interests.

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