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Double and triple burden of malnutrition and the role of geo-socio-ecological factors in Ethiopia: a bayesian geostatistical analysis

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Abstract

Background Developing countries face a nutrition transition, leading to a double or triple burden of malnutrition. In Ethiopia, the extent and socioecological drivers of this burden remain understudied. This study aims to analyze the spatial distribution of the double and triple burden of malnutrition and the role of socioeconomic and environmental factors in children aged 6–59 months.

Method Data on stunting and overweight/obesity were obtained from the 2016 Ethiopian Demographic and Health Survey (EDHS), while data on micronutrient deficiencies were sourced from the Ethiopian Public Health Institute. A geostatistical model using Integrated Nested Laplace Approximation (INLA) within a Bayesian framework was employed to examine the role of Geo-socio-ecological Factors and predict the distribution of overweight/obesity, stunting, and micronutrient deficiencies and their co-occurrence.

Result We observed significant overlaps in different types of malnutrition: stunting and overweight/obesity in Oromia; and overweight/obesity and zinc deficiency in Amhara, Tigray, Oromia, and Somali regions. There was also a notable regional variation in the triple burden of malnutrition: Oromia region faces overweight/obesity, stunting, and iron deficiency, while the central Ethiopia and Amhara regions experience overweight/obesity, stunting, and vitamin A deficiency. The Diphtheria Tetanus Pertussis (DTP) vaccine was negatively associated with vitamin A deficiency (β = -0.23; 95% CrI: -0.43, -0.04) and stunting (β = -0.13; 95% CrI: -0.22, -0.04). Additionally, soil nitrogen (g/kg of soil), which affects agricultural productivity, is associated with a decrease in iron deficiency (β = -0.57; 95% CrI: -0.93, -0.23) and zinc deficiency (β = -0.44; 95% CrI: -0.67, -0.19).

Conclusion The present finding shows that Ethiopia is experiencing both a double and triple burden of malnutrition, with a significant overlap of overweight/obesity, stunting, and micronutrient deficiencies (i.e. triple burden) across the country. This highlights the need for geographically targeted integration of services that address all forms of malnutrition. The Diphtheria Tetanus Pertussis (DTP) vaccine was negatively associated with stunting and VAD, likely due to its role in reducing infectious and diarrheal diseases, highlighting the potential for integrating health coverage with nutritional intervention. Soil nitrogen density was also negatively associated with iron and zinc deficiencies, possible due to its role on plant growth and nutrient composition, underscoring the need to promote soil-specific fertilizer use as part of nutrition-sensitive agricultural strategies.

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Keywords Malnutrition, Double burden, Triple burden, Bayesian geostatistical analysis, Ethiopian children

Background

Malnutrition, with its multifaceted nature and complex life course trajectory, can result in low productivity and higher healthcare costs due to adult obesity and other obesity-related non-communicable diseases rooted in early-life undernutrition [1]. Various anatomical and physiological disruptions can amplify these health effects over time. For example, undernutrition during infancy has been linked to adverse alterations in glucose metabolism in children [1]. These metabolic changes, when compounded by later overweight, significantly increase the risk of non-communicable diseases by placing a high metabolic load on an already compromised capacity for homeostasis [1, 2]. Therefore, it is crucial to understand the geographical distribution of malnutrition in the population, especially among children, and the effective public policies that can address malnutrition during this critical period.

With the rapid global nutrition transition, more people are experiencing multiple forms of malnutrition throughout their lives. The double burden of malnutrition (DBM), that is, the coexistence of undernutrition and overnutrition within the same population [3], can manifest at both individual and community levels. In some regions, even within the same household, individuals may simultaneously face both forms of malnutrition [4]. For instance, in certain developing countries, disparities exist where one household may struggle with overweight members while another faces undernutrition [5]. A child who begins life stunted may later become overweight due to treatment with high-energy foods or various socioeconomic factors [6]. The increased availability of cheap, ultra-processed foods and beverages in low-income countries, combined with a reduction in physical activity caused by the widespread adoption of labor-saving technologies, has led to a double burden of undernutrition and overnutrition in less developed nations [7, 8].

There is also a growing concern about the triple burden of malnutrition, which refers to the coexistence of undernutrition, overnutrition and micronutrient deficiencies within a population [9]. Micronutrient deficiency is defined as a lack of essential vitamins, such as vitamin A, and minerals, such as iron and zinc, which are required in small amounts by the body but are crucial for proper growth and development [10]. Micronutrient deficiencies are particularly prevalent in low-income countries [11], where poverty and limited household resources often compel people to prioritize low cost, energy-dense staple foods [12]. Many countries are facing a complex nutrition landscape that includes undernutrition, overnutrition and micronutrient deficiencies, often referred to as hidden hunger [12, 13]. Since hidden hunger is less visible than other nutritional issues, it can lead to severe health consequences before being detected. Micronutrient deficiencies are associated with several serious health problems, including anemia, a condition characterized by a low red blood cell count or hemoglobin concentration. Low levels of iron, folate, and vitamins B12 and A are significant contributors to anemia, a global concern affecting 42% of children under the age of five [14]. Anemia can also affect other forms of nutrition, such as stunting and childhood overweight/obesity, due to a lack of energy for exercise [14, 15]. In some cases, children may become overweight due to the consumption of energy-dense diets, while simultaneously suffering from micronutrient deficiencies caused by a lack of dietary diversity. These issues shift the focus of malnutrition from merely addressing undernutrition or overnutrition to the double and triple burden of malnutrition.

The multifaceted life-course trajectories of malnutrition are influenced by social driving forces such as changing diets, norms of eating, and patterns of physical activity, as well as broader ecological factors [9, 16]. According to Bronfenbrenner's ecological systems theory [17], child development is shaped by a network of interconnected environmental influences, ranging from family and neighbors to broader cultural and political factors. In low- and middle-income nations, the triple burden of malnutrition is frequently prevalent in urban areas and among the most impoverished populations. Undernutrition and micronutrient deficiencies are more prevalent in rural regions, whereas overweight and obesity are more frequent in urban environments [16, 18–20]. This pattern can be attributed to urbanization and economic development, which lead to changes in dietary habits and lifestyles that promote overweight and obesity [20, 21]. Conversely, poverty and limited access to nutritious foods and healthcare in rural areas increase the risk of undernutrition and micronutrient deficiencies [9].

There are significant gaps in the evidence regarding the concurrent occurrence of various forms of malnutrition and the impact of geo- socio-ecological factors on children under five [22]. Two studies [23, 24] conducted in Ethiopia have used the Bayesian approach to examine the spatial distribution of underweight, undernutrition, and stunting. These studies found that factors such as temperature, altitude, population density, and proximity to water bodies significantly influence undernutrition. However, these studies focused solely on undernutrition and stunting separately, rather than studying the spatial overlap of the double and triple burdens of malnutrition in Ethiopia, a critical gap that our research aims to fill.

Moreover, they did not consider micronutrient deficiency and the key socioeconomic factors affecting nutrition, such as wealth and per capita expenditure, and the role of health service utilization, such as vaccinations and antenatal and postnatal follow-ups, which were highlighted as limitations in a previous study [24].

Some other studies [25, 26] demonstrated area-specific disparity in the prevalence of malnutrition in Ethiopia. However, these studies primarily focused on describing the spatial distribution of individual problems and failed to investigate the associations between geo-referenced determinants and childhood malnutrition. Moreover, the country has faced continuous political instability and conflict over the past decades, which may have significantly impacted the environment, including food access and transportation. In this context, ecological factors could play a crucial role in the high levels of malnutrition, particularly in the eastern and southern regions of Ethiopia, where wars and conflicts are prevalent [27, 28]. The double and triple burden of malnutrition among children is a complex issue that demands a multidimensional approach. Tackling this challenge requires comprehensive policy programs that go beyond individual-level interventions, focusing on necessary changes to environmental and societal conditions linked to nutrition and public health [29]. However, the area disparities in the double and triple burden of malnutrition, as well as the role of socioeconomic and environmental factors in Ethiopia, remain poorly documented.

Therefore, this study aims to examine the double and triple burden of malnutrition and the role of geo-socio-ecological factors in children aged 6–59 months. Collecting data from every village or small area to achieve a comprehensive understanding of malnutrition across specific areas is often impractical. Therefore, we apply a spatial prediction model that uses data from nearby areas to provide a more accurate representation of malnutrition at the national level [30]. Providing such granular predictions (at one km^2) capture subtle spatial heterogeneity and variations that might be missed when data is aggregated into larger spatial units like regions, zones, or districts.

Additionally, nutritional factors can vary significantly even over short distances, such as within one km. Modelling at such a fine scale, facilitates observing the influence of these covariates and allows for accurate predictions by incorporating both structured (spatially correlated) and unstructured (random noise) effects in the data [31]. We employ a geostatistical model using Integrated Nested Laplace Approximation (INLA) within a Bayesian framework to examine of the role of geo-socio-ecological factors and predict the distribution of overweight/obesity, stunting, and micronutrient deficiencies and their co-occurrence. Using INLA within a Bayesian framework offers several key advantages over the frequentist methods commonly used in previous literature. It not only estimates how prevalent each form of malnutrition is in each area but also quantifies the uncertainty around those estimates. Unlike frequentist approaches, the Bayesian method combines actual data with prior knowledge about malnutrition, accounts for spatial relationships between areas, and borrows information from both geography (spatial relationships between nearby areas) and existing evidence to produce more accurate and reliable predictions [30]. This approach therefore provides robust scientific evidence to support initiatives, highlighting specific geographical areas with high concentrations of malnutrition and identifying key determinant factors.

Data source and methods

Theoretical framework

Ecological system theory by Bronfenbrenner [17], states that child development is influenced by a series of interconnected environmental systems, ranging from immediate surroundings, such as family and neighbors, environmental factors and broader societal structures, such as culture and political systems. Climate change disrupts the food supply, increases food prices, and ultimately reduces access to nutrient-dense and healthy foods, particularly for vulnerable populations [32]. In addition, UNICEF's nutritional framework highlights that children living in low-income countries are especially susceptible to environmental hazards, which significantly compromise their nutrition. The organization emphasizes the importance of collaboration among social, financial, public, and private sectors in addressing child nutrition [33]. Similarly, Fisher, Matthew, et al. [34], and Wilkinson, and Marmot [35] argue for the critical role of socio-economic factors, such as socioeconomic status, education, employment, wealth distribution, empowerment, and social support, in shaping health outcomes. This evidence underscores the complex and interconnected nature of the factors contributing to malnutrition. Analyzing the geographical distribution of malnutrition and its contributing factors is crucial, as spatial variations often reveal patterns and clusters essential for targeted interventions. Previous studies [26, 36, 37] using frequentist models such as spatial autocorrelation, generalized linear mixed models, geographically weighted regression and multilevel robust Poisson regression analysis, failed to incorporate prior information and lacked the flexibility to handle complex data structures, including hierarchical, multilevel, and spatial frameworks. These limitations restrict their ability to accurately capture underlying patterns and intricate relationships within the dataset, making Bayesian model-based geostatistics (MBG) a more suitable approach [38]. To address these complexities, our study employs a Bayesian MBG analysis to see the effect of geo-socio-ecological factors on the triple burden of malnutrition and to identify the spatial pattern of both double and triple burden of malnutrition using spatial prediction. Spatial prediction involves using spatial modeling techniques to estimate the distribution of each form of malnutrition and their overlap across different areas. Geo-socio-ecological factors in this study refer to the combined influence of geographic (e.g., vegetable storage sites, cereal storage sites and other infrastructure), social (e.g., wealth index, maternal education, women's decision-making power, and annual expenditure), and ecological (e.g., climatic and environmental conditions such as temperature and altitude) factors on malnutrition.

Data

Survey locations

The EDHS data were collected from 9 regions and 2 city administrations in Ethiopia, covering 645 georeferenced clusters (28 households per cluster). Similarly, the Ethiopian National Micronutrient Survey (ENMS) data were obtained from 366 clusters (11 households per cluster) across the same 9 regions and 2 city administrations [39] (see Fig. 1). As illustrated in Fig. 1, data in both datasets have been collected across all regions of Ethiopia. The EDHS provides better overall representation; however, in both datasets, data collected in the Somali region is sparse. Conversely, the southern, central, and northern parts of the country have more data points in both datasets (see Fig. 1).

Data source

Data for the outcome variable were obtained from the 2016 EDHS and the 2015 ENMS sourced from the Ethiopian Public Health Institute (EPHI). The data were collected across Ethiopia's eleven regions and two city administrations, with each region further divided into zones and districts. Both datasets include georeferenced information, such as latitude and longitude, and provide national representation for Ethiopia. The 2016 Ethiopia demographic and health survey datasets, which are freely available to all registered users, were obtained and downloaded from the Measure DHS program website (https://dhsprogram.com/data/datasetadmin/login main.cfm).

The Demographic and Health Survey (DHS) used a stratified, two-stage cluster sampling technique to select children aged 6–59 months. First, the national list of enumeration areas (EAs) was obtained from the Central Statistics Agency (CSA) of Ethiopia and used as the sampling frame. Ethiopia's administrative units are hierarchically

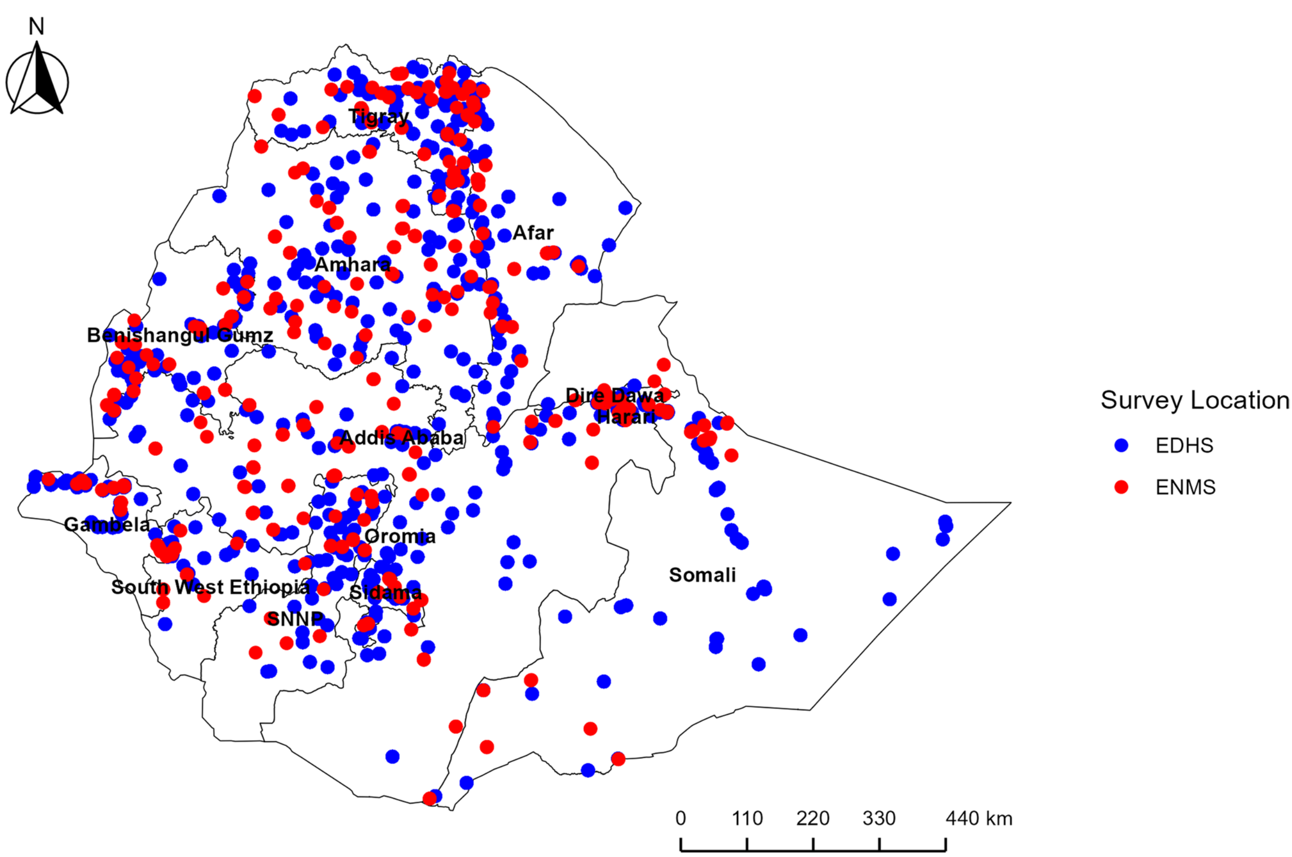

Fig. 1 Geographic distribution of survey locations for malnutrition and micronutrient deficiencies in Ethiopia

organized into regions, zones, woredas (districts), and kebeles (wards/villages). Enumeration areas, which are villages within a kebele, are selected by the Central Statistics Agency for research purposes. Then, a household listing operation was conducted, with up to 300 households found per cluster, depending on whether the area was urban or rural. Afterward, 28 households per cluster were selected using systematic random sampling with equal probability for the final data collection.

The 2015 National Micronutrient Survey also used enumeration areas (EAs) obtained from the same institution, the Central Statistics Agency (CSA), and followed the same two-stage sampling process. Enumeration areas were randomly selected using probability proportional to the total population, meaning areas with larger populations had more EAs selected. In the second stage, data collectors listed all households (150–200 households) in each selected EA, and 11 households were randomly chosen. All children aged 6–59 months from the selected households were included in the final data collection. All data collection, transportation, storage, and other techniques have been documented in the 2015 National Micronutrient Survey reports [39]. Height-for-age and other anthropometric measurements were collected for children aged 6–59 months in both datasets. Given the complex sampling design of the DHS data, we applied sampling weights for obesity/overweight, stunting, and the comorbidity of anemia with stunting and obesity/overweight prior to estimation.

In addition to the outcome variables, we obtained covariates in raster format, where information is stored as a grid of cells or pixels. These covariates provide high-resolution, country-wide representative data for Ethiopia and are plausibly associated with various forms of malnutrition. The data were sourced from the Malaria Atlas Project, the WorldClim website, the Shuttle Radar Topography Mission database, World Population data, the Food and Agriculture Organization of the United Nations (FAO), the Ethiopian Socioeconomic Survey (ESS), and the 2016 DHS. Raster covariates are used because they provide continuous, spatially aligned, and standardized environmental information that integrates well with the spatial random effects in the Integrated Nested Laplace Approximation (INLA) models. Since our model is a Bayesian Model-Based Geostatistics (MBG) approach using the SPDE (Stochastic Partial Differential Equation) technique, raster covariates align well with our spatial random effects. For modelling purposes, the value of each covariate from the raster was extracted at specific latitude-longitude locations of our point data and integrated with the outcome variables.

Outcomes variables

Vitamin A deficiency (VAD) is defined by a serum retinol concentration below 0.70 μmol/L [40]. Iron deficiency is determined as a soluble transferrin receptor (sTfR) value greater than 4.4 mg/L in children aged 6 to 59 months [41]. Zinc deficiency is defined as a concentration of less than 70 μg/dL in children under five, according to the International Zinc Nutrition Consultative Group (IZiNCG) recommendations [42]. Stunting is defined as a height-for-age z-score (HAZ) less than -2 standard deviations (SD) below the median of the reference population [43]. Overweight/obesity is defined as a weight-for-height value exceeding 2 standard deviations (SD) above the WHO Child Growth Standards median (WHZ $> +2$) [43]. Anemia in children aged 6–59 months was defined according to WHO criteria as a hemoglobin level below 110 g/L [44]. The coexistence of anemia with stunting and overweight/obesity is defined as the simultaneous presence of anemia with stunting and overweight/obesity in the same individual. The double burden of malnutrition is defined as specific geographic regions where overweight/obesity coexists with any one form of undernutrition, such as stunting, iron deficiency, vitamin A deficiency (VAD), or zinc deficiency, with their prevalence exceeding the 75th percentile threshold. The triple burden of malnutrition refers to geographic regions where overweight/obesity, stunting, and any one of iron deficiency, VAD, or zinc deficiency coexist, with their prevalence exceeding the 75th percentile threshold. We estimated the predicted prevalence of each form of malnutrition and divided it into quartiles. The threshold refers to the point that separates the top 75% of prevalence rates. We used 75th percentile as a cut-off because our goal is to identify high-burden hotspots for public health interventions by targeting the top 25% of all malnutrition forms. We chose a percentile-based threshold over a fixed cut-off for several reasons. First, since this analysis is conducted at the geographic level, we focused on public health prioritization. Using the top quartile allows us to identify communities with the most severe forms of malnutrition relative to the national distribution, providing a flexible and data-driven method. Fixed cut-off values may not be appropriate across diverse geographic areas, as they either overestimate or underestimate the burden depending on the overall prevalence in the country. In addition, our aim is not to compare Ethiopian's prevalence with other countries, but rather to highlight the most affected areas for intervention, aiming for a balance between sensitivity and specificity without being overly restrictive or arbitrary. This statistical threshold approach is widely used by previous studies [24, 45].

Covariate data

Our covariates were limited to those with high-resolution, nationally representative data that were plausibly associated with each form of malnutrition, some of which had been mentioned in previous literature [23, 24]. Data on travel times to the nearest city and healthcare facility were obtained from the Malaria Atlas Project [46]. Climatic covariates, including mean annual temperature and mean annual precipitation, were obtained from the WorldClim website [47]. We also used the Shuttle Radar Topography Mission database to obtain data about altitude [48]. Data on population density (people/km2), maternal education status (proportion of children aged 12 to 23 months born to mothers who had no formal education), antenatal care coverage, postnatal care coverage, Diphtheria-Tetanus-Pertussis (DTP) vaccine coverage, measles vaccine coverage, proportion of women aged 15 to 49 years who did not participate in decision-making, and health insurance coverage were obtained from World Population data [49]. For maternal education, we also considered higher educational levels, such as the proportion of mothers attending primary school or higher, obtained from DHS data. However, these variables were less significant than those derived from World Population data in one-on-one tests (examining the outcome against a single independent variable), as indicated by their very low beta coefficients. Although it may seem unusual to include variables specific to children aged 12 to 23 months in a study focused on children aged 6 to 59 months, our regression was conducted at the geographical level (grid level) rather than the individual level. In this context, we believe that a high proportion of uneducated mothers corresponding to children aged 12 to 23 months in each area can serve as a broader reflection of maternal education. Additionally, variables obtained from World Population data had lower WAIC values than the corresponding education variables from DHS, so we included them in our final model. Variables measured at the national level in Ethiopia and stored as raster data (pixels), including soil nitrogen, soil bulk density, vegetable storage sites, annual milk production, and cereal storage sites, were obtained from the Food and Agriculture Organization of the United Nations (FAO). The FAO identified suitable cereal and vegetable storage sites using various criteria, including production amount, market accessibility, population density, and infrastructure [50–52], which could affect malnutrition. Socio economic variables such as per capita annual expenditure for food consumption and wealth index were obtained from the 2015–2016 Ethiopian Socioeconomic Survey (ESS) as point data with latitude and longitude [53]. We also obtained point data with latitude and longitude on minimum dietary diversity and household size from 2016 DHS data. The minimum dietary diversity is defined as the percentage of children 6–23 months receiving 5 out of 8 food groups in the previous day [54].

For analysis purposes and to ensure consistency with other covariates, we estimated the proportion of diet diversity, household size, wealth index, and annual per capita food expenditures across Ethiopia at a high-resolution using Bayesian Kriging interpolation techniques [55, 56]. This technique has been used in a related previous study [57].

Method

Model specification

Bayesian model-based geostatistics (MBG) were used to generate high-resolution (1 km²) spatial estimates of national prevalence for stunting, overweight/obesity, and micronutrient deficiencies. Within the MBG framework, logistic regression models were applied to prevalence data, incorporating both fixed effects (spatial-level factors such as altitude, temperature and population density) and spatial random effects to account for unmeasured spatial variation. Before estimating the double burden of malnutrition and the triple burden of malnutrition, separate models were developed for each outcome. These outcomes included stunting, overweight/obesity, iron deficiency, vitamin A deficiency, zinc deficiency, anemia-stunting coexistence, and overweight/obesity-anemia coexistence. A spatial binomial regression model was fitted within the MBG framework, accounting for the spatial correlation of neighboring areas. This approach allows the model to represent how different forms of malnutrition vary across locations. Spatial correlation was modeled using spatially structured random effects, ensuring that the model reflects the assumption that outcomes are not independent but are influenced by nearby areas. The model also includes fixed effects for covariates that are assumed to have a direct and consistent influence across different levels of the data, such as observations, individuals, groups, or periods. Additionally, geostatistical random effects are incorporated to control unmeasured spatially varying factors, capturing variations in malnutrition that cannot be explained by fixed effects alone. This is based on the assumption that areas in close proximity are more likely to exhibit similar random effects compared to more distant areas [58]. The prevalence (Y) of stunting, overweight/obesity, stunting-anemia, overweight/obesity-anemia, and micronutrient deficiencies at each location (j), was assumed to follow a binomial distribution, where each location corresponds to a grid.

$$\mathrm{Yj} \sim \mathrm{Binomial}\left(\mathrm{N_j},\ \mathrm{P_j}\right)$$

where $\mathrm{N_j}$ is the total number of children assessed for these conditions, P is the predicted prevalence of each form of malnutrition. The mean predicted prevalence of stunting, overweight/obesity, and micronutrient deficiencies was first modeled using a logit link function with a linear predictor, defined as follows:

$$Logit\,(\mathrm{pj}) = a_0 + \sum_{Z=1}^{Z} \beta\mathrm{jZj} + \sum_{j \neq i} \mathrm{WijSj} + \zeta$$

where pj represents the observed prevalence of malnutrition at location *j*, α_0 is the intercept, β is a covariate coefficient, and Z is a set of covariates. The formula $\sum_{j \neq i} \mathrm{W}i\mathrm{jSj}$ represents the spatial correlation, where $\mathrm{W}ij$ is the spatial correlation weight determined by the distance between location *i* and location j. Here, Sj denotes the spatially structured random effect at location j, which influences location *i*. In other words, nearby locations affect each other, capturing the spatial dependence within the model. ζ captures non-spatial random effects used to represent spatial variation caused by unobserved time-variant characteristics within each location (e.g., norms, culture, weather). The random effect is modeled using a zero-mean Gaussian Markov random field with a Matérn covariance function [59].

The integrated nested Laplace approximation (INLA) approach was used to estimates all the parameters [30, 60]. INLA offers fast and accurate Bayesian inference for latent Gaussian models by avoiding costly Markov Chain Monte Carlo (MCMC) simulations. It efficiently approximates posterior distributions, making it especially advantageous for spatial and hierarchical models. The Matérn correlation function estimates the correlation between points in the spatial field created by the a Stochastic Partial Differential Equation (SPDE) approach [30, 61]. The prediction process has been detailed in Additional file 1: Figure S1. Since no prior information was available, we applied a non-informative prior for all model parameters [62]. To balance the need for analyzing malnutrition at lower administrative levels while aligning with the fact that most health programs and resource allocations occur at higher levels (such as regions, zones, and districts), we selected zones (the third administrative level) for aggregation.

Model validation

After fitting our models, we evaluate the validity for our models using the conditional predictive ordinates (CPO) [63].

The formula for the conditional predictive ordinates (CPO) is as follows.

For a dataset with observations $y_1, y_2, \ldots, y_n$, the CPO for the *j*-th observation y_i is defined as:

$$\mathrm{CPO_j} = \mathrm{p}\left(\mathrm{y_i}\,|\mathrm{y_{-j}}\right)$$

where: $p(y_j \mid y_{-j})$ is the posterior predictive density of y_j given the remaining data.

y_{-j} represents the dataset with the *j*-th observation removed, meaning that the CPO values reveal the posterior probability of observing the outcome at location j when the model is fitted to all data except y_j. This implies how well the model predicts the outcome variable at location j without using the data at that location, based on the posterior distribution of the model parameters. This information helps us understand how well the model predicts unseen data [64, 65]. The CPO values range between 0 and 1, with large CPO values (close to 1) indicate a better fit as they show a higher probability of predicting the true value using the remaining data, while small values (close to 0) suggest a poorer fit of the model to the observed data. Additionally, we assess the log-Conditional Predictive Ordinates (log-CPO) values. Although there is no established cutoff value in the literature, we use − 10 as a rule of thumb. For instance, if the log-CPO value is −10, the corresponding CPO value for that observation is 5^{-10}, which is approximately zero. Observations with log-CPO values below − 10 considered as there are potential outliers in the data.

For our final model for each form of malnutrition, we used a stepwise variable selection approach and the WAIC to assess predictive accuracy and identify the best-fitting model. We first fit a basic model and then sequentially added covariates, observing how the WAIC changed. This criterion balances model fit and complexity, if a variable is not relevant, the WAIC value increases significantly [66, 67]. After testing different covariate combinations, we selected the model with the lowest WAIC value [66, 68]. Initially, we applied a similar set of covariates to all forms of malnutrition, if most covariates could influence each outcome. However, based on WAIC and CPO values, we selected the best-fitting model for each outcome, leading to different sets of covariates in the final models. Since predictive accuracy is crucial, we recognized that covariate affecting stunting may not necessarily influence obesity or micronutrient deficiencies. Therefore, we report the best final model for each malnutrition form, ensuring an optimal balance between fit and relevance.

Geoprocessing

First, we extracted each covariate in raster format. A raster is a data structure that stores information in a grid of square cells, with each cell representing a geographic area on the map of Ethiopia. Each cell contains a single value corresponding to a specific attribute, such as altitude, temperature, or population density. Since the covariates were obtained from different sources and had varying, we standardized them to a common resolution of 1 × 1 km using resampling technique before stacking them for analysis. Additionally, since the covariates have different units and scales of measurement, a variable with a large scale could dominate other variables in the analysis. Therefore, we calculated the arithmetic mean and standard deviation (SD) for each covariate and standardized them to a z-score scale based on their mean and SD. This approach has been widely used in many previous related studies [69, 70].

Result

Sample description

Approximately 20% of children from the 2015 ENMS and 16% of the EDHS data were excluded due to the absence of geographical coordinates in the global positioning system (GPS). We analyzed a total of 8,855 data points for stunting (undernutrition) and 8,919 for overweight/obesity (overnutrition), sourced from 645 georeferenced clusters in the 2016 Ethiopian Demographic and Health Survey (EDHS). From 2015 Ethiopian National Micronutrient Survey (366 clusters), we obtained 1,115 data points for iron deficiency, 1,156 for vitamin deficiency and 1,114 for zinc deficiency. Of these, we included 873 for VAD, 851 for Zinc deficiency and 862 for Iron deficiency (refer to Additional file 2 Figure S2).

Our outcome data consisted of point data with latitude and longitude, where prevalence ranged from 2.3% for obesity/overweight to 38% for stunting; see Table 1. Additionally, the prevalence of iron deficiency was 30%; see Table 1). The prevalence of each form of malnutrition, based on raw data aggregated by zones (the third administrative units in Ethiopia), before our prediction is presented in Additional file 3: Figure S3.

All covariates were represented as raster data covering the entire country. For instance, the average annual temperature in °C at a 1 km x 1 km pixel level was 22.69 °C (SD = 4.22), while altitude ranged from − 117.84 to 3,874.01 m, with a mean of 1,214.10 m above sea level; see Table 1. Annual per capita food expenditure at the 1 km x 1 km pixel level ranged from 5,070.5 to 42,146.3 Ethiopian Birr, with a mean of 18,449.02 ETB; see Table 1. The proportion of children born to mothers in the poor/poorest wealth ranged from 0 to 1, with a mean of 0.60; see Table 1)

Factors are associated with stunting and overweight/obesity

After fitting multiple models, by adding covariates in a stepwise fashion, we chose the best model based on the lowest WAIC values (refer to Additional file 4: Table S1) and the highest overall CPO values. The CPO values for stunting (0.89) and overweight/obesity (0.92) are close to 1, indicating that our analysis is supported by high predictive accuracy.

The estimates showed that receiving the full course of the DTP vaccine was associated with a reduction in stunting by 0.16 units (β = −0.16; 95% CrI: −0.27, −0.05; see Table 2), holding all other covariates and spatial effects constant. An increase in household size by one person decreased the likelihood of stunting by 0.15 units (β = −0.15; 95% CrI: −0.23, −0.07; see Table 2). This finding is unexpected, as an increase in family size is typically associated with food shortages, which can lead to a higher rate of stunting. However, the relationship may be influenced by local factors such as large families may found in less risky areas. Another possible explanation could be reverse causality: healthier children may grow faster and survive better, contributing to large family sizes.

The presence of appropriate vegetable storage facilities was associated with a decreased in childhood stunting by 0.28 units (β = −0.28; 95% CrI: −0.43, −0.14; see Table 2). Conversely, in areas where there were sufficient cereal storage facilities, the likelihood of stunting increased by 0.30 units (β = 0.30; 95% CrI: 0.16, 0.44; see Table 2). This is also an unexpected result. In areas with cereal storage sites, there is high chance of high cereal production. However, many cultural and socioeconomic factors such as depending highly on a single staple food may contribute to this counterintuitive finding. Overweight/obesity was negatively associated with travel time to city, with a minute increase in travel time to city decreased overweight/obesity by 0.57 units (β = −0.57; 95% CrI: −1.12, −0.05; see Table 2).

Factors associated with micronutrient deficiencies

We initially tested similar sets of variables for each type of micronutrient deficiency and selected the best-fitting model (i.e., model with the largest CPO and lowest WAIC values). The differences in the set of covariates for each micronutrient deficiency stem from the CPO and WAIC values. The level of soil nitrogen, travel time to the nearest city in minutes, and high temperature in °C were significantly associated with iron deficiency. A one-unit increase in soil nitrogen density (g/kg of soil) was associated with a 0.57-unit decrease in iron deficiency (β = −0.57; 95% CrI: −0.93, −0.23; see Table 3), holding all other covariates and spatial effects constant. A one-minute increase in walking travel time to the nearest city increased the risk of iron deficiency by 0.55 (β = 0.55; 95% CrI: 0.02, 1.09; see Table 3). Similarly, a one-unit increased in temperature in °C corresponds to a 0.43-unit decreased in iron deficiency (β = −0.43; 95% CrI: −0.78, −0.10; see Table 3). Similarly, a one-unit increase in soil nitrogen density (g/kg of soil) was associated with a 0.44-unit decrease in zinc deficiency (β = −0.44; 95%

Table 1 Descriptive statistics

Variables		Mean	SD
Outcome variables at individual level			
Obesity/overweight (no = 0, yes = 1)		0.02	0.08
Variation of obesity/overweight between clusters (no = 0, yes = 1)		0.03	0.06
Stunting (no = 0, yes = 1)		0.38	0.48
Variation of stunting between clusters (no = 0, yes = 1)		0.33	0.20
Iron deficiency (no = 0, yes = 1)		0.30	0.46
Variation of iron deficiency between clusters (no = 0, yes = 1)		0.29	0.32
Vitamin A deficiency (no = 0, yes = 1)		0.14	0.35
Variation of vitamin A deficiency between clusters (no = 0, yes = 1)		0.14	0.23
Zinc deficiency (no = 0, yes = 1)		0.35	0.48
Variation of Zinc deficiency between clusters (no = 0, yes = 1)		0.35	0.32
Obesity/overweight anemia comorbidity (no = 0, yes = 1)		0.01	0.06
Variation of obesity/overweight anemia comorbidity between clusters (no = 0, yes = 1)		0.01	0.03
Stunting- anemia comorbidity (no = 0, yes = 1)		0.13	0.34
Variation of stunting anemia comorbidity between clusters (no = 0, yes = 1)		0.11	0.12
Independent Variables Measured at Pixel Level (1 km × 1 km)			
Annual mean environmental air temperature (°C) (range: 5.22-32)		22.69	4.22
Altitude (range: −117.84-3874.01)		1214.10	674.09
Precipitation (range: 102.01-1990.95)		798.83	449.81
Travel time to city in minutes (range: 0-1408)		245.61	179.28
Annual food expenditure per capita (Ethiopian Birr) (range: 5070.5-42146.3)		18449.02	6268.87
Predicted mean household size in each 1 km^2 (range:2–8)		5.08	1.01
Proportion of women without decision-making power (range: 0.02–0.93)		0.38	0.14
Diphtheria-tetanus-pertussis (DTP) coverage (range: 0.01-1)		0.31	0.23
Measel vaccine coverage (range: 0.001–0.98)		0.26	0.17
Dietary diversity coverage (0-0.65)		0.08	0.1
No antenatal care (range:0–1)		0.63	0.28
No postnatal care (range:0.3-1)		0.95	0.05
Health uninsured rate (range: 0.63-1)		0.98	0.04
Wealth index at pixel level			
	Poor/poorest (range: 0–1)	0.60	0.32
	Medium (range: 0-0.73)	0.14	0.15
	Rich/richest (range: 0–1)	0.26	0.27
Children born from uneducated mothers' proportion (range: 0–1)		0.81	0.17
Population density (people/km2) (range: 1–53,389)		89.37	358.62
Soil nitrogen density (g/kg of soil) (range:445–8332)		1401.58	659.91
Soil bulk density (gram/cm^3) (range: 819.62-1600.89)		1402.12	99.57
Number of vegetable storage sites (range:0–86)		39.21	7.37
Annual milk production (liter/km^2) (range:0–8,175,229)		3580.25	37955.9
Cereal storage sites (range:0–86)		40.6	9

Note: All independent variables are analyzed at a 1 km × 1 km grid level

CrI: −0.67, −0.19; see Table 3). An unexpected result indicated that zinc deficiency was positively correlated with milk production, as areas with higher milk production exhibited a 2.42 unit increase in zinc deficiency (β = 2.42; 95% CrI: 1.05, 3.83; see Table 3). Moreover, in areas with higher DTP coverage, the probability of vitamin A deficiency decreased by 0.22 units (β = −0.22; 95% CrI: −0.42, −0.02; see Table 3).

Factors associated with comorbidity of anemia with overweight/obesity and stunting

Based on our final and best model, several factors were significantly associated with anemia-stunting comorbidity. In areas with high diet diversity, the prevalence of stunting-anemia was reduced by 0.13 units (β = −0.13; 95% CrI: −0.22, −0.05; see Table 4). In areas with higher DTP vaccine coverage, the prevalence of anemia-stunting comorbidity decreased by 0.20 units (β = −0.20; 95% CrI: −0.35, −0.04; see Table 4). Similarly, household size was associated with a reduction in anemia-stunting

Table 2 Socioecological factors linked to stunting and overweight in Ethiopian under-fives

Covariates		Stunting		Overweight/obesity	
		Coefficient (95% CrI)	**SD**	**Coefficient (95% CrI)**	**SD**
Dietary diversity		−0.05 (−0.11, 0.01)	0.03	0.09 (−0.08, 0.27)	0.09
Diphtheria-tetanus-pertussis (DTP)		**−0.16 (−0.27, −0.05)**	0.06		
Measel vaccine		0.08 (−0.12, 0.28)	0.10		
Annual per capita expenditure for food consumption		−0.06 (−0.15, 0.04)	0.05	−0.05(−0.33, 0.22)	0.08
Household size		**−0.15 (−0.23, −0.07)**	0.04	0.15(−0.10, 0.39)	0.12
Decision-making		0.08 (−0.09, 0.24)	0.08	−0.37(−0.81, 0.04)	0.22
Health insurance		−0.03 (−0.11, 0.05)	0.04		
Mother education		0.14 (−0.01, 0.30)	0.08		
Wealth index	Poor/poorest	0.08 (−0.07, 0.23)	0.08		
	Medium	−0.03 (−0.10, 0.04)	0.04		
	Rich/richest	−0.08 (−0.17, 0.01)	0.05		
Population density (people/km2)		−0.01(−0.01, 0.01)	0.01	0.01(−0.01, 0.02)	0.01
Vegetable storage site		**−0.28 (−0.43, −0.14)**	0.08	0.13(−0.19, 0.46)	0.17
Cereal storage site		**0.30 (0.16, 0.44)**	0.07		
Travel time to city in minutes		−0.13 (−0.30, 0.04)	0.09	**−0.57(−1.12, −0.05)**	0.27
Soil nitrogen density (g/kg of soil)		0.02 (−0.09, 0.13)	0.06		
Temperature in °C		−0.04 (−0.19, 0.11)	0.08		
Precipitation		0.23 (−0.01, 0.48)	0.12		
Intercept		**−0.50 (−0.78, −0.23)**	0.14	**−5.04(−5.8, −4.37)**	0.37
Model diagnosis					
Overall Conditional Predictive Ordinates (CPO)		0.89		0.92	

Note: CrI: *Bayesian credible intervals*

comorbidity by 0.14 units (β = −0.14; 95% CrI: −0.26, −0.02; see Table 4). Area with a high proportion of rich or richest household and vegetable storage sites showed a lower prevalence of stunting-anemia comorbidity (β = −0.22; 95% CrI: −0.35, −0.08; see Table 4) and (β = −0.24; 95% CrI: −0.46, −0.02; see Table 4). Temperature in °C was also associated with a reduction in anemia-stunting comorbidity by 0.39 units (β = −0.39; 95% CrI: −0.58, −0.21; see Table 4). However, in areas lacking women's decision-making power, anemia-stunting comorbidity increased by 0.22 units (β = 0.22; 95% CrI: 0.02, 0.40; see Table 4). Similarly, in areas with appropriate cereal storage sites, anemia-stunting comorbidity increased by 0.26 units (β = 0.26; 95% CrI: 0.04, 0.47; see Table 4). Additionally, higher soil bulk density (gram/cm^3) was associated with an increase in anemia-stunting comorbidity by 0.27 units (β = 0.27; 95% CrI: 0.05, 0.50; see Table 4). Travel time to city in minutes was negatively associated with overweight/obesity- anemia comorbidity; each one-minute increase in travel time to city reduced comorbidity by 2.2 times (β = −2.20; 95% CrI: −3.60, −0.87; see Table 4).

Geospatial distribution of malnutrition in Ethiopia

The predicted prevalence of overweight/obesity, stunting, and micronutrient deficiencies among children under five is presented at a resolution of 1 × 1 km, as shown in Additional file 5: Figure S4. The predictive accuracy of the model was assessed using CPO, which ranged from 0.89 to 0.95 for all outcomes. These values, being close to 1, reveal high predictive accuracy. The map reveals significant variations in the geographical distribution of overweight/obesity, stunting, iron deficiency, vitamin A deficiency, and zinc deficiency among children under five in Ethiopia (refer to Additional file 5: Figure S4). There was significant spatial variation in the prevalence of overweight/obesity across Ethiopia, with pixel-level prevalence ranging from zero to 22%. The estimated prevalence of overweight/obesity indicated the highest levels in the central part of Ethiopia, particularly in Addis Ababa and some specific areas of the Oromia region. Similarly, the predicted prevalence of stunting revealed significant disparities across Ethiopia, with pixel-level prevalence ranging from 7.33 to 73.3%. The highest prevalence at the pixel level (73.3%) was observed in large parts of the Amhara region, Afar region, and Benishangul-Gumuz region. Parts of Tigray, Oromia, the Southern Nations, Nationalities, and Peoples' Region (SNNPR), and the Somali region also experienced high prevalence rates of stunting. The lowest prevalence of stunting (7.33%) was observed in the central and eastern parts of Ethiopia. A substantial spatial variation in the predicted prevalence of iron deficiency was noted across Ethiopia, with pixel-level prevalence ranging from 1 to 85%. The Somali region exhibited the highest prevalence. Certain areas within the Gambella region, Benishangul-Gumuz region, and Oromia region also exhibited high pixel-level prevalence of iron deficiency. A similar variation was observed for zinc deficiencies, with notably high

Table 3 Socioecological factors of micronutrient deficiencies in Ethiopian children under five (2016)

Dependent variables	Covariates		Coefficient (95% CrI)	SD
Iron deficiency	Diet diversity		0.17 (−0.02, 0.35)	0.10
	Diphtheria-tetanus-pertussis (DTP)		−0.02 (−0.23, 0.19)	0.17
	Measel vaccine		0.32 (−0.15, 0.80)	0.24
	Annual per capita expenditure for food consumption		−0.06 (−0.26, 0.14)	0.10
	Household size		0.10 (−0.12, 0.33)	0.11
	Postnatal care		−0.02 (−0.24, 0.21)	0.11
	Decision-making		0.28 (−0.13, 0.68)	0.21
	Mother education		0.16 (−0.14, 0.47)	0.15
	Wealth index	Poor/poorest	−0.17 (−0.50, 0.16)	0.17
		Medium	0.05 (−0.19, 0.29)	0.12
		Rich/richest	−0.07 (−0.30, 0.15)	0.12
	Population density (people/km2)		−0.01 (−0.04, 0.02)	0.02
	Travel time to city in minutes		**0.55 (0.02, 1.09)**	0.28
	Vegetable storage site		0.07 (−0.38, 0.53)	0.23
	Soil nitrogen density (g/kg of soil)		**−0.57 (−0.93, −0.23)**	0.18
	Temperature in °C		**−0.43 (−0.78, −0.10)**	0.17
	Intercept		−0.66 (−4.38, 3.24)	1.63
	Model diagnosis			
	Overall Conditional Predictive Ordinates (CPO)		0.89	
Zin Deficiency	Diet diversity		0.08 (−0.08, 0.24)	0.08
	Diphtheria-tetanus-pertussis (DTP)		−0.07 (−0.25, 0.12)	0.10
	Annual per capita expenditure for food consumption		0.07 (−0.10, 0.23)	0.08
	Household size		−0.08 (−0.27, 0.12)	0.10
	Antenatal care		−0.04 (−0.41, 0.35)	0.19
	Mother education		0.12 (−0.15, 0.38)	0.14
	Population density (people/km2)		−0.02 (−0.05, 0.02)	0.02
	Travel time to city in minutes		−0.35 (−0.80, 0.09)	0.23
	Annual milk production (liter/km^2)		**2.42 (1.05, 3.83)**	0.71
	Cereal storage site		−0.11 (−0.42, 0.19)	0.15
	Soil nitrogen density (g/kg of soil)		**−0.44 (−0.67, −0.19)**	0.12
	Intercept		−0.65 (−7.30, 6.15)	4.20
	Model diagnosis			
	Overall Conditional Predictive Ordinates (CPO)		0.91	
Vitamin A deficiency	Diet diversity		−0.09 (−0.29, 0.10)	0.10
	Diphtheria-tetanus-pertussis (DTP)		**−0.22 (−0.42, −0.02)**	0.10
	Annual per capita expenditure for food consumption		0.16 (−0.03, 0.35)	0.10
	Household size		−0.09 (−0.34, 0.15)	0.12
	Travel time to city in minutes		−0.44 (−0.90, 0.03)	0.24
	Intercept		−2.05 (−4.25, 0.16)	1.03
	Model diagnosis			
	Overall Conditional Predictive Ordinates (CPO)		0.93	

Note: *CrI: Bayesian credible intervals*

prevalence in specific locations within the central part of Ethiopia, where pixel-level prevalence reached 100%. The highest level of zinc deficiency was also observed in the Tigray and Afar regions. The lowest prevalence of zinc deficiency was recorded in the western part of the Oromia and Benishangul-Gumuz regions (refer to Additional file 5: Figure S4).

The highest prevalence of vitamin A deficiency was observed in the central parts of Ethiopia, such as the Oromia region, and the northern parts, such as the Afar and somali region, with a pixel-level prevalence of 36%. In contrast, the Benishangul-Gumuz region, the Amhara region, and the Southern Nations, Nationalities, and Peoples' Region experienced the lowest prevalence, with a pixel-level prevalence of 3% (refer to Additional file 5: Figure S4).

Table 4 Socioecological factors linked to comorbidity of anemia with overweight/obesity and stunting in Ethiopian Under-Fives

Dependent variables	Covariates		Coefficient (95% CrI)	SD
Stunting anaemia comorbidity	Dietary diversity		**−0.13 (−0.22, −0.05)**	0.04
	Diphtheria-tetanus-pertussis (DTP)		**−0.20 (−0.35, −0.04)**	0.08
	Annual per capita expenditure for food consumption		0.06 (−0.07, 0.20)	0.07
	Household size		**−0.14 (−0.26, −0.02)**	0.06
	Decision-making		**0.22 (0.02, 0.40)**	0.10
	Mother education		0.02 (−0.18, 0.22)	0.10
	Wealth index	Poor/poorest	0.04 (−0.15, 0.24)	0.20
		Medium	−0.06 (−0.16, 0.04)	0.05
		Rich and above	**−0.22 (−0.35, −0.08)**	0.07
	Population density (people/km2)		−0.01 (−0.01, 0.01)	0.01
	Vegetable storage site		**−0.24 (−0.46, −0.02)**	0.11
	Cereal storage site		**0.26 (0.04, 0.47)**	0.11
	Travel time to city in minutes		−0.17 (−0.42, 0.08)	0.13
	Soil bulk density (gram/cm^3)		**0.27 (0.05, 0.50)**	0.12
	Precipitation		0.02 (−0.25, 0.33)	0.15
	Temperature in °C		**−0.39 (−0.58, −0.21)**	0.10
	Intercept		**−1.98 (−2.23, −1.73)**	0.13
	Model diagnosis			
	Overall Conditional Predictive Ordinates (CPO)		0.93	
Overweight/obesity-anaemia comorbidity	Dietary diversity		−0.14 (−0.48, 0.21)	0.18
	Diphtheria-tetanus-pertussis (DTP)		−0.37 (−0.96, 0.18)	0.29
	Decision-making		0.15 (−0.69, 0.92)	0.41
	Population density (people/km2)		0.01 (−0.02, 0.03)	0.01
	Travel time to city in minutes		**−2.2 (−3.60, −0.87)**	0.70
	Intercept		**−8.11 (−9.87, −6.47)**	0.70
	Model diagnosis			
	Overall Conditional Predictive Ordinates (CPO)		0.95	

Note: CrIs: Bayesian credible intervals

Geospatial distribution of malnutrition by zones (third-level administrative units)

There is substantial variation in the prevalence of malnutrition across regional zones in Ethiopia. The highest prevalence of overweight/obesity among children under five (6%) was observed in Harari. A moderate level of overweight and obesity (4%) was recorded in Addis Ababa. In contrast, the lowest zonal prevalence of overweight/obesity (2%) was observed in the Amhara, Afar, Tigray, Benishangul-Gumuz, Gambella, and Somali regions. Zones in the Amhara, and the South West Ethiopia region reported the highest prevalence of stunting, reaching 50%. Conversely, the central parts of Ethiopia, including Addis Ababa, as well as the Somali region, certain zones in southern Ethiopia, and the eastern parts of the country, exhibited the lowest levels of stunting prevalence, around 2%; refer to Fig. 2).

Zones in the Somali and Gambella regions exhibited a substantially higher prevalence of iron deficiency, estimated at 50%. In contrast, zones in the Amhara, Afar, and Tigray regions reported the lowest levels of iron deficiency, with a zonal prevalence of 2%. Harari region had the highest prevalence of vitamin A deficiency, at 20%. Conversely, some zones in the Amhara, Tigray, and Benishangul-Gumuz regions recorded the lowest levels of vitamin A deficiency, with a prevalence of 10%. Zones in the southern parts of Ethiopia, such as Wolayita and Kembata Tembaro, as well as the northwestern areas of the Tigray region, showed the highest levels of zinc deficiency, estimated at 50%. Meanwhile, a certain zones in the South west Region and Sidama region, recorded the lowest zinc deficiency prevalence, at 2% (see Fig. 2).

Double burden of malnutrition

Geographical co-distribution of overweight/obesity, stunting and anemia

We found spatial variation in the prevalence of comorbidity of anemia with overweight/obesity and stunting at 1 km-by-1 km pixel level. There is a high predicted prevalence of anemia and overweight/obesity comorbidity at the pixel level (21.6%) in some areas of the Oromia regions. The Afar, Somali regions and southern part of Oromia region exhibited the highest levels of anemia and stunting comorbidity at the pixel level, with a prevalence of 50% (refer to Additional file 6: Figure S5).

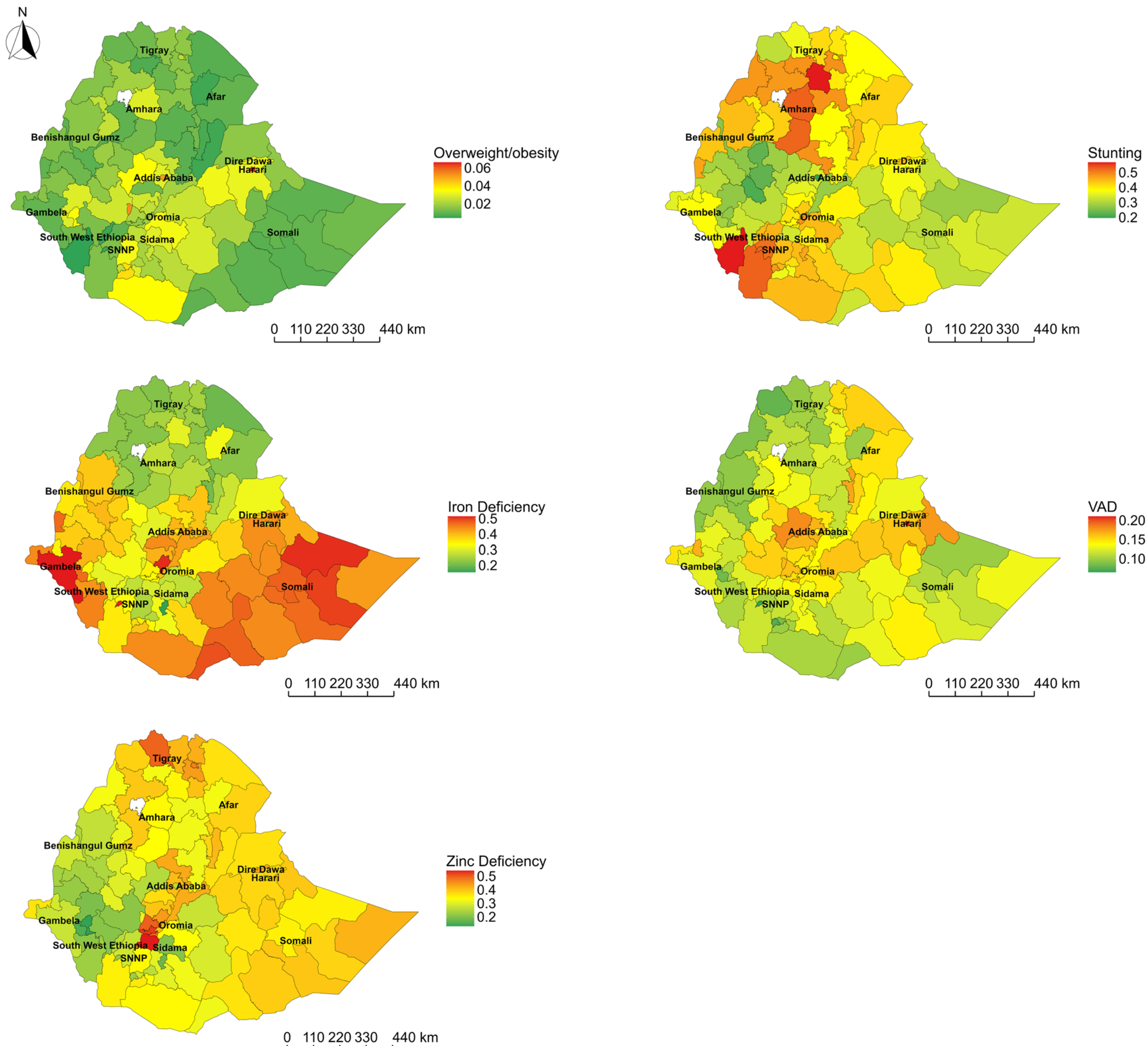

Fig. 2 Zonal prevalence estimates of malnutrition in Ethiopia

Zonal co-distribution of overweight/obesity, stunting, and anemia

We observed spatial variation in the prevalence of anemia comorbid with overweight/obesity and stunting at the zonal level. Addis Ababa exhibited the highest prevalence of overweight/obesity and stunting comorbidity at 2%. The Liban zones in the Somali region and borena zones in Oromia region recorded the highest prevalence of anemia and stunting comorbidity, reaching 20%. Zones within the Amhara, Tigray, Oromia, and SNNPR regions showed the lowest prevalence of anemia and stunting comorbidity, at 5% (see Fig. 3).

Geographical overlapping of overweight/obesity with stunting and micronutrient deficiencies

There is a significant overlap in the predicted prevalence of stunting and obesity in Oromia, and parts of the SNNPR, as well as in the northern part of the country, including the Amhara and Tigray regions. The overlapping of overweight/obesity and iron deficiency is also highest in the central part of Ethiopia, and in the southern areas such as the Borena zone in the Oromia region. A notable overlap between overweight/obesity and vitamin A deficiency has been observed in the central part of Ethiopia, particularly in the Oromia, SNNR and Somali regions. Additionally, the Amhara, Tigray, Oromia, SNNPR and Somali regions exhibit a significant overlap in the predicted prevalence of overweight/obesity and zinc deficiency (see Fig. 4).

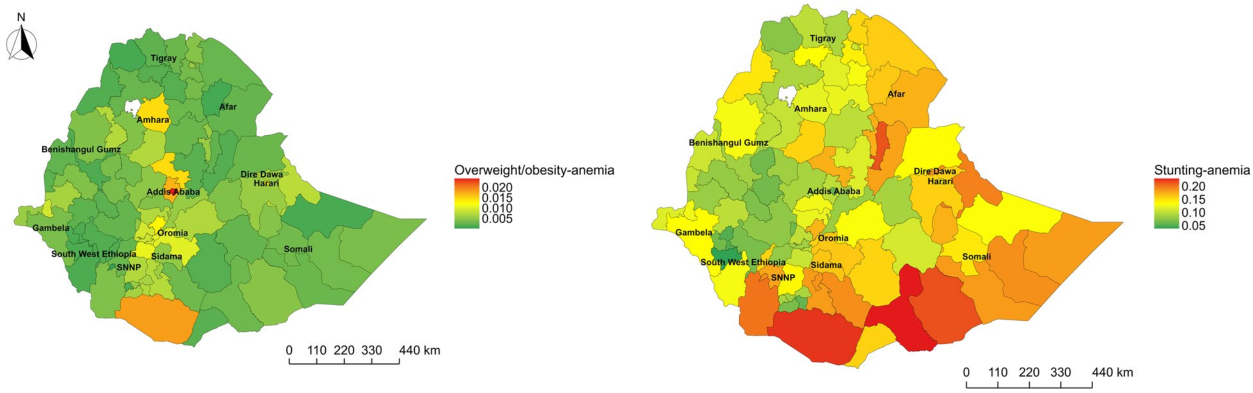

Fig. 3 Zonal prevalence of anemia comorbid with stunting and overweight/obesity in Ethiopia

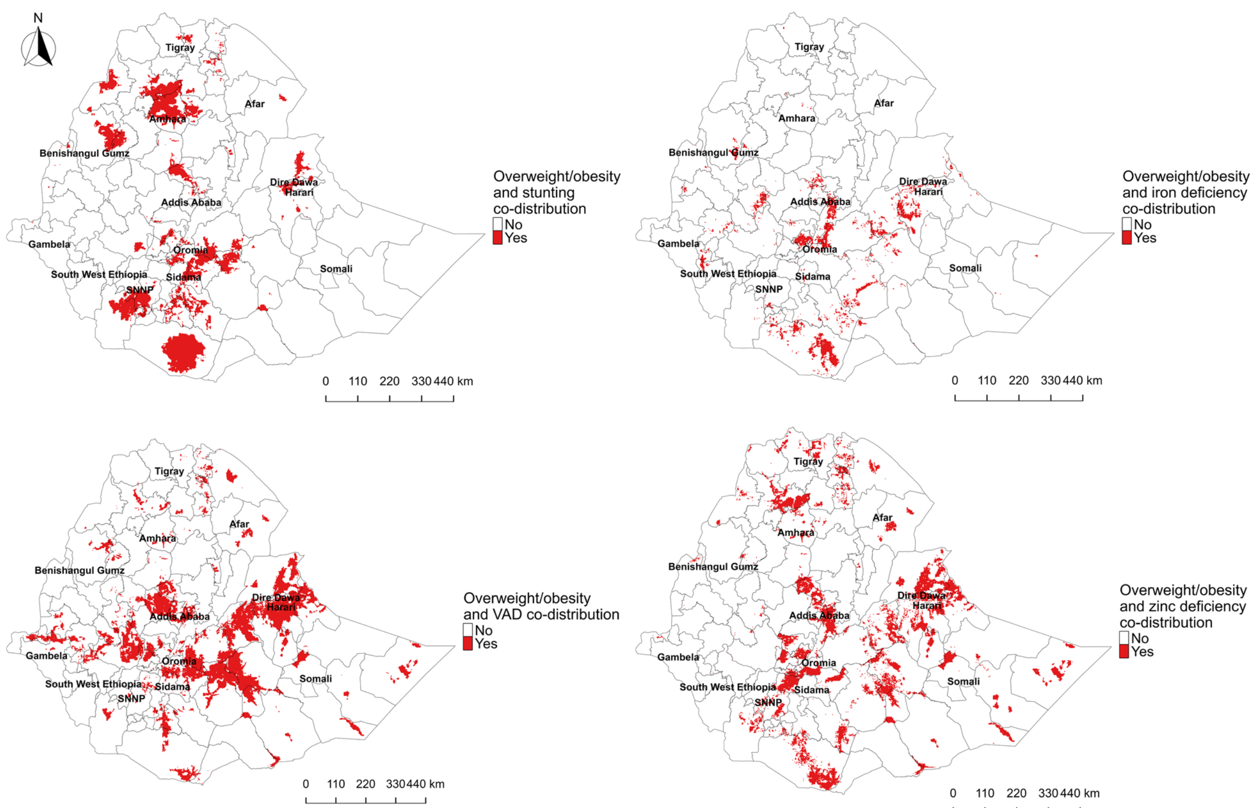

Fig. 4 Predicted geospatial overlaps of overweight/obesity with stunting and micronutrient deficiencies

Geographical overlapping of stunting and micronutrient deficiencies

We also identified a significant geographical overlap between the predicted prevalence of stunting and micronutrient deficiencies. Specifically, there is an overlap between iron deficiency and stunting in the Benishangul-Gumuz, Southwest Ethiopia, Oromia, SNNPR, and Somali regions. The burden of both stunting and vitamin A deficiency was high in the Afar and some part of Oromia and Somali regions. Furthermore, substantial overlap between the predicted prevalence of stunting and zinc deficiency was found in the Tigray, Amhara and Afar regions. Some part of the SNNPR, Oromia, and Somali regions also had both stunting and zinc deficiency (see Fig. 5).

Triple burden of malnutrition

Geographical overlapping of overweight/obesity with stunting and micronutrient deficiencies

Our predicted map reveals that certain areas in the southern part of Ethiopia, such as the Oromia region, experienced the triple burden of malnutrition, characterized by the overlapping of overweight/obesity, stunting, and iron deficiency. Similarly, parts of central and eastern

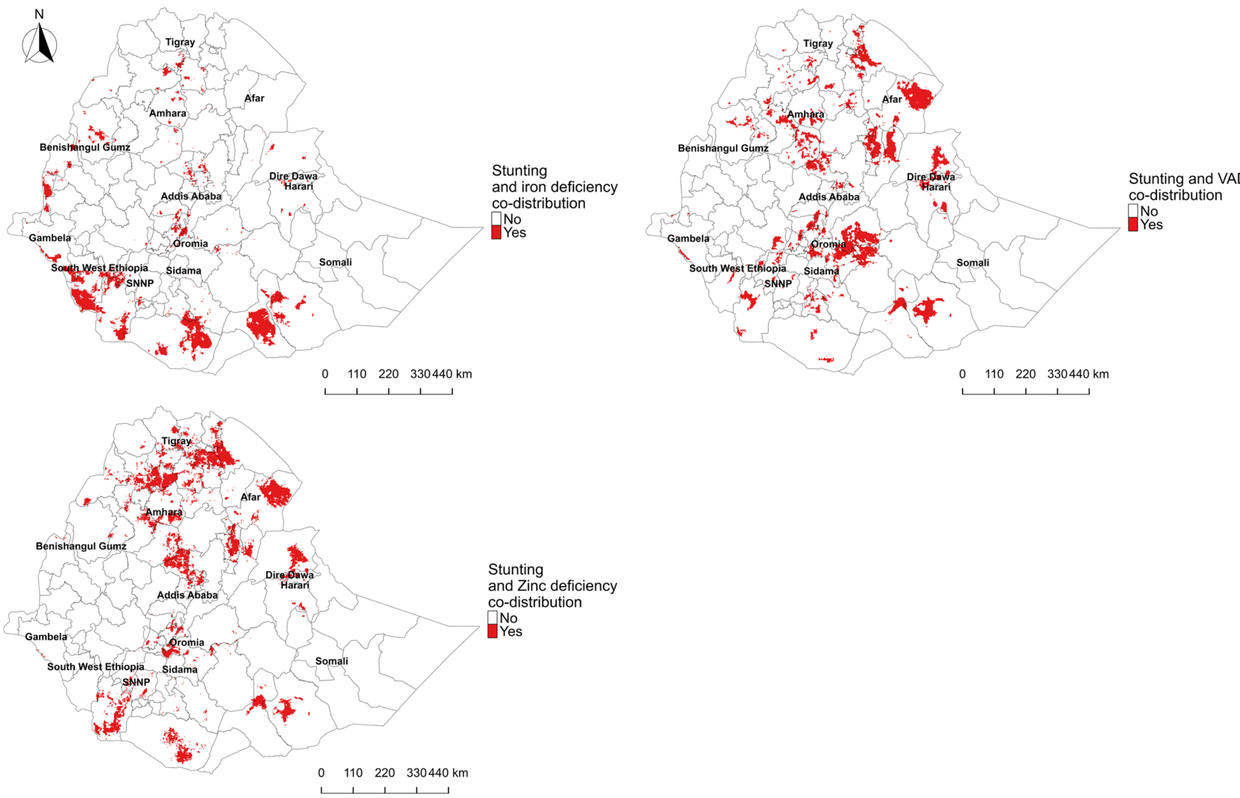

Fig. 5 Predicted geospatial overlap of stunting and micronutrient deficiencies

Ethiopia such as Harari and some areas in the Amhara region show overlapping occurrences of overweight/obesity, stunting, and VAD. The Amhara and Afar regions also exhibit significant zones with the triple burden, where overweight/obesity, stunting, and zinc deficiency coincide geographically. Furthermore, smaller areas within the Somali region and the SNNPR experience overlapping prevalence of overweight/obesity, stunting, and zinc deficiency (see Fig. 6).

Discussions

This analysis examines Ethiopia's nutrition challenge, focusing on the double and triple burden of childhood malnutrition while considering socioeconomic, climatic, and environmental factors using Bayesian inference. Data collection in resource-limited countries like Ethiopia is challenging due to constraints and irregular sampling, complicating conventional analysis. Bayesian inference provides a smoothing solution to address these complexities effectively [71]. The high CPO values (all above 0.89) confirm the strong predictive performance of our models [64]. There is a significant geographical distribution of double and triple burden of malnutrition across Ethiopia, with environmental factors and health service-related variables playing a crucial role.

Anemia-stunting comorbidity is highest in Ethiopia's Somali regions and some part of Oromia region such as borena zone. The Afar region also faces high stunting with vitamin A and zinc deficiency, while the Somali region has highest stunting-iron deficiency comorbidity. A high proportion of people in these areas depend on pastoral activities. Communities engaged in pastoral based economy often rely on monotonous diets, typically sourced through imports from other areas or sometimes through aids [72, 73]. Heavy dependence on camel milk further increases the risk [74], as milk consumption has been linked to iron deficiency anemia [75]. Additionally, both regions have very low immunization coverage [76], increasing the risk of child diarrheal diseases, a major contributor to malnutrition in developing countries. Frequent droughts further worsen nutritional challenges [77]. Addressing micronutrient deficiencies and stunting requires integrated policies, combining environmental management with nutritional programs.

The Oromia region shows a significant overlap in obesity/overweight with stunting, iron deficiency, and vitamin A deficiency, a pattern also observed in parts of West and Central Africa [78]. Southern Oromia faces the double and triple burden of malnutrition, where overweight/obesity, stunting, anemia and iron deficiency coexist. This dual challenge of overnutrition and undernutrition may be driven by urbanization and demographic shifts that impact food availability and dietary habits. For instance, the overlap of overweight/obesity with vitamin

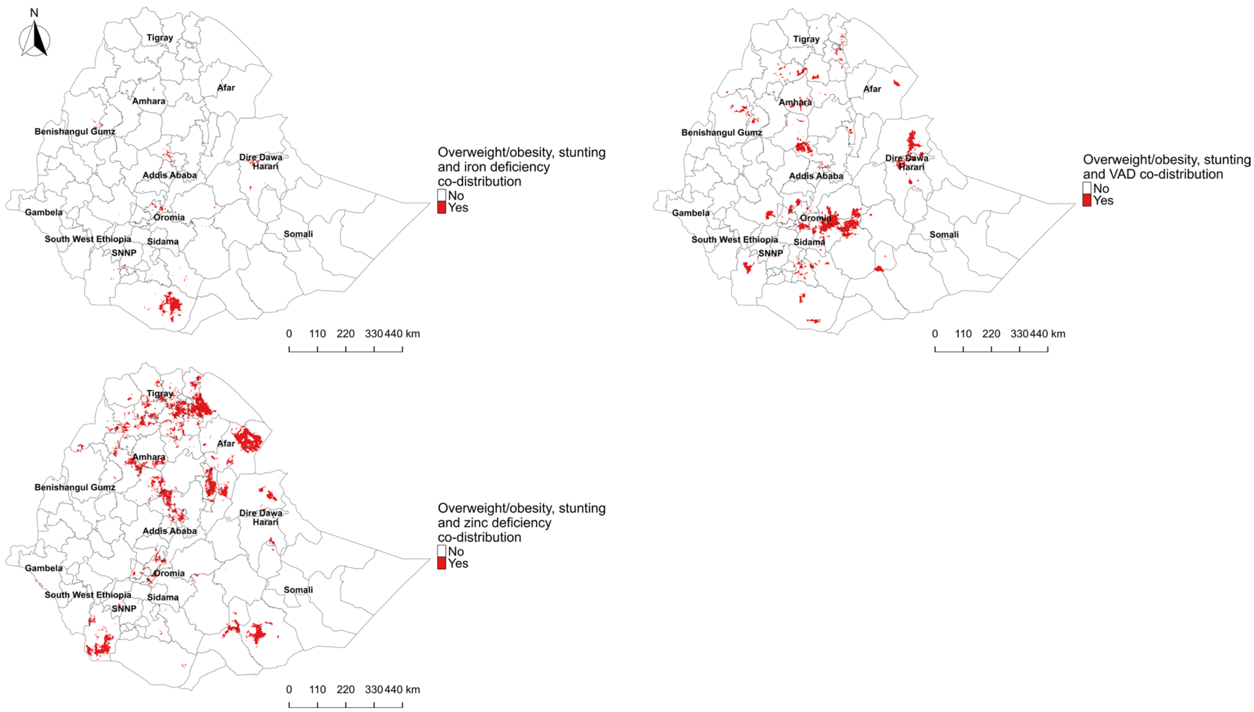

Fig. 6 Predicted geospatial overlap of overweight/obesity, stunting, and micronutrient deficiencies

A deficiency is concentrated around the capital city and the Rift Valley Basin, areas experiencing rapid urbanization growth [79]. Similarly, parts of central Ethiopia, known for its urbanization [80], exhibit an overlap of overweight/obesity, stunting, and vitamin A deficiency. Additionally, Ethiopia's drought patterns, particularly in the eastern, southeastern, and Rift Valley regions, have fluctuated over the past fifty years [81]. Severe droughts, such as the 2015-16 El Niño event [81], might trigger food insecurity and nutrient depletion, pushing communities toward low-cost, high-calorie diets that contribute to overweight/obesity and anemia at the same time. Addressing this crisis requires integrating child nutrition programs into a strategic framework, particularly in disaster-prone and rapidly urbanizing areas.

The Amhara and Afar regions also showed a significant area with the triple burden, where overweight/obesity, stunting, and zinc deficiency geographically overlapped. This may be attributed to significant clusters of inadequate dietary diversity (hotspots) observed in districts of northern Ethiopia, particularly in the Amhara, and Afar regions [82]. Consuming a monotonous diet high in carbohydrates but lacking nutrient diversity and essential micronutrients can result in reliance on a single type of food. Limited intake of these energy-dense foods may contribute to stunting, while excessive consumption can lead to overweight/obesity in children. The high prevalence of stunting in these areas may also increase the risk of nutritional imbalances, including zinc deficiency. A previous study established a link between stunting and zinc deficiency, showing that zinc supplementation can promote linear growth in stunted children [83]. Another experimental study on mice revealed that zinc deficiency was associated with metabolic disturbances, such as increased leptin production in obese mice. This suggests that zinc deficiency could contribute to metabolic imbalances, potentially leading to being overweight/obesity. Implementing zinc supplementation may help alleviate zinc deficiency, reduce its associated burdens, and support growth recovery in stunted children, as demonstrated in previous research [84].

Our Bayesian geostatistical analysis shows that in areas with higher temperature, the prevalence of iron deficiency, anemia-stunting comorbidity is lower. In addition, in areas with a high density of soil nitrogen, there is a lower prevalence of iron and zinc deficiencies. Soil nitrogen and temperature are likely linked to agricultural productivity, either independently or through their interaction. Higher environmental air temperature enhances microbial activity and accelerates the turnover of soil nitrogen, making it more available to plants. This increased nitrogen availability can boost crop production and improve food supply [85]. In Ethiopia, tropical regions and areas with moderate temperature are the most suitable for crop production [86], which can reduce nutritional deficiencies. This suggests that maintaining an appropriate environment for agricultural production and soil management, such as utilising nitrogen-based fertilisers, may effectively mitigate micronutrient deficits and anemia-related stunting comorbidities.

Higher soil bulk density is linked to increased stunting and anemia comorbidity. High soil density restricts root growth, nutrient uptake, and water availability, which negatively influences crop productivity [87]. Crops and other edible fruits grown in compacted soils often exhibit reduced nutritional quality, impacting the overall nutritional value of plant-based food sources [88]. This can disrupt child feeding systems, highlighting the need for sustainable soil management. Additionally, low decision-making power among women is associated with higher prevalence of stunting-anemia comorbidity. Evidence from over 30 African countries shows that child nutrition improves with increased women's empowerment [89]. This improvement may result from factors such as maternal education and socioeconomic status, which significantly affect a child's nutritional well-being. These findings stress the importance of empowering women as a critical strategy in combating malnutrition.

In this analysis, longer travel time to cities appear to reduce overweight/obesity and its comorbidity with anaemia. This may be attributed to environmental factors, such as dietary patterns; in more remote areas, access to processed food and other energy-dense foods mya be limited [90]. Our spatial prediction also shows that overweight/obesity is more concentrated in urban areas, particularly around cities like Harari and Addiss Abeba, while rural areas exhibited lower level of overweight/obesity. The low level of overweight/obesity in rural areas could explain low level of overweight/obesity-anemia comorbidity in rural areas. This may be due to limited access to diverse diets or other socioeconomic factors, highlighting the need for a multisectoral approach to raise awareness and promote balanced nutrition in the city to reduced overweight and obesity.

The presence of appropriate vegetable storage facilities helps reduce stunting. The FAO prioritizes storage site locations based on vegetable production, market access, population density, and infrastructure [50–52]. In this analysis, regions with higher vegetable and fruit production, like the south [91], have lower stunting rates. This suggests that areas near vegetable storage sites likely have higher production and accessibility to vegetables, which are probably a staple in the local diet. Consuming vegetables and fruits can help reduce stunting. On the other hand, the presence of appropriate cereal storage sites is linked to stunting and its co-occurrence with anemia. This is also reflected in our prediction map, where cereal-dominant regions [92], such as Amhara region exhibit high levels of stunting in the country. People living in areas reliant on cereal production may depend on low-cost, monotonous cereal-based diets. Even if individuals wish to consume vegetables, limited market availability, lack of vegetable storage facilities, and inadequate infrastructure for transporting fruits may make access difficult.

On the other hand, in areas with high milk production, zinc deficiencies tend to increase. However, milk production and consumption do not inherently cause zinc deficiency. Instead, dietary practices and various environmental factors within these communities may contribute to this phenomenon. Given that our research is conducted at the population or geographical level, the presence of milk production does not ensure that the population residing in areas with high milk production will necessarily consume milk. They may utilise it for sale and employ it as an economic resource rather than for consumption, necessitating further investigation to evaluate their consumption patterns and truly signal the necessity for additional exploration. Another possibility may be that in areas with substantial milk production; individuals can depend significantly on milk as their primary daily food source. Previous study suggests that in pastoralist communities with high milk production, meals mostly consist of milk [93], which may be deficient in important micronutrients such as zinc.

Completing the full Diphtheria-Tetanus-Pertussis (DTP) vaccination is linked to lower rates of stunting, overweight/obesity-anemia comorbidity, stunting-anemia comorbidity, and vitamin A deficiency. In developing countries, respiratory diseases and other infections are leading to risk factors for malnutrition [94]. Diseases like diphtheria can also cause diarrhea, leading to severe nutrient loss and malnutrition [95]. Vaccines like DTP are effective in boosting children's immunity, helping to prevent other infectious diseases and thereby reducing the risk of malnutrition. Dietary diversity was also linked to low level of stunting-anemia comorbidity. Dietary diversity indirectly reflects the consumption of a variety of foods rich in both micro and macronutrients. Practicing good dietary diversity may play a significant role in reducing anemia and anemia-stunting comorbidity. These findings highlight the importance and potential benefits of expanding vaccination programs and improving dietary diversity for children as a strategy to reduce malnutrition.

There is a negative association between household size and stunting and its comorbidity with anaemia. Previous study indicate that an increase in household size without a corresponding increase in income creates challenges in affording essential goods and food items, which can lead to malnutrition [96]. Although the scenario may seem paradoxical, the validity of our finding aligns with our spatial analysis. The 2016 area database [97] estimation shows that Somali and Oromia, with the highest household sizes, have low stunting levels, whereas Amhara, with smaller household size, has high stunting rates. The negative association between stunting-anemia comorbidity and household size may be explained by the lower prevalence of stunting in regions with larger household sizes, such as Somali and Oromia region. Another explanation is that, since a significant portion of Ethiopia's population depends on agriculture, having more children could be a source of Labor. For instance, we performed a basic correlation analysis to look at the relationship between Ethiopian household size and agricultural land coverage using data from the Ethiopian Socioeconomic Survey (ESS) [53]. The results showed a positive correlation between higher agricultural coverage per km^2 and household size ($r=0.10$, $p<0.001$). Households may have better access to food in areas with high agricultural coverage, which could lower the risk of stunting. Furthermore, reverse causality may also be a factor: children experiencing stunting may have a higher mortality rate, while healthier children are likely to survive better, resulting in larger families.

In summary, Ethiopia is experiencing a double and triple burden of malnutrition, and environmental factors such as temperature, soil nitrogen, soil bulk, cereal and vegetable storage cities, diet diversity, Diphtheria-Tetanus-Pertussis (DTP) vaccination, women's decision power, and wealth index all play a significant role in the spatial variation of different types of malnutrition. Ethiopian dietary policies and initiatives, such as the Strategic Objectives of the Seqota Declaration, focus on education, women's empowerment, water, sanitation, and hygiene (WASH), while promoting multisectoral collaboration, with varying emphasis across regions. These initiatives include agriculture, food security, and maternal and child health services in regions such as Amhara, Afar, and Oromia, while also integrating environmental factors in pastoralist and drought-affected areas like Afar and Somali [98]. However, do not explicitly consider environmental factors such as climate and soil characteristics, including soil nitrogen and soil density. As we enter phase two of the Seqota Declaration, our study underscores a critical finding: incorporating soil-related contextual factors may substantially mitigate malnutrition. In addition to the WASH program, our study emphasizes the critical role of specific immunizations, such as DTP, which has now been updated to the pentavalent vaccine, in addressing malnutrition. This should be emphasized by the Seqota Declaration and other initiatives as integral to the ongoing expansion of health services. Finally, by providing detailed spatial predictions of malnutrition patterns at a granular resolution (one km^2), our study highlights specific hotspots for each type of malnutrition. Nutritional initiatives must prioritize mitigating double and triple burden in Oromia region, stunting in the Amhara region, zinc deficiency in Tigray, anemia and iron deficiency in the Somali region, and obesity in Harar and Addis Ababa.

Strengths and limitations

Our advanced Bayesian geospatial model used to estimate the double and triple burden of malnutrition among children in Ethiopia at both local and zonal levels, mitigates some of the limitation of this analysis, though not fully eliminate them. For confidentiality reasons, the DHS Global Positioning System (GPS) coordinates were displaced by up to 2 km for urban clusters and up to 5 km for rural clusters. Bayesian spatial models try to mitigate this limitation using a spatial smoothing technique to borrow strength from nearby areas, allowing our model to utilise data from the true surrounding area to predict the prevalence of each type of malnutrition [30]. Additionally, since we lack longitudinal data, we were unable to analyze the trends and transitions of the double and triple burden of malnutrition over time.

Conclusion

This study is the first in Ethiopia to use an advanced geospatial model to estimate the association between socio-ecological factors and the double and triple burden of malnutrition among children under five. The highest levels of anemia and overweight/obesity comorbidity were observed Addis Ababa. Additionally, a significant overlap in the predicted prevalence of stunting and overweight/obesity was identified in the Amhara, Oromia region and SNNPR. The co-occurrence of overweight/obesity and iron deficiency is most prominent in central Ethiopia, and in southern areas such as the Borena Zone of the Oromia region. Similarly, a notable overlap between overweight/obesity and vitamin A deficiency is evident in central Ethiopia, along the Rift Valley Basin. Furthermore, the Amhara, Tigray, Oromia, SNNPR and Somali regions exhibit a significant overlap in the predicted prevalence of overweight/obesity and zinc deficiency. Our predicted map highlights that areas in Southern Oromia face a triple burden of malnutrition, with overlapping cases of overweight/obesity, stunting, and iron deficiency. Likewise, parts of central Ethiopia and some areas in the Amhara region exhibit overlapping instances of overweight/obesity, stunting, and VAD. Amhara, afar and Tigray region had also significant overlapping of overweight/obesity, stunting, and zinc deficiency. Our Bayesian geostatistical analysis revealed that completing a full round of DTP vaccination was associated with a lower prevalence of stunting, stunting-anemia comorbidity, and vitamin A deficiencies. Soil bulk density was linked to stunting-anemia comorbidity, while vegetable storage sites were associated with reductions in stunting prevalence. Additionally, factors such travel time to cities in minutes correlated with overweight/obesity and its comorbidity with anemia. Areas with high soil nitrogen density exhibited lower levels of iron and zinc deficiencies, whereas regions with higher levels of milk production showed increased zinc deficiency.

These findings highlight the need for geographically targeted, integrated services that address both undernutrition and overnutrition while considering key socioeconomic and environmental factors. Previous policies in Ethiopia primarily focused on individual forms of malnutrition, primarily focused on stunting with interventions implemented at the individual level. However, a more comprehensive approach is required to address overweight/obesity, stunting, and hidden hunger (micronutrient deficiency), which includes environmental interventions such as soil management and policies that promote the production of diverse, nutrient-rich foods like fruits, vegetables, and legumes, beyond staple cereals. Additionally, improving food distribution networks, enhancing storage facilities, and implementing social interventions, such as empowering women, may be more effective in addressing the root causes of the double and triple burden of malnutrition. Finally, more study should be done to find out why some children are overweight or obese and others are still stunted in the same population. It might be useful to explore what social, economic, and behavioral factors could be causing this difference through individual based study.

Abbreviations

CPO	The conditional predictive ordinates
DTP	Diphtheria-Tetanus-Pertussis
EDHS	Ethiopian Demographic and Health Survey
INLA	Integrated Nested Laplace Approximation
Km	kilometre
MBG	Bayesian model-based geostatistics
SNNPR	Southern Nations, Nationalities, and Peoples' Region
VAD	vitamin A deficiency
WAIC	Watanabe-Akaike Information Criterion

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

Supplementary Material 3.

Supplementary Material 4.

Supplementary Material 5.

Supplementary Material 6.

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Authors' contributions

GD: Conceptualization, Methodology, Literature review, Formal analysis, Data interpretation, Writing– original draft, Writing– review & editing.JL: Conceptualization, Methodology, Supervision, Data interpretation, Writing– review & editing.SN: Conceptualization, Methodology, Supervision, Data interpretation, Writing– review & editing.TD: Conceptualization, Methodology, Supervision, Data interpretation, Writing– review & editing.All authors read and approved the final manuscript.

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Data availability

All data would be available upon request to data owners (Ethiopian public health institute, DHS and all other data sources). We do not have the right to share data.

Declarations

Ethics approval and consent to participate

This study received ethical approval from the Australian National University (Protocol 2023/211). Data were obtained from the Ethiopian Public Health Institute, DHS, and other publicly available sources, where consent to participate was not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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