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Science & Technology in childhood Obesity Policy

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PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
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1 Introduction

Examining countries' progress in fulfilling their malnutrition targets using national surveys is of great interest in global health analyses. The United Nations' second Sustainable Development Goal aims to achieve a reduction in stunting and wasting, as well as no increases in overweight for children under five years of age. Malnutrition, poverty, and disease are often interlinked in a vicious cycle. Monitoring and assessing progress towards these targets for children under the age of five is therefore an important task.

Tracking the changes in stunting and overweight prevalence however is often complicated by infrequent health and nutrition surveys in many countries. This makes tracking country-level estimates throughout the years more difficult, given the expected non-linear patterns of these estimates. Flexible statistical modelling is therefore an important technique used to accommodate data sparsity; modelling can provide smoothed trends by borrowing information from data-rich countries and periods. The UNICEF-WHO-WB Joint Child Malnutrition Estimates (JME) group will release country-level model-based estimates for stunting and overweight for the first time in March 2021. The exercise included data from 157 countries around the world. For some countries an age adjustment was applied based on the age-related proportions from other countries in their region. Age adjustments are applied before data are included in the global modelling exercise. For the WHO European region, the coverage is low, with existing data for those indicators covering age interval 0 to 59 months only available for 27 countries out of the 53 countries in the region. The main source of anthropometric data for children under 5 years of age are home-based surveys; countries in the European region rely mostly on nursery/pre-school data collection for children under 5 years of age. This results in several of the available datasets covering only a small part of the indicators full age range and thus most are not included in the JME global exercise despite the fact that they are nationally representative and with no major data quality concerns. Given increasing concerns and the current data gaps of the child overweight in this region, utilising all the available data are a high priority. The WHO European region has strengthened their surveillance and monitoring of child obesity with the implementation of the WHO European Childhood Obesity Surveillance Initiative (COSI) since its launch in 2007, covering age group 6 to 9 years. Moving forward, the plan is to extend the initiative to cover under 5 years of age, nevertheless the need to assess historical data aimed at monitoring of nutrition targets and for informing actions and policies on child malnutrition remains of critical importance.

This report provides a summary of our assessment for existing child malnutrition data in the WHO European region. We conducted a modelling exercise using various data sources such as surveys or studies considered nationally representative and of adequate quality to illustrate the usefulness of modelled estimates in filling in data gaps. As for the global modelling performed by the JME group, this exercise will be done only for stunting and overweight.

One implementation of this modelling exercise, which this report focuses on, is in modelling the changes in stunting and overweight prevalence for children under five years (i.e., children in the 0-59 months age interval). In addition to the fact that several of the data sources do not cover the complete 0-59 months interval, other challenges with this exercise include: sparse data arising from sporadic administration of national surveys, inconsistent measurements taken from year to year, and lack of methodology standardisation between different data sources. Available data from the database were re-analysed before included in the model to harmonize the methodology in calculating prevalence estimates across data sources.

A heteroscedastic penalised longitudinal model was used to estimate the yearly prevalence for children aged 0-59 months. The methods are applied to stunting and overweight separately and result in confidence and prediction intervals using asymptotic techniques, which incorporate data from multiple sources with varying age group intervals. Partial age intervals are used to predict the estimates where complete age intervals are missing. Adjustment for the countries' income group (based on the World Bank Income Classification over the last 10 years) was used as an additional covariate in the model. Lastly, a pilot model including a sex factor, in addition to age and income adjustments, is used to derive estimates stratified by sex.

The estimates are based on available data on childhood stunting and overweight for countries in Europe between 1990 to 2020. Validation was conducted to check model efficiency, especially for determining the efficiency of partitioning the age group intervals in the overweight model. Bootstrapped simulations were used to measure the models' power. Finally, estimates from this regional exercise were compared to those obtained from the global model for these countries to assess whether the regional-model approach can benefit of using more sub-age group data.

This exercise builds heavily on the technique developed by McLain et al. (2016) (McLain et al. 2019) and more recently, updates for the JME 2021 edition of penalized longitudinal models with multi-source summary measures, and implementation is conducted using the statistical software R (R Core Team 2013).

2 Data

This analysis used data on the prevalence of stunting and overweight in the WHO European region available between 1990 and 2020. Stunting is defined as the height-for-age of a child aged less than five years old being less than two standard deviations (SD), whilst overweight is defined as the child's weight-for-height being greater than two SDs, from the WHO Child Growth Standards median. In this section we will discuss the process used in constructing the dataset for this modelling exercise and preliminary data analysis.

2.1 Database management

We obtained malnutrition prevalence estimates from different data sources with varying quality. The dataset used for this exercise is the October 2020 WHO-EURO database, which consists of national and sub-national data compiled from various sources included in the JME Database and in the WHO Global Database on Child Growth and Malnutrition (for studies not included in the JME database).

The database consists mostly of population-based surveys such as the Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS). These surveys cover the whole 0-59 months age interval and have standardised estimates based on the WHO Child Growth Standards (WHO Multicentre Growth Reference Study Group 2006). Other sources include administrative data from national nutritional surveillance programs and independent research data. In collaboration with the WHO EURO office, these sources were gathered, and the available data were re-analysed to align with the indicator definition (e.g., based on the WHO Child Growth Standards). In this section, we discuss the process used in compiling the database.

2.1.1 Data collection

Effective data collection was done through a collaborative effort between the WHO EURO office and Headquarters. There were two rounds in the data collection process: the first involved a literature search, where raw data was requested to surveys and authors of peer-reviewed publications.

For the literature search round of data collection, scientific databases were searched to identify prevalence of overweight and obesity. These included Scopus, Web of Science and Pubmed, where a combination of keywords including "prevalence", "incidence", "overweight", "obesity", "body mass index", "child" and "infant" were employed. Moreover, to supplement the literature search, the snowball technique was applied, particularly through a paper published in 2017 by colleagues from the Regional Office for Europe (Jones et al, 2017).

The following were defined as inclusion and exclusion criteria;

Inclusion criteria

- Studies with measured data on height, weight, waist circumference, or hip circumference;

- Studies where participants were 5 years of age and younger;
- Data from population samples at the national, sub-national (i.e., covering one or more sub-national regions, more than three urban communities or more than five rural communities), or community level.

Exclusion criteria

- Studies with self-reported weight and height;
- Studies that had included or excluded people based on their health status or cardiovascular risk;
- Studies whose participants were only ethnic minorities;
- Studies on specific educational, occupational, or socioeconomic subgroups;

The second round was conducted after data analysis and quality assessment of surveys from the first round (refer to the subsequent section 'Data analyses') as well as consulting with the EURO office and country representatives. In the second round, country representatives provided information on the representativeness of data and new data sources. A new search was also done to look for new sources. In both rounds, the following standard variables were requested: date of birth, date of visit, sex, weight, length/height, and measurement position.

2.1.2 Data analyses

The raw data was cleaned and subsequently analysed using the WHO Anthro Survey Analyser which provides prevalence estimates across the main anthropometric indices (weight-for-height, weight-for-age, height-for-age and BMI-for-age) for the full distribution cut-offs (-3SD, -2SD, -1SD, +1SD, +2SD, +3SD). Prevalence estimates, their standard errors, and 95% confidence intervals were calculated for the main malnutrition indicators such as stunting and overweight based on the standard approach using the WHO Child Growth Standards recommended by the Working Group on Anthropometric Data Quality of the WHO-UNICEF Technical Expert Advisory Group on Nutrition Monitoring (World Health Organization and the United Nations Children's Fund (UNICEF) 2019). Details for using the WHO Anthro Survey Analyser can be found in its Quick Guide (World Health Organization 2019).

2.1.3 Data quality

After the analysis of each country's dataset using the WHO Anthro Survey Analyser, data quality characteristics were assessed to determine whether there were any issues that might led to biased estimates which could have an impact on interpretability or limit the potential use of findings. The characteristics assessed were those used for the JME review process:

- Sampling methodology: Information of sampling design, target population, coverage and methods for recruitment were assessed (avoiding selection bias). The study population had to be representative at the national level, or if regional, had to be considered homogenous to their national population demographics.
- Completeness of the data assessed by percentage of missing values. Overall, the countries analyzed did not have a high percentage of missing values.

- Sex ratio by sample size distribution and stratifying by age groups in months and years. The sex ratio was overall evenly distributed amongst all countries.
- Age heaping: depicted by graphs with the objective of identifying any significant peaks. When age heaping was significant, weighting was calculated to adjust for the prevalence. Some countries only presented data on certain age groups. Whenever considered relevant it is recommended to adjust to cover for the 0 to 5 age range.
- Digit preference of height and weights: usually detecting a data quality issue when peaks were significant in decimals. Instances of 0.0 and 0.5 being significant digits were suspected of possible rounding when reporting and/or entering the data, or possible limitations in the use of the equipment.
- Implausible score values by taking into consideration standard WHO flags. Overall, there were no significant implausible values.
- Z-score distribution: shifts were reported when significant, allowing interpretation of the nutritional status of the population compared with the WHO standards.

Furthermore, discussions regarding data inclusion in regard to data representativeness were conducted; consultation with EURO office, country representatives and members of the JME group were taken into consideration when assessing the quality and representativeness of the data.

After data quality assessment, prevalence values were analyzed and compared with publication values. Where significant differences were found between re-analyzed values and published values, other reference frameworks were used (e.g., IOTF cut-off points, interpretation of other values from the WHO references). Additionally, age ranges were not always the same in the re-analyzed data.

2.1.4 Data description

In total, the October 2020 WHO-EURO database included 2944 records from 32 countries spanning the years 1976 to 2019. We then selected the relevant observations from the database to be included in our modelling exercise. The criteria we have specified for data to be included are:

- the data point is from 1990 onwards;
- stunting or overweight prevalence is not missing;
- the recorded age interval is between 0 to 5 years (i.e. 0 to 60 months);
- even if the data point has stratification for sex, an overall estimate for both sexes exist;
- the data point is at the national level, i.e. the data point is not stratified by administration level, wealth quintile, mother’s education, or urban/rural location; and
- an unweighted sample size is provided.

Ultimately there were a total of 1,786 data points for stunting prevalence and 1,769 data points for overweight prevalence from 27 countries, spanning 1991 to 2019, including all age partitions, all sex groups, as well as the 0 to 59 months entire interval, that were used for the modelling exercise. The time coverage by country and by year is provided in the appendix A.

2.2 Descriptive statistics

Summary statistics for stunting and overweight prevalence stratified by age and sex groups are provided in Table 1. Observing the crude mean prevalence only, we observe no clear patterns signifying differences between age groups for each estimate. Observing the estimates for overweight only, there seems to be a pattern of higher overweight prevalence for boys than for girls across age groups.

Table 1. Summary statistics for stunting and overweight prevalence, stratified by age and sex.

Age group	Stunting			Overweight		
	Both sexes	Girls	Boys	Both sexes	Girls	Boys
0 – 60 (*n*)	85	66	66	65	63	64
Mean (SD)	13.92 (9.48)	13.52 (8.42)	14.75 (9.15)	9.44 (5.37)	8.96 (5.95)	10.13 (5.92)
Min - max	0.84-39.50	1.02-38.18	0.00-40.61	1.19-25.53	0.01-32.69	0.50-25.63
0 - 6 (*n*)	65	63	64	81	66	66
Mean (SD)	12.02 (7.35)	10.69 (7.80)	13.45 (7.86)	10.61 (6.29)	10.54 (6.37)	11.83 (6.81)
Min - max	1.91-38.75	1.44-43.49	1.44-40.93	2.67-30.06	2.38-30.70	2.36-29.42
6 - 12 (*n*)	71	68	68	71	68	68
Mean (SD)	11.36 (7.90)	10.41 (7.66)	12.85 (8.68)	14.28 (8.57)	13.44 (8.35)	15.26 (9.33)
Min - max	0.93-39.45	0.45-33.47	1.24-42.54	2.76-33.57	0.78-39.03	2.62-37.17
12 - 24 (*n*)	72	68	68	71	69	69
Mean (SD)	16.04 (9.42)	14.90 (8.89)	17.76 (10.45)	12.38 (7.03)	11.99 (7.38)	12.57 (7.00)
Min - max	1.04-43.51	1.20-41.48	0.01-45.37	2.66-36.49	0.86-36.97	2.92-35.98
24 - 36 (*n*)	72	69	69	69	67	67
Mean (SD)	18.07 (11.62)	17.00 (10.97)	19.07 (12.65)	10.68 (6.67)	9.87 (6.69)	11.61 (7.26)
Min - max	0.54-50.36	0.45-49.98	0.01-50.75	1.85-28.32	2.01-28.96	1.00-29.28
36 - 48 (*n*)	70	67	67	70	68	68
Mean (SD)	15.16 (10.15)	15.26 (10.16)	15.17 (10.60)	9.72 (6.42)	8.98 (6.72)	10.58 (7.27)
Min - max	0.47-43.88	0.32-45.27	0.00-42.67	1.49-30.32	0.01-28.31	0.32-34.58
48 - 60 (*n*)	71	68	68	70	68	68
Mean (SD)	12.71 (9.38)	13.14 (9.76)	12.42 (9.60)	11.19 (6.63)	11.35 (7.21)	11.36 (7.15)
Min - max	0.00-45.49	0.00-46.30	0.00-44.55	2.24-28.42	0.96-33.40	2.12-30.54

Table 2. Summary statistics for stunting and overweight prevalence, stratified by age and income class.

Age group	Stunting		Overweight	
	LMICs[1]	HICs	LMICs	HICs
0 - 60 (*n*)	177	15	177	15
Mean (SD)	12.75 (7.64)	3.98 (1.60)	10.08 (5.59)	2.80 (2.06)
Min - Max	1.44-43.49	1.44- 6.32	0.01-32.69	0.93- 7.26
0 - 6 (*n*)	188	29	186	27
Mean (SD)	15.94 (8.21)	1.81 (0.94)	11.89 (6.39)	4.60 (1.61)
Min - Max	3.70-40.61	0.00- 3.46	3.10-30.70	2.36- 9.81
6 - 12 (*n*)	190	18	189	18
Mean (SD)	17.50 (9.07)	2.77 (2.38)	15.18 (8.65)	5.33 (2.16)
Min - Max	3.75-45.37	0.01-10.59	2.32-39.03	0.78- 8.59
12 - 24 (*n*)	189	21	188	21
Mean (SD)	19.94 (10.83)	1.03 (0.69)	12.94 (7.07)	6.65 (4.57)
Min - Max	2.46-50.75	0.01- 2.60	0.86-36.97	1.90-19.35
24 - 36 (*n*)	180	24	179	24
Mean (SD)	17.08 (9.41)	1.03 (0.81)	11.65 (6.80)	3.77 (0.96)
Min - Max	2.21-45.27	0.00- 3.32	1.00-29.28	1.90- 5.83
36 - 48 (*n*)	183	24	182	24
Mean (SD)	14.31 (9.04)	0.92 (1.22)	10.39 (6.79)	4.99 (4.86)
Min - Max	0.90-46.30	0.00- 4.76	0.01-34.58	0.32-26.00
48 - 60 (*n*)	189	18	188	18
Mean (SD)	12.44 (7.91)	2.05 (1.32)	12.05 (6.81)	3.47 (1.69)
Min - Max	2.20-42.54	0.45- 5.31	0.96-33.40	2.11- 8.38

When we compare countries based on their World Bank Income Classification as provided in Table 2Table 2, we find greater differences in mean prevalences for both stunting and overweight. The mean stunting and mean overweight prevalence are both on average higher for low- and middle-income countries than for high income countries. This indicates that adjusting for the countries' income classification could enhance model fitting.

2.2.1 Age grouping

Table 3 provides a breakdown of the data points by age grouping for both stunting and overweight. There were 85 and 83 data points that covered the entire 0-60 months age interval and both sex groups for stunting and overweight respectively.

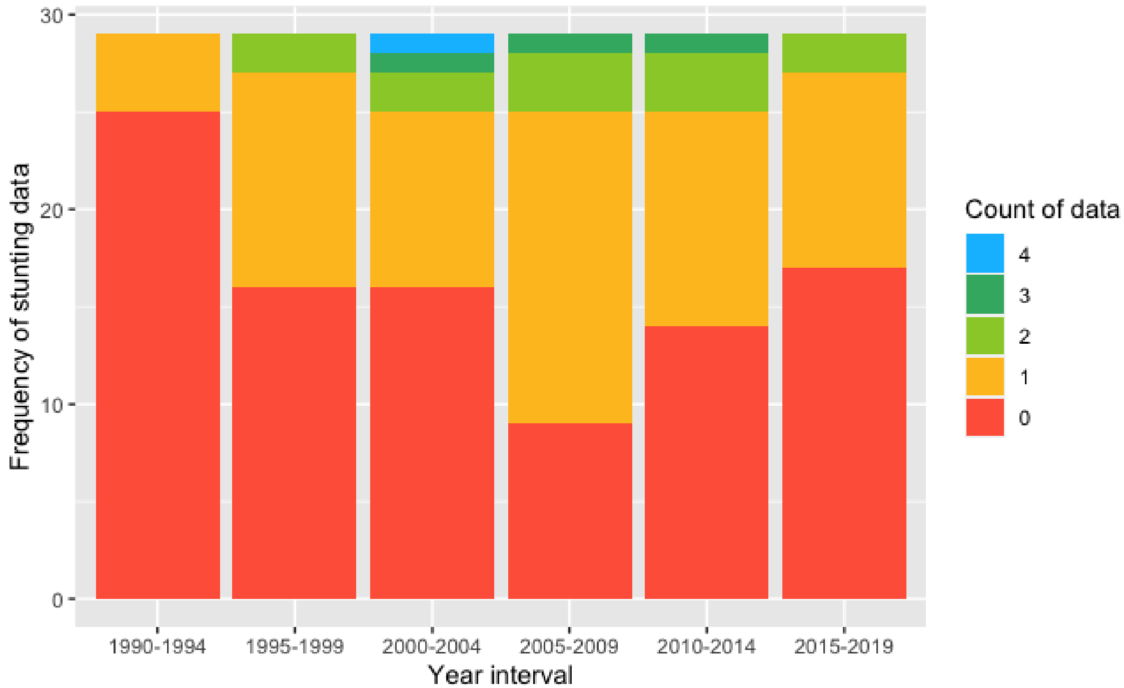
[1] LMICs are low- and middle-income countries; HICs are high-income countries as per the World Bank Income Classification scheme.

Table 3. Count of data points used for analysis, stratified by age and sex.

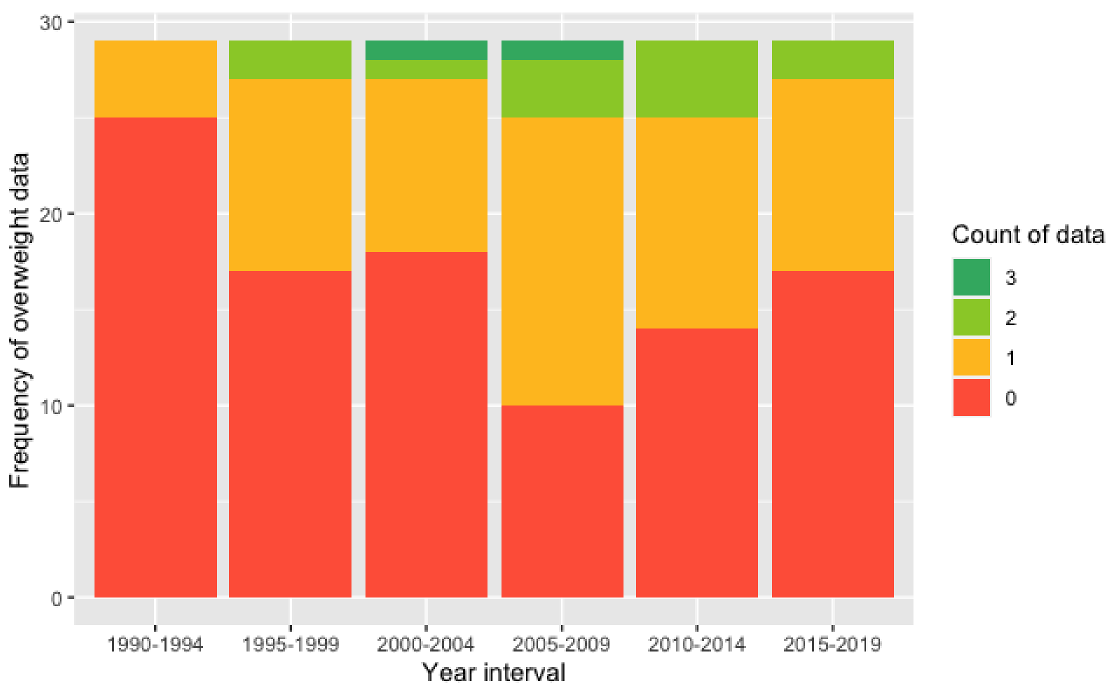
Age group	Stunting			Overweight		
	Both sexes	**Girls**	**Boys**	**Both sexes**	**Girls**	**Boys**
0 - 60	85	66	66	81	66	66
0 - 6	65	63	64	65	63	64
6 - 12	71	68	68	70	68	68
12 - 24	72	68	68	71	68	68
24 - 36	72	69	69	71	69	69
36 - 48	70	67	67	69	67	67
48 - 60	71	68	68	70	68	68

2.2.2 Missing data over time

One of the objectives of this modelling exercise is to explore prevalence estimate trends where data is missing for a country in a given year. In Figure 1, it can be observed that for both stunting and overweight, there exists few data points in the period of 1990-1994; the data coverage improves only marginally in subsequent years. In the periods 2010-2014 and 2015-2019 however, the data coverage drops again. As mentioned previously, data sparsity is a major issue in exercises such as these. Our data contained averages of 22 and 21 age-group specific observations per country over a 30-year period for stunting and overweight respectively.



(a) Stunting



(b) Overweight

Figure 1: Frequency of existing data for each country in each five-year interval.

3 Modelling methodology

This modelling exercise aimed to assess efficacy of a potential approach to predict missing data based on available stunting or overweight estimates and information on their accuracy. We use national-level data available between 1989-90 to 2019 that adheres with the definition for a malnutrition indicator as discussed in the Data section. The resulting trajectories can potentially be used to fill in data gaps in the target period to inform progress assessment of the nutrition targets and SDGs on stunting and overweight.

3.1 Modelling

There are three components to our modelling approach. First, a major component of this exercise is flexibly modelling the time effects using penalised B-spline methods. Second, we impute the sampling standard error (SSE) for sources where measures of accuracy around prevalence are missing (standard error (SE) of the prevalence). The SSE values are fed into the model to control for the heterogeneous sampling error among data sources. Third, disjoint partitions of the complete 0-59 month age interval are used as covariates in the mixed model to predict estimates where complete age intervals are missing. In addition, a covariate corresponding to the countries' income group (most frequent over the last 10 years) was included in the model.

3.1.1 Model specification

For both stunting and overweight, we implemented a penalised longitudinal model with heterogenous error terms, where the non-linear longitudinal patterns in the outcomes were captured using penalised cubic B-splines. Between-country heterogeneity in the longitudinal pattern is captured using country-specific intercepts, in addition to the cubic B-splines. The analysis was run using the most recent program by Dr. Alexander McLain based on his 2019 publication (McLain et al. 2019). A version available to the public can be found on his GitHub page (found here; downloaded on 22 December 2020).

The following section provides a summary of the model specification outlined in the 2019 article by McLain et al. Refer to McLain et al. (2019) for further explanation and mathematical justification.

Let $D_i = \{\mathbf{Y}_i, \mathbf{X}_i, \mathbf{t}_i, \mathbf{S}_i\}$ denote the observed data for country i whereby $\mathbf{Y}_i$, $\mathbf{X}_i$, $\mathbf{t}_i$, and $\mathbf{S}_i$ are n_i vectors of the outcome, covariates, time, and heterogeneity data respectively. The unpenalised log-likelihood for the i-th country, denoted by $l_i(\boldsymbol{\theta}|D_i)$, is formed by noting that $\mathbf{Y}_i$ is multivariate Gaussian with mean $\beta^{*\prime}X_i^* + \gamma'\mathbf{B}_i$ and covariance matrix $\mathbf{B}_i^r\sigma_b\mathbf{B}_i^{r\prime} + \sigma^2\mathbf{V}_i(\delta)$, where $\mathbf{B}_i = [\mathbf{B}_{ij}]$ and $\mathbf{B}_i^r = [\mathbf{B}_{ij}^r]j = 1, \ldots, n_i$ are column-stacked matrices of spline functions with dimensions of $K \times n_i$ and $K^r \times n_i$ respectively.

We assume the penalisation can be stated through a q-order difference in the B-spline coefficients; assuming N independent replicates of $D = D_1, \ldots, D_N$ are observed, the penalised likelihood is:

$$l^p(\boldsymbol{\theta}|D) = \sum_{i=1}^{N} l_i\,(\boldsymbol{\theta}|D_i) - \lambda\gamma'\mathbf{D}_q{}'\mathbf{D}_q\gamma,$$

where λ is a penalty term used to control the smoothness of the curves. The penalised likelihood above can be optimised via its equivalence with a mixed-model.

The penalised model is estimated using the *lme* function in R's *nlme* package (Pinheiro et al. 2019).

3.1.2 Missing sampling standard errors

The surveys have varying sample sizes and sampling strategies, sothe prevalence estimates' sampling standard errors (SSE) are important in quantifying precision. We find however that many of the surveys in our database report prevalence estimates without SSE values. A reliable method is therefore needed to incorporate them. To do this, surveys with complete information were used to estimate a model for the SSE values; the model used to predict SSE was a log-regression function of the observed prevalence, sample size, and survey type. The type of survey is included to account for the different sampling strategies employed by different organisations. Specifically, the model takes the form

$$\log(SSE) = \beta_0 + \beta_1 \log\left[Y_{ij}\left(1 - Y_{ij}\right)\right] + \beta_2 \log(n_{ij}) + \beta_3 \mathrm{Type}_{ij} + d_i + \varepsilon_{ij},$$

where Y_{ij} is the prevalence estimate for country i in year j, n_{ij} is the sample size for country i in year j, and Type is the survey type. The resulting estimated SSE is given by:

$$\widehat{SSE} = e^{\mu_{ij} + \sigma_{ij}}$$

whereby μ_{ij} is the predicted value of the $\log(SSE)$ according to the log-regression function given above, and the standard error σ_{ij} is added to increase the uncertainty for those sources that require SSE predictions.

This log regression function was run using the *lme* function in R's *nlme* package (Pinheiro et al. 2019).

3.1.3 Partial age intervals

As previously mentioned, the data points obtained can be so sparse that sometimes, only partial age intervals are captured. To overcome this, data with partial age intervals are still incorporated into the modelling process as an additional covariate. The data points with partial age intervals are still utilised to estimate the malnutrition prevalence for the whole age interval. This is done through 'partitioning' the partial age intervals.

- Partitioning the partial age intervals, or the age sub-groups, involve breaking the whole age interval of 0-60 months to six sub-groups or 'partitions'. The following sub-division is used:
- Partition 1 (P1) includes the age interval of 0-6 months;
- P2 includes the age interval of 6-12 months;
- P3 includes the age interval of 12-24 months;

- P4 includes the age interval of 24-36 months;
- P5 includes the age interval of 36-48 months; and
- P6 includes the age interval of 48-60 months.

These partitions are dummy variables that reflects the age interval captured in the data. As an example, a data point covering the whole age interval of 0-60 months would be denoted as ‘1’ for all variables P1 through to P6. A data point covering the age interval 2-5 years, i.e. 24-60 months, would be denotes as ‘0’ for variables P1, P2 and P3 and ‘1’ for variables P4, P5 and P6. In the instance of non-standard age intervals, the overlapping partition is still included; i.e. in the instance of 0.25 to 5 years, this data point will be denoted ‘1’ for all variables P1 through to P6.

An example of what this set of covariates would look like is included in Table 4. We remove the first partition P1 from our list of covariates as it would otherwise introduce the issue of perfect collinearity.

3.1.4 Sex grouping

For the final model, in addition to age adjustment and country income, the model was expanded to include sex as a factor. This allowed for the generation of stunting and overweight estimates stratified by sex. The following covariates were included:

- BS is a binary variable which was coded ‘1’ if the observation included both sexes;
- SM is a binary variable which was coded ‘1’ if the observation is for males only; and
- SF is a binary variable which was coded ‘1’ if the observation is for females only.

3.2 Data preparation

Both models require a specific format for the data input. A major component of this exercise, therefore, is preparation of the data to comply with the format required for modelling. Specifically, the following steps were conducted to prepare the data for analysis. These steps were done separately for the stunting and overweight data.

1. Subset the observations of interest. In this exercise, we are interested in: a) a non-missing value for the malnutrition indicator of interest; b) a non-missing non-weighted sample size to impute missing SSEs; and c) data at the national level, i.e. not stratified for sex, area, geographical region, wealth quintile, or mother’s education. We also remove data points where the sample covers age intervals beyond 0-5 years.
2. Subset the variables of interest. In this exercise, data is subset for each malnutrition indicator we want to run the analysis on (i.e. stunting or overweight), sex, and age group only.
3. Transform the stunting and overweight prevalence to proportions (i.e. transforming the prevalence range from 0 to 100 to that of a proportion ranging from 0 to 1) and their corresponding standard errors.
4. Generate age group partitions, i.e. the variables *P1* to *P6* as previously discussed in the section ‘Partial age intervals’. This was done through hard coding based on the age groups that are in the existing dataset.

5. Generate dummy variables for sex, i.e. the variables 'BS', 'SM' and 'SF' as previously discussed in the section 'Sex grouping'.
6. Create rows for each country by year by age group and by sex combination that we would like the model to predict estimates for. We ultimately have at least 19,530 data points with standard age groupings; some data points may fall outside of the standard age interval, leading to more data points. This number is obtained from a combination of 31 countries, 30 years, seven age groupings, and three sex groupings ($31 \times 30 \times 7 \times 3 = 19{,}530$).
7. Impute missing SSE, as outlined in the section on Modelling. SSE values were generated in 3 instances for stunting and in no instances for overweight.

Subsequently we also add the countries' income classification as an additional covariate in our model. This classification specifies whether a country is considered low-or-middle income or high-income, as specified by the World Bank, consistently over the last ten years.

Annotated R scripts are provided to accompany the steps provided here; the list of R scripts are provided in the appendix B.

The program specifically requires one row in the input data for each country-year-covariate combination the user wants to generate predictions for. Refer to Table 1 for an example of the main input for analysis and Table 4 for an example of the input of covariates. In our instance, there are six main variables (country, year, prevalence estimate, SE of estimate, estimated sampling standard error, and SE of SSE) and five covariates (P2, P3, P4, P5, P6).

Table 4. An example of the main input for analysis.

Country	Year	Y	SE_var	SE_pred	SE_pred_SE
ALB	2000	0.3915548	0.0215892	0.01968386	NA
ALB	2000	0.3874635	0.0599717	0.05896529	NA
ALB	2000	0.3944845	0.0589265	0.06136705	NA
ALB	2000	0.3739524	0.0388744	0.0407101	NA
ALB	2000	0.5035591	0.0366909	0.04106956	NA
ALB	2000	0.3433378	0.0359457	0.03575273	NA
ALB	2000	0.3542901	0.041592	0.04445121	NA
ALB	2000	0.4014087	0.0277085	0.02706451	NA
ALB	2000	0.3176965	0.0975914	0.08250077	NA
ALB	2000	0.4253965	0.0730929	0.07746109	NA
ALB	2000	0.363217	0.0549758	0.05529695	NA
ALB	2000	0.5074915	0.055553	0.05670418	NA

ALB	2000	0.365635	0.0443582	0.049137	NA
ALB	2000	0.3993222	0.0648556	0.06398366	NA
ALB	2000	0.3817849	0.0261786	0.0269806	NA
ALB	2000	0.4349435	0.0739678	0.077702	NA
ALB	2000	0.334749	0.0860914	0.09162929	NA
ALB	2000	0.3854382	0.0546375	0.05649914	NA
ALB	2000	0.4997782	0.051578	0.05608469	NA
ALB	2000	0.3214488	0.0454076	0.04894323	NA

Table 5. An example of the input of covariates for analysis, corresponding to the main input.

P2	P3	P4	P5	P6	SM	SF
1	1	1	1	1	1	1
0	0	0	0	0	1	1
1	0	0	0	0	1	1
0	1	0	0	0	1	1
0	0	1	0	0	1	1
0	0	0	1	0	1	1
0	0	0	0	1	1	1
1	1	1	1	1	1	0
0	0	0	0	0	1	0
1	0	0	0	0	1	0
0	1	0	0	0	1	0
0	0	1	0	0	1	0
0	0	0	1	0	1	0
0	0	0	0	1	1	0
1	1	1	1	1	0	1
0	0	0	0	0	0	1
1	0	0	0	0	0	1
0	1	0	0	0	0	1

0	0	1	0	0	0	1
0	0	0	1	0	0	1

The variables Y, SE_var and SE_pred in Table 3 refer to the malnutrition prevalence of interest (either stunting or overweight), the associated SSE, and the predicted SSE where the SSE is not available respectively. The variables $P2$ to $P6$ in Table 4 are the age partitions previously mentioned. The variable $P1$ was removed to prevent the issue of perfect collinearity; we consider it as a reference variable.

For our data, we have generated individual rows for each country-year combination for our 30 countries spanning the years 1990 to 2020. Ultimately for the instance of stunting, we have 19,549 rows with 1,786 rows populated by existing data; for the instance of overweight we have 19,549 rows with 1,769 points populated by existing data.

4 Analysis

Our analysis is concerned with modelling stunting and overweight prevalence for countries in the WHO European region. The data used for our model spanned the 30-year period 1990 to 2020. For stunting, we have 643 data points from 30 countries, 172 of which were obtained from the DHS survey, 250 from MICS, and 221 from other sources. As for overweight we have 628 data points from 29 countries, 171 of which were obtained from the DHS survey, 250 from MICS, and 207 from other sources. We imputed missing SSE for three data points for stunting and none for overweight.

For all models, the number of splines and covariance structure were determined through a model selection process based on the Akaike information criterion (AICc). The AICc is the suggested estimator in model selection for penalised models (Currie and Durban 2002).

For the instance of stunting, we have two observations with a recorded stunting prevalence and standard error of zero. We consider these instances to be a limit of detection problem and replaced the prevalence with the value of $1/2n$, n being the unweighted sample size for that survey (Nie et al. 2010). We predicted the standard errors for these observations as per the methodology outlined in the Methods section.

Subsequently we conducted a logit transformation for the outcome variables of stunting proportion and overweight proportion. We inspected histograms and normal quintile-quintile plots for the original outcome, as well as its logarithmic and square root transformation, prior to the analysis. Through the use of residual plots, we did not find evidence of a relationship between residual variance and the predicted values for either outcome.

Plots of the model results are provided on the following pages. Plots of the age group-adjusted model results for stunting and overweight are provided in Figure 2 and Figure 3 respectively. Plots of the age group-adjusted and countries' income group-adjusted model results for stunting and overweight are provided in Figure 4 and Figure 5 respectively. In all figures, survey prevalence estimates with error bars ($\pm 2 \times (\mathrm{SSE} + \mathrm{NSE})$, whereby NSE is the non-sampling error estimated from the model) are presented along with point estimates, 95% point-wise prediction intervals and confidence intervals. The survey prevalence estimates for the complete 0-60 months age interval are provided in black; data points for partial intervals are provided in blue. Prediction intervals for country-year pairs with no data were constructed using the median observed SSE value.

The data points for Croatia, Hungary, Italy and the United Kingdom did not fulfil the criteria we have specified to be included in our analysis. Therefore in the following figures we observe predicted values, confidence intervals, and prediction intervals for these countries but no observed values.

4.1.1 Age-adjusted models

From Figure 2, we observe that there is a general decreasing trend in stunting prevalence. With the countries' income classification taken into account (Figure 4), we find that on average, the decline in stunting is steeper for countries in the low-income group whilst the stunting prevalence for countries in the high-income group are consistently close to zero.

As for overweight, we observe on average a slightly increasing prevalence up until the mid-2000s, at which point it slightly decreases. The confidence and prediction intervals taper slightly upwards from 2015 onwards (Figure 3). When we take income classification into account (Figure 5), we observe that on average countries in the low-income group still have a similar trajectory, but countries in the high-income group have a seemingly stable overweight prevalence at 10% over our time period.

For both models, countries with no observed data points (namely Croatia, Hungary, Italy and the United Kingdom) have wider confidence intervals and prediction intervals, as expected.

We find that for both stunting and overweight, data for countries in the high-income group are more sparsely populated than the data we have for countries in the low-income group. We also observe that data for countries in the low-income group have high standard errors in comparison to the countries in a high-income group; this suggests that better data quality is needed from these countries for us to precisely monitor stunting and overweight rates.

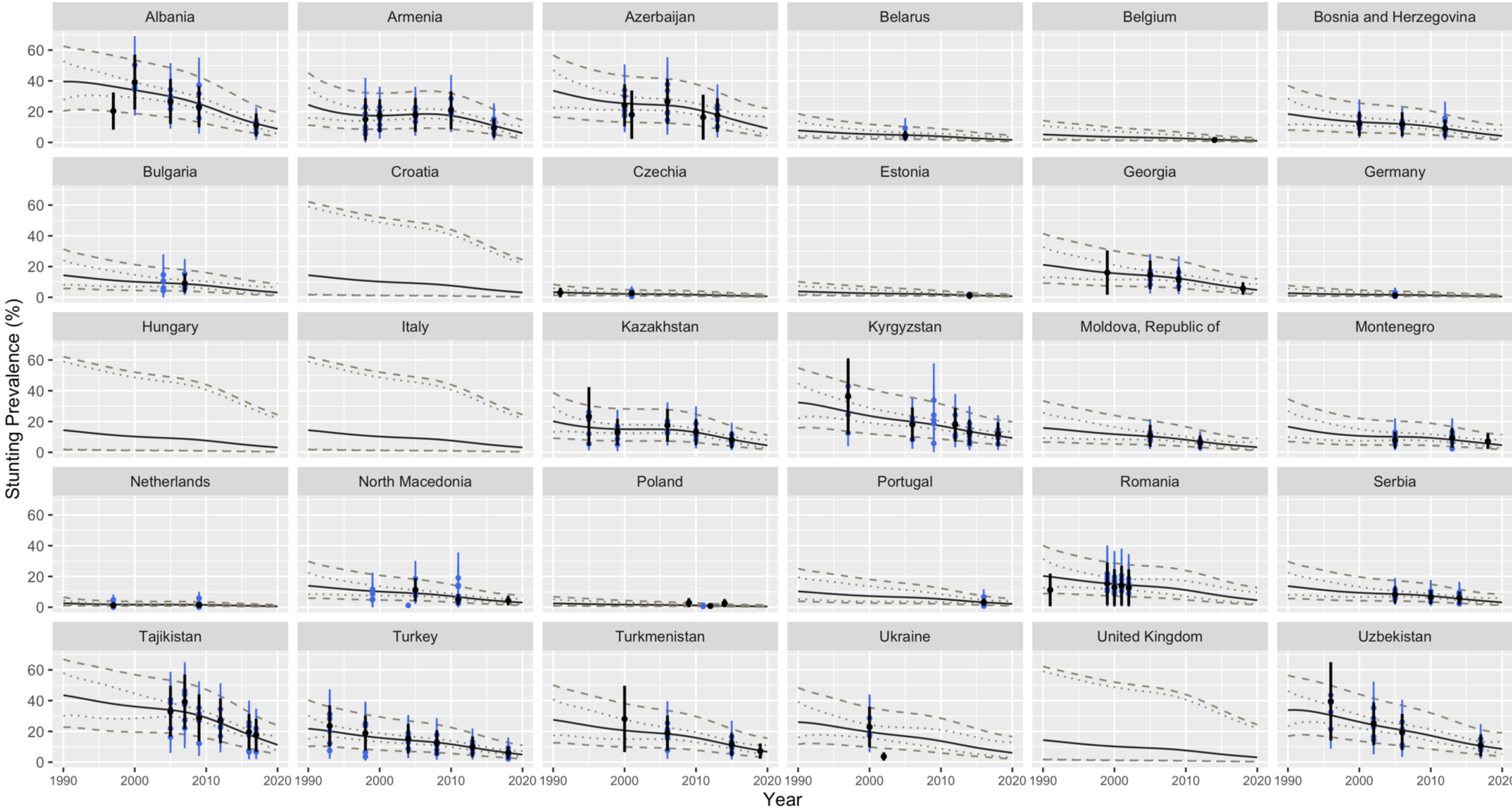


Figure 2. Age group-adjusted stunting prevalence estimates by country, by year. Data points for 0-60 months are denoted by black points (•) whilst data points for age subgroups are denoted by blue points (•). Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

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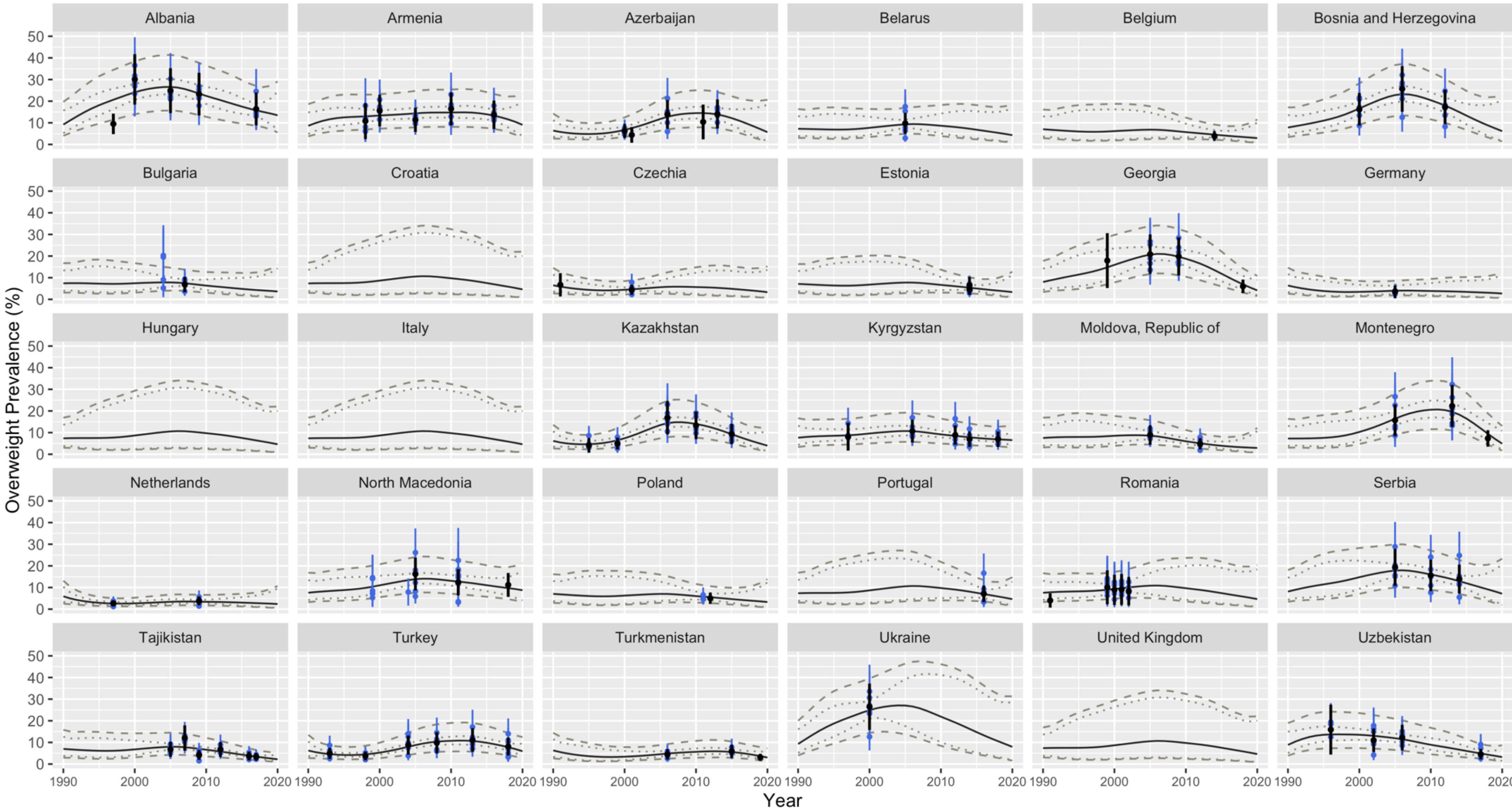

Figure 3. Age group-adjusted overweight prevalence estimates by country, by year. Data points for 0-60 months are denoted by black points (•) whilst data points for age subgroups are denoted by blue points (•). Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

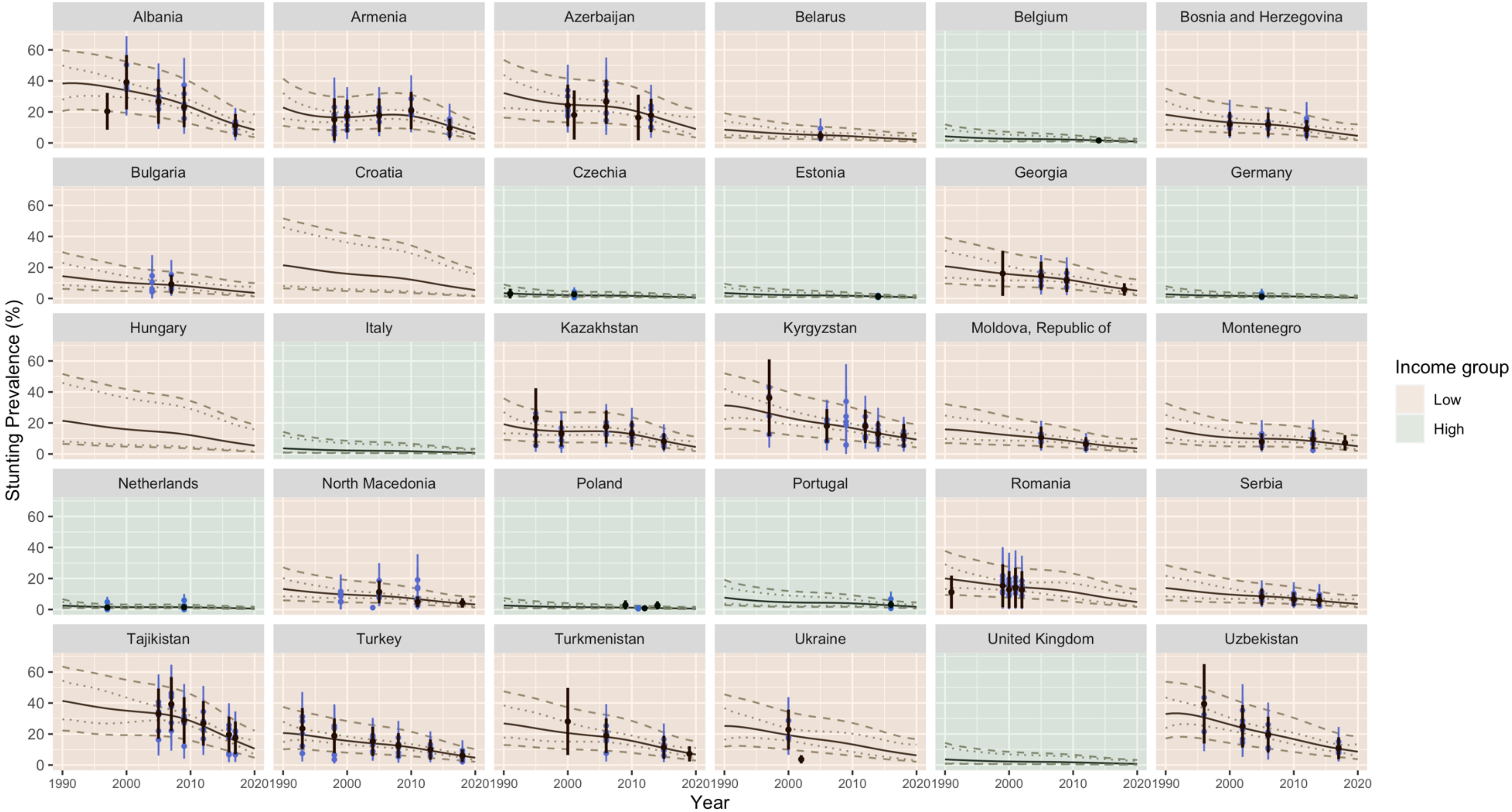

Figure 4. Age group-adjusted stunting prevalence estimates by country, by year, with the country's World Bank Income Classification taken into account as an additional covariate. Data points for 0-60 months are denoted by black points (•) whilst data points for age subgroups are denoted by blue points (•). Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

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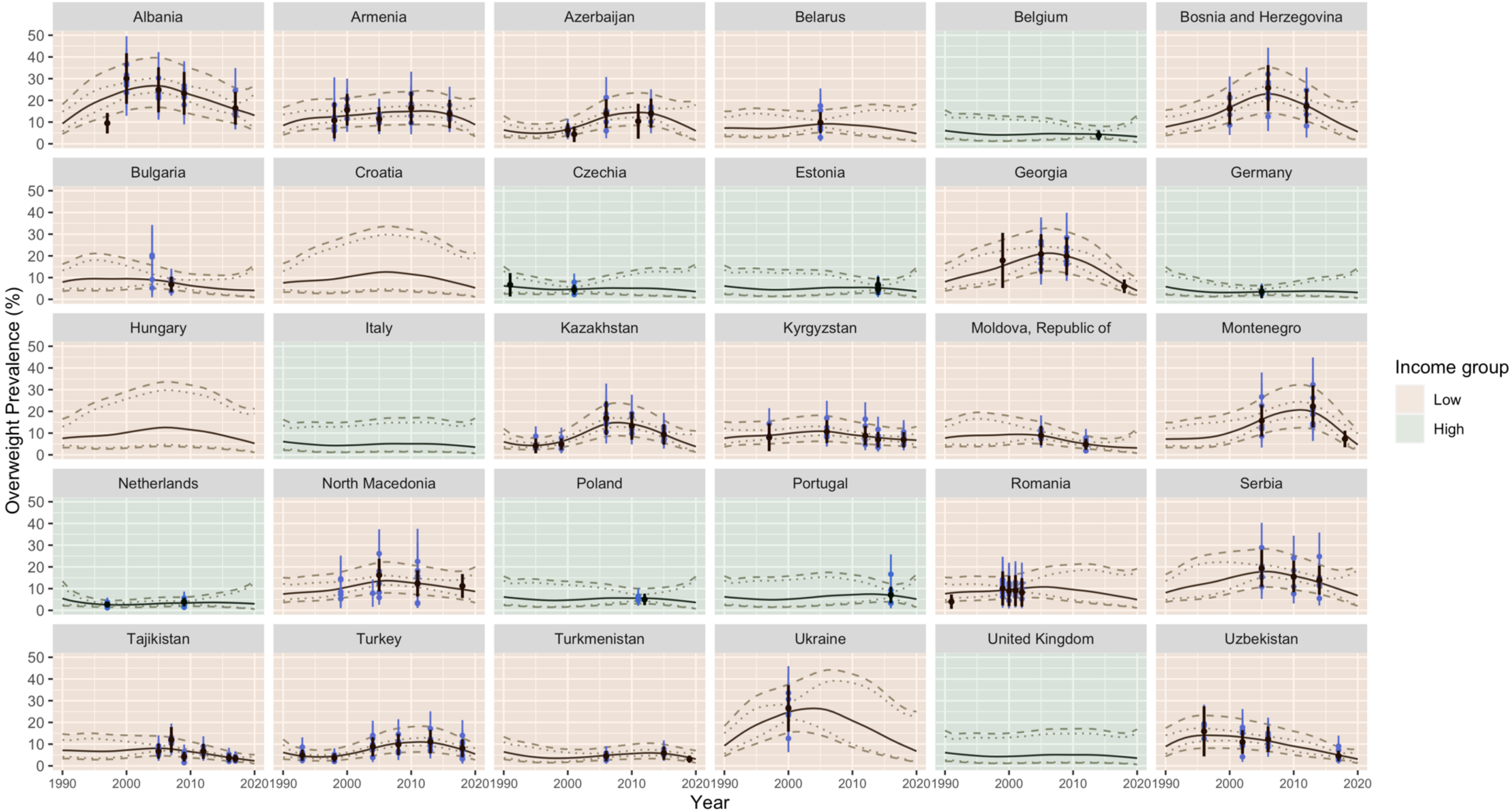

Figure 5. Age group-adjusted overweight prevalence estimates by country, by year, with the country's World Bank Income Classification taken into account as an additional covariate. Data points for 0-60 months are denoted by black points (•) whilst data points for age subgroups are denoted by blue points (•). Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

4.1.2 Age-adjusted models, stratified by sex

We observe a similar, generally decreasing trend in stunting prevalence in Figure 6. Unlike the age model (Figure 2) however, where there is an initial increase in stunting between the years 1990-1995, there is no initial increase when we take into account sex stratification in our model. For all countries, the stunting prevalence decreases over time.

In Figure 8 where income classification is taken into account, we find that on average, the decline in stunting is steeper for countries in the low-income group whilst the stunting prevalence for countries in the high-income group are consistently close to zero.

As for our overweight model depicted in Figure 7, we observe on average an increasing prevalence up until the mid-2000s, at which point the overweight prevalence slightly decreases. For most countries, the confidence and prediction intervals also taper slightly upwards from 2015.

Taking into account income classification as depicted in Figure 9, we observe no discernible pattern in the trend for overweight prevalence for countries in the low-income group. On average however we observe the overweight prevalence to be lower for countries in the high-income group than for countries in the low-income group.

For all models, countries with no observed data points (namely Croatia, Hungary, Italy and the United Kingdom) have wider confidence intervals and prediction intervals, which was expected.

We find that for both stunting and overweight, data for countries in the high-income group are more sparsely populated than the data we have for countries in the low-income group. We also observe that data for countries in the low-income group have higher standard errors in comparison to the countries in a high-income group; this suggests that better data quality is needed from these countries for us to precisely monitor stunting and overweight rates.

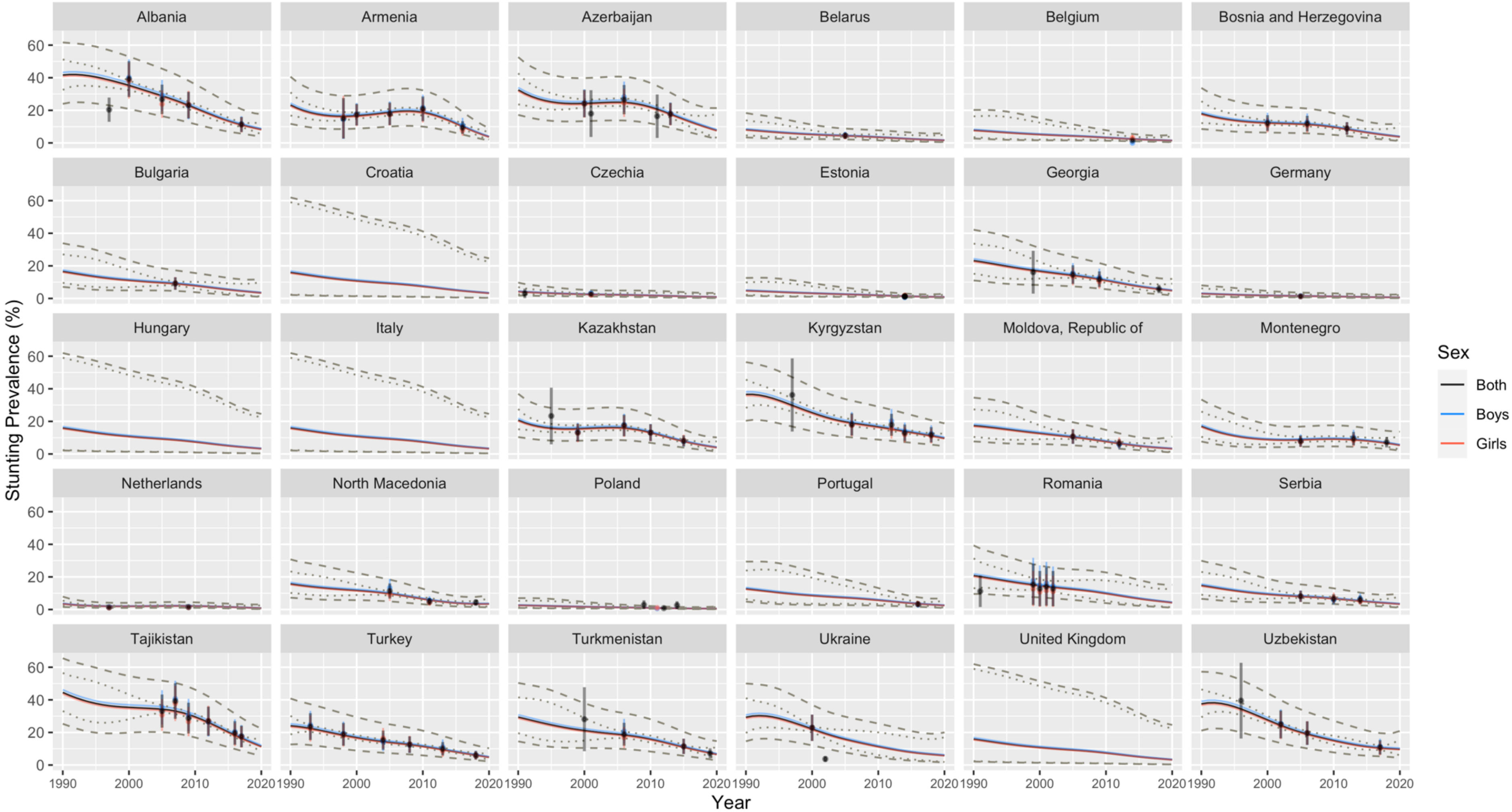

Figure 6. Age group-adjusted and sex-stratified stunting prevalence estimates by country, by year. Sex groups are denoted by different colours as shown in the legend. Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

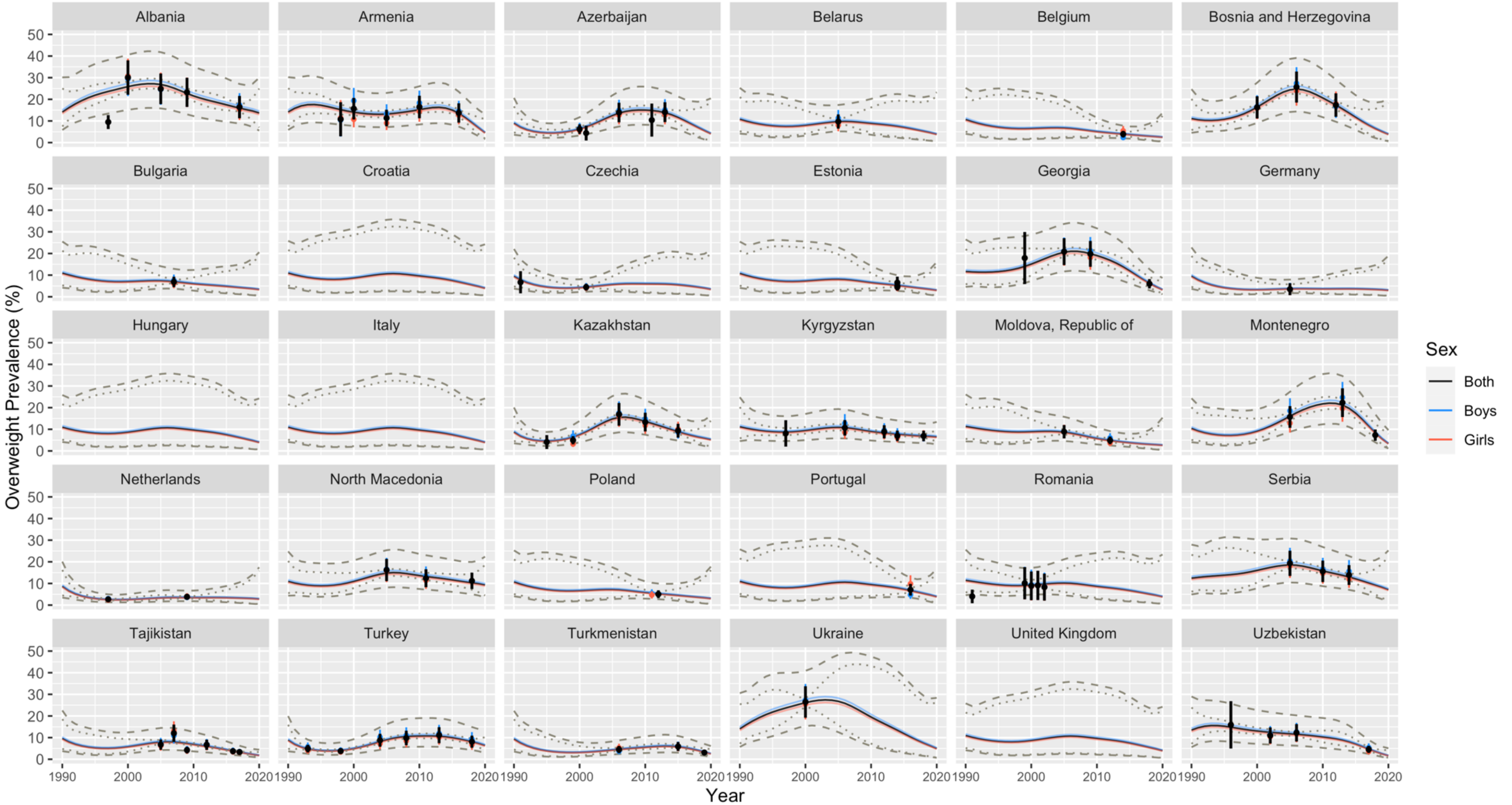

Figure 7. Age group-adjusted and sex-stratified overweight prevalence estimates by country, by year. Sex groups are denoted by different colours as shown in the legend. Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

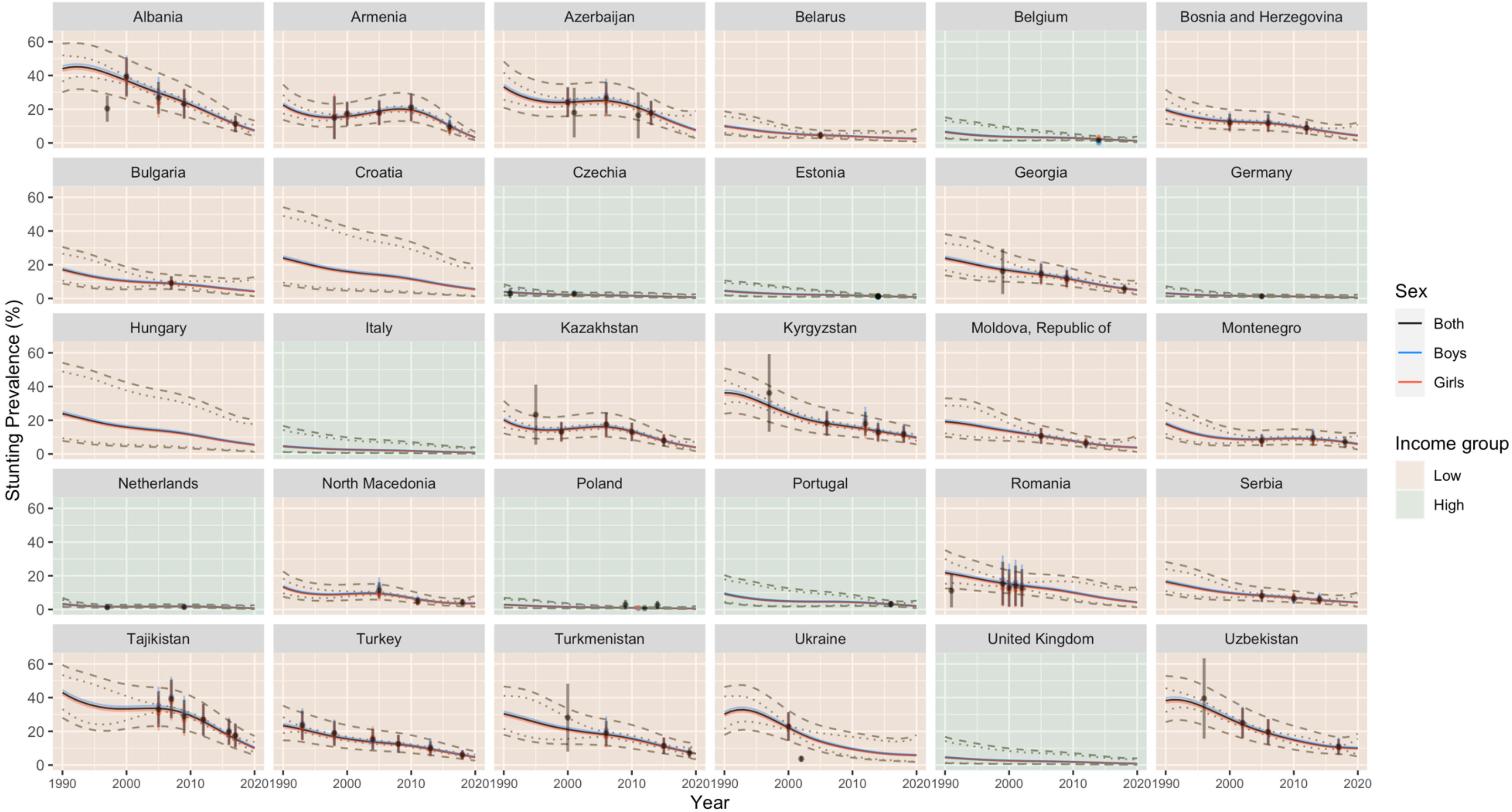

Figure 8. Age group-adjusted and sex-stratified stunting prevalence estimates by country, by year, with the country's World Bank Income Classification taken into account as an additional covariate. Sex groups and income classification groups are denoted by different colours as shown in the legend. Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

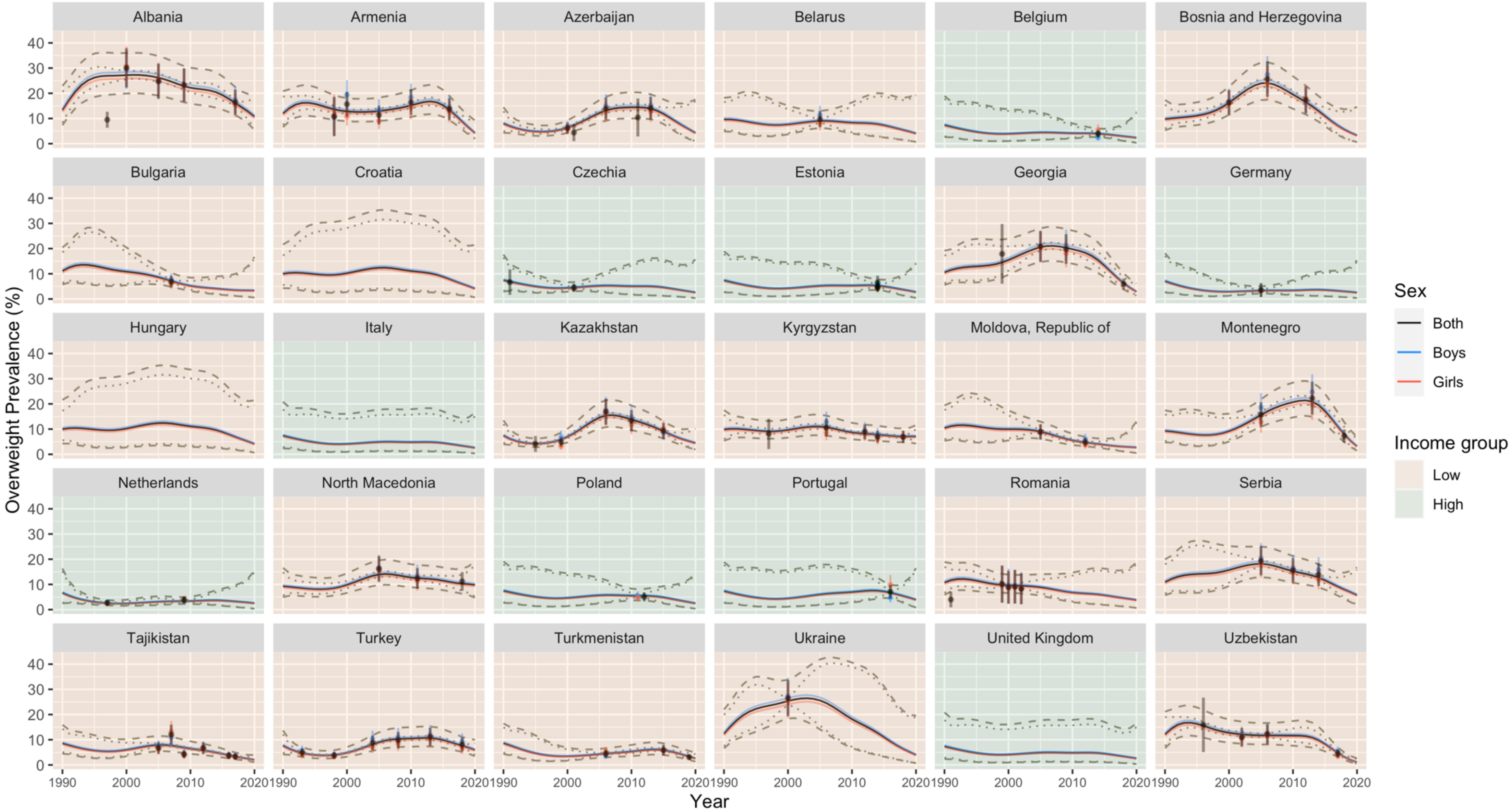

Figure 9. Age group-adjusted and sex-stratified overweight prevalence estimates by country, by year, with the country's World Bank Income Classification taken into account as an additional covariate. Sex groups and income classification groups are denoted by different colours as shown in the legend. Predicted estimates are denoted by the solid grey line; 95% confidence intervals in dotted grey lines; and prediction intervals in dashed grey lines.

5 Model validation

A k-fold cross validation was conducted to check the validity and robustness of our model. This method consists of randomly dividing the data into k number of groups at the survey level and re-running the model without group k. Subsequently, estimators such as coverage probability, bias and root mean squared error obtained from this cross-validation will be calculated to assess model accuracy.

This validation method provides a measure for the precision of our model estimates and their associated uncertainties (James et al. 2013). Further, it allows us to check how robust the model is in estimating malnutrition indicators for the data we have with incomplete age partitions.

Method

A 10-fold cross-validation was implemented in this exercise. First, the data points were grouped at the survey level; that is, data points from the same source, even with the differing age groups, are considered as one 'survey'. This set of surveys is then randomly split into ten non-overlapping groups, or 'folds'. Each of these tenths are considered the 'validation set' and the remainder are the 'training set'.

Starting with the first validation set, we take out the validation set and fit our model on the remaining training set. We then compute the following based on data points in the training set: coverage probability, average bias, median bias, mean squared error (MSE), root MSE, and median absolute deviation. We repeat this procedure ten times where each time, a different validation set is used. We therefore obtain ten estimates; the 10-fold cross-validation estimate is computed by averaging these values. These values are provided in Table 6.

Table 6. Estimates of coverage probability, bias, test errors, and median absolute deviation obtained from our 10-fold cross validation for stunting and overweight.

	Stunting	Overweight
Coverage Probability	0.938	0.855
Average Bias	0.006	-0.002
Median Bias	0.002	-0.005
Mean Squared Error (MSE)	0.004	0.003
Root MSE	0.061	0.056
Median Absolute Deviation	0.045	0.042

For the measures we have used: the coverage probability is the proportion of times the 95% prediction interval of the estimated summary mean contains the true value. It is desirable to have a coverage of near 95%. Bias is the average difference between the true (simulated) mean and its estimate across the 10 simulation replicates; it is desirable to have a bias near zero. The mean squared error (MSE) is the average squared difference between the true (simulated) mean and its estimate across the ten simulation replicates, and it is desirable to have an MSE close to zero. The root mean squared error (RMSE) can be interpreted as the standard deviation of the unexplained variance, which indicates the distribution of our errors. It is in the same unit as our response variable and lower values of RMSE indicate a better fit of the model. Finally, the median absolute deviation (MAD) provides a robust measure for the spread of our data.

We will now discuss the results we have computed for each of these cross-validation measures. We observe from Table 6 that our coverage probability for stunting is close to 95% whilst for overweight it is lower at 85.5%. This indicates that the standard error estimates were inaccurate in the overweight model. We found the bias and MSE to be close to zero for both models, and the RMSE to be a low value of 0.056. The MAD of 0.045 for stunting indicates that our predictions will be within 0.045 of the observed value fifty per cent of the time; the MAD for overweight at 0.042 is similarly close. These results are desirable and indicates that both stunting and overweight models were robust in estimating the indicators for data with incomplete age partitions.

6 Global model comparison

A global modelling exercise has also been conducted for stunting and overweight by the UNICEF-WHO-WB Joint Child Malnutrition (JME) group (UNICEF, WHO and WB Group. 2021); we now compare our model estimates to that of the global model. Figure 10 provides the model comparison for stunting and Figure 11 provides the model comparison for overweight. Predicted estimates, confidence intervals, and prediction intervals obtained from this modelling exercise are provided in blue whilst the same estimates obtained from the global modelling exercise are provided in red. Of note is the fact that the global model includes other covariates such as the socio-demographic index (SDI)[2], type of data source for stunting and overweight, and additionally for stunting: the average health system access over the previous five years.

We observe that the predicted estimates for both stunting and overweight are quite close for most countries with existing data points in our modelling exercise. The most divergent estimates occur for the years 1990-2000, such as seen in the stunting model for Albania and Armenia and the overweight model for Albania, Tajikistan, Turkmenistan, and Uzbekistan. Even so however, the confidence and prediction intervals for both models are not too different.

Estimates for the countries which did not have observed data points in our modelling exercise, i.e. Croatia, Hungary, Italy and the United Kingdom, mostly diverged greatly from the global model's estimates. The one exception is the overweight model for Hungary, whereby the estimates from this exercise and the global model exercise seem similar.

[2] SDI is a summary measure that identifies where countries or other geographic areas sit on the spectrum of development. Expressed on a scale of 0 to 1, SDI is a composite average of the rankings of the incomes per capita, average educational attainment, and fertility rates of all areas in the Global Burden of Disease study

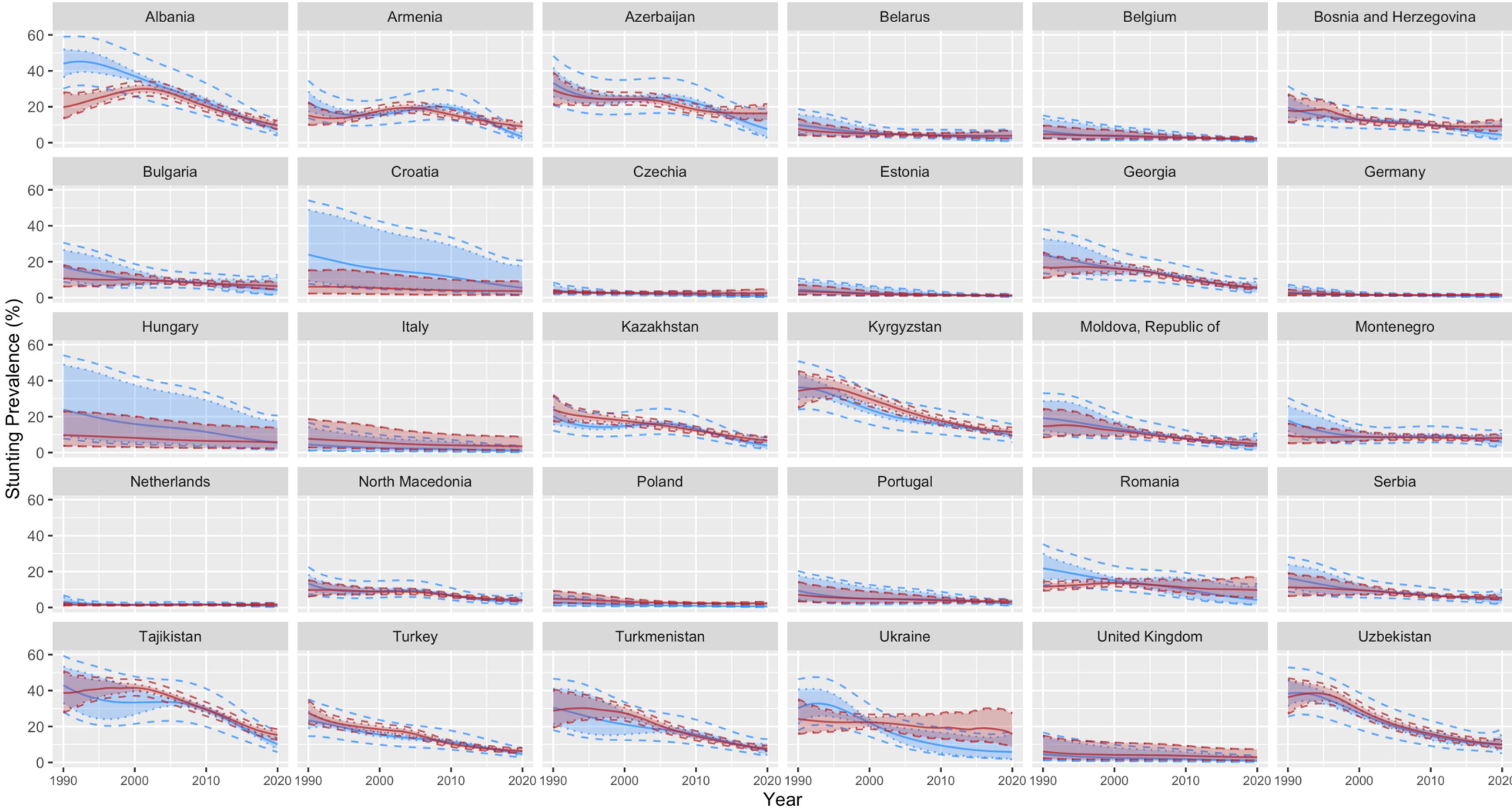

Figure 10. Predicted estimates for stunting from this modelling exercise are in blue (—) and from the global model in red (—). 95% confidence intervals are provided by the dotted lines with shading; prediction intervals are provided by the coloured dashed lines.

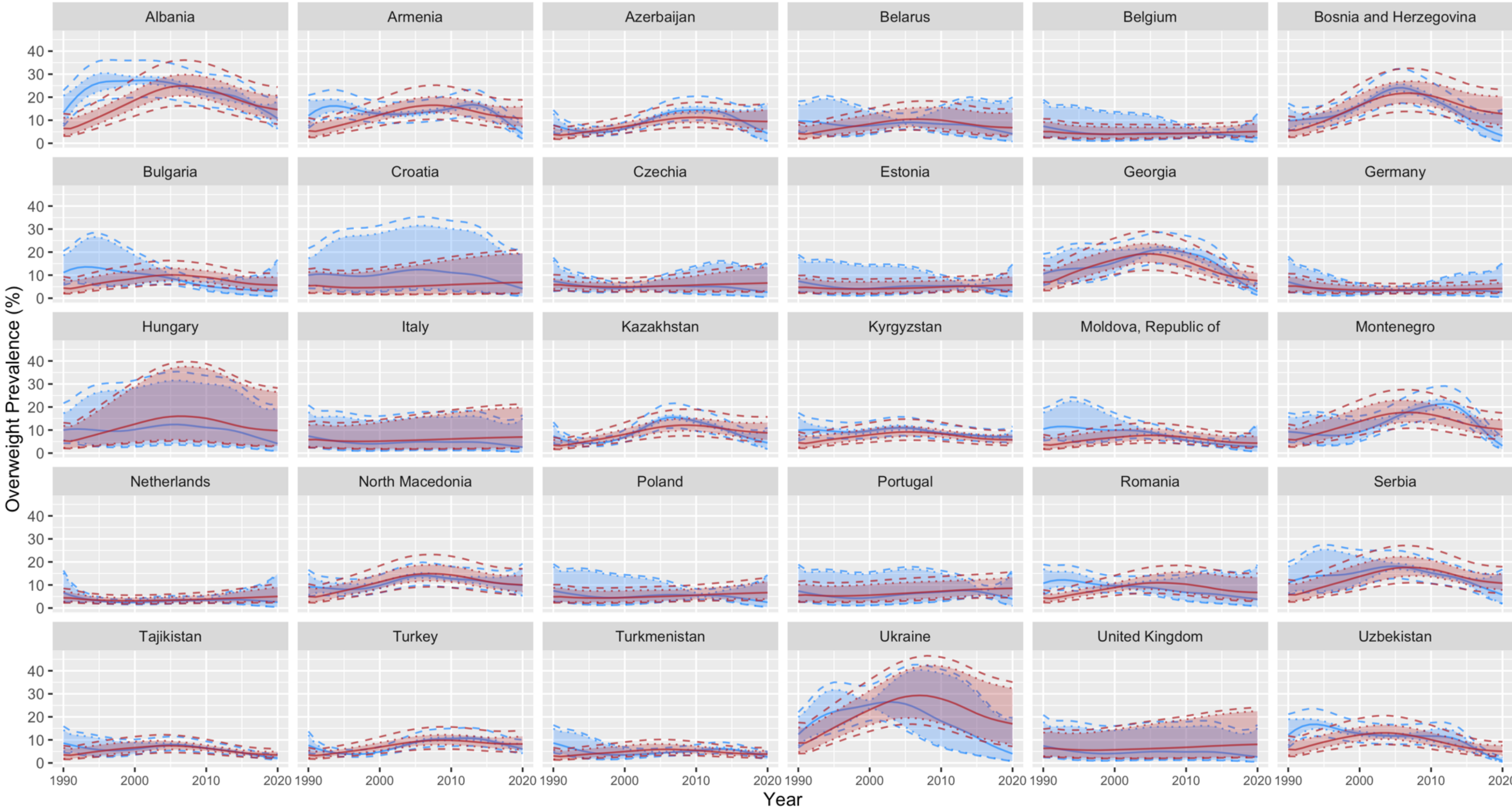

Figure 11. Predicted estimates for overweight from this modelling exercise are in blue (—) and from the global model in red (—). 95% confidence intervals are provided by the dotted lines with shading; prediction intervals are provided by the coloured dashed lines.

7 Discussion

Monitoring childhood malnutrition is a global health public concern. At the 2012 World Health Assembly, all WHO Member States endorsed the Global Nutrition Framework which includes six nutrition-related global targets. Three of these targets concern indicators of childhood malnutrition, namely stunting, wasting and overweight, for children under 5 years of age. These three indicators are also part of the SDG framework and the WHO General Program of Work 2019-2023 (GPW13), which specifically contributes to the target of having one billion additional people enjoy healthier lives.

The data included in this report is the result of multiple studies from across the WHO European Region, in addition to the UNICEF-WHO-WB Joint Child Malnutrition (JME) Database. Data in the included studies were collected through a variety of methods, using different equipment to assess nutritional status. Most studies do not specify specifically which equipment was used for the measurements, thus leading to a risk of bias. Similarly, they do not mention if data collectors followed a standard protocol, which may in turn introduce measurement bias.

UNICEF and WHO are the SDG data custodian agencies for the SDG indicators 2.2.1 and 2.2.2. This project's objective is to assess the benefit of considering sources of data additional to those already included in the JME Database, which are based on nationally representative data covering most of the indicators' targeted age group, that is, 0 to 59 months, mostly from surveys. Whilst in other regions there are several surveys implemented on a regular basis, for the European region, most of the countries' data collection relies heavily on the kindergarten system, covering only a small part of the targeted age group in most cases. Additionally, there are specific studies carried out by research institutions in some countries which are not necessarily collected throughout the country territory; however this collected data might be considered nationally representative where social-economic equity is clearly no issue.

This report includes important information on data availability after quality scrutiny and gathering information on representativeness for all data that were made available for use. Its dissemination will not only highlight the importance of collecting anthropometric data across the entire age range 0 to 59 months, but also the importance of increasing practices that enhance data quality.

This exercise focused on stunting and overweight. Based on all data available that met the inclusion criteria, penalized longitudinal models were developed with multi-source summary measures to estimate prevalence and its uncertainty, implemented in R. The modelling procedure was conducted for stunting and overweight prevalence with data from the WHO European region ranging from the years 1990 to 2020.

The model estimates were obtained using data from any country which had at least one survey estimate for the malnutrition prevalence indicator of interest. We specified models adjusting for age group using age partition covariates and adjusting for the countries' income groups. SSEs were imputed where they are missing in the original dataset. Model validation showed the model has excellent properties, largely accurate for stunting, while less accurate for overweight, as expected, due to the elasticity of weight-related indicators. It also demonstrated unbiasedness for both stunting and overweight.

We also compared the predicted stunting and overweight estimates from this exercise to the estimates obtained from the global modelling exercise, which used estimates mostly covering the entire age interval 0 to 59 months. For some countries, e.g. Croatia and Italy, the additional information included in the model (age sub-intervals) resulted in notable differences in trends for both stunting and overweight. Hungary and United Kingdom also presented similar patterns for stunting, and Portugal for overweight.

This exercise is useful in predicting trajectories for malnutrition indicators of interest where data are sparse, either due to lack of surveys conducted for a country in a given year or the recording of incomplete age intervals. A potential use of the model would be to use predicted estimates to input into the global model exercise, if only age adjustment was considered. Otherwise, the model incorporating adjustment for countries' income groups can be considered as a separate model to the global one excluding the European region, due to the specific characteristics in this region with respect to data availability. A regional technical consultation will be carried out with the European countries' data stakeholders, the WHO European Region Office and the JME group to assess the best way to proceed in addressing current data gaps, resulting in recommendations for Member States in the region. Furthermore, if circumstances due to the COVID-19 pandemic permits, we might conduct primary data collection among children under 5 using kindergarten-based sampling in three countries of the WHO European Region to test feasibility of obesity surveillance among this age group.

Finally, the EURO database can also be used for research to compare data with those from clinics to evaluate the impact on data quality or the actual prevalence estimates, as part of the STOP project.

The methods implemented in this exercise is also easily reproducible on the standard computing software R, so that non-statisticians can also implement these techniques whilst taking into account their unique data characteristics. The methods in this exercise are proposed as an effective way to produce estimates from sparse data.

8 Conclusions

This report provided a summary of findings from the assessment of existing data on child malnutrition (including stunting and overweight) for countries in the WHO European Region. The report found that there is a dearth of recent primary research data on measured anthropometrics of children under the age of five years.

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Appendix

Appendix A: Time coverage by country

Table 7. Time coverage by country for stunting (at least one age group; has both sex groups).

Country	Year
Albania	1997
Albania	2000
Albania	2005
Albania	2009
Albania	2017
Armenia	1998
Armenia	2000
Armenia	2005
Armenia	2010
Armenia	2016
Azerbaijan	1996
Azerbaijan	2000
Azerbaijan	2001
Azerbaijan	2006
Azerbaijan	2013
Azerbaijan	2011
Belgium	2014
Bulgaria	2007
Bulgaria	2004
Bulgaria	2014
Bosnia and Herzegovina	2000
Bosnia and Herzegovina	2006
Bosnia and Herzegovina	2012
Belarus	2005

Czech Republic	1991
Czech Republic	2001
Germany	2005
Germany	2016
Estonia	2014
United Kingdom	1976
Georgia	2009
Georgia	1999
Georgia	2005
Georgia	2018
Croatia	1994
Croatia	1995
Croatia	1996
Hungary	1984
Italy	1976
Kazakhstan	1995
Kazakhstan	1999
Kazakhstan	2006
Kazakhstan	2010
Kazakhstan	2015
Kyrgyzstan	1997
Kyrgyzstan	2006
Kyrgyzstan	2012
Kyrgyzstan	2009
Kyrgyzstan	2014
Kyrgyzstan	2018
Moldova, Republic of	2005
Moldova, Republic of	2012
North Macedonia	1999
North Macedonia	2004

North Macedonia	2005
North Macedonia	2011
North Macedonia	2018
Montenegro	2005
Montenegro	2013
Montenegro	2018
Netherlands	1997
Netherlands	2009
Netherlands	1980
Poland	2012
Poland	2011
Portugal	2016
Romania	1991
Romania	1999
Romania	2000
Romania	2001
Romania	2002
Serbia	2005
Serbia	2010
Serbia	2014
Tajikistan	2005
Tajikistan	2007
Tajikistan	2012
Tajikistan	2009
Tajikistan	2017
Tajikistan	2016
Turkmenistan	2006
Turkmenistan	2015
Turkmenistan	2019
Turkey	1993

Turkey	1998
Turkey	2004
Turkey	2008
Turkey	2013
Turkey	2018
Ukraine	2000
Uzbekistan	1996
Uzbekistan	2002
Uzbekistan	2006
Uzbekistan	2017

Table 8. Time coverage by country for overweight (at least one age group; has both sex groups).

Country	Year
Albania	1997
Albania	2000
Albania	2005
Albania	2009
Albania	2017
Armenia	1998
Armenia	2000
Armenia	2005
Armenia	2010
Armenia	2016
Azerbaijan	1996
Azerbaijan	2000
Azerbaijan	2001
Azerbaijan	2006
Azerbaijan	2013
Azerbaijan	2011
Belgium	2014

Bulgaria	2007
Bulgaria	2004
Bulgaria	2014
Bosnia and Herzegovina	2000
Bosnia and Herzegovina	2006
Bosnia and Herzegovina	2012
Belarus	2005
Czech Republic	1991
Czech Republic	2001
Germany	2005
Germany	2016
Estonia	2014
United Kingdom	1976
Georgia	2009
Georgia	1999
Georgia	2005
Georgia	2018
Croatia	1994
Croatia	1995
Croatia	1996
Hungary	1984
Italy	1976
Kazakhstan	1995
Kazakhstan	1999
Kazakhstan	2006
Kazakhstan	2010
Kazakhstan	2015
Kyrgyzstan	1997

Kyrgyzstan	2006
Kyrgyzstan	2012
Kyrgyzstan	2009
Kyrgyzstan	2014
Kyrgyzstan	2018
Moldova, Republic of	2005
Moldova, Republic of	2012
North Macedonia	1999
North Macedonia	2004
North Macedonia	2005
North Macedonia	2011
North Macedonia	2018
Montenegro	2005
Montenegro	2013
Montenegro	2018
Netherlands	1997
Netherlands	2009
Netherlands	1980
Poland	2012
Poland	2011
Portugal	2016
Romania	1991
Romania	1999
Romania	2000
Romania	2001
Romania	2002
Serbia	2005
Serbia	2010
Serbia	2014
Tajikistan	2005

Tajikistan	2007
Tajikistan	2012
Tajikistan	2009
Tajikistan	2017
Tajikistan	2016
Turkmenistan	2006
Turkmenistan	2015
Turkmenistan	2019
Turkey	1993
Turkey	1998
Turkey	2004
Turkey	2008
Turkey	2013
Turkey	2018
Ukraine	2000
Uzbekistan	1996
Uzbekistan	2002
Uzbekistan	2006
Uzbekistan	2017

Appendix B: Programming workflow

The following annotated R scripts were used in this exercise:

1. *01-prep-all.R* prepares the raw dataset for modelling. It is recommended that the user familiarise theirselves with the data prior to running this script through the use of a spreadsheet software such as Microsoft Excel, or within R itself.
2. *02-prep-stunt-model.R* and *01-prep-ovw-model.R* further prepares the data from the previous step for modelling. The preparation is conducted separately for stunting and overweight as the user needs to adapt the data cleaning and preparation to the data.
3. *run-model-stunt.R* and *run-model-ovw.R* provides code for the modelling stage and for the resulting plots and tables.
4. *run-wbclass-stunt.R* and *run-wbclass-ovw.R* runs the model again with the World Bank Income Classification as an additional covariate.
5. *prep-cv-stunt.R* and *prep-cv-stunt.R* prepares the data and resulting model from the previous stage for cross-validation.
6. *cv-stunt.R* and *cv-ovw.R* provides the process for cross-validation of the data and models.