Exposure and Health (2026) 18:47
https://doi.org/10.1007/s12403-026-00782-z

ORIGINAL PAPER

Drinking Water Hardness (as a Proxy for Calcium) Significantly Modifies the Relationship Between Dental Caries Prevalence in 5 Year Old Children and Drinking Water Fluoride and Socio-economic Inequalities in England

Mohammad Mehrabi[1] · Yang Han[2] · Deborah Moore[3] · Matthew J. Ascott[4] · Anne-Marie Glenny[5] · David A. Polya[1]

Received: 11 December 2025 / Revised: 24 March 2026 / Accepted: 19 April 2026

Abstract

Dental caries (DC) is the most prevalent chronic disease. Previous studies have revealed negative associations between DC prevalence and both drinking water fluoride concentration (F) and socioeconomic status but further predictors, notably drinking water calcium, have been little explored, particularly in the UK. Therefore, this study employed multiple linear regression (MLR) to model the dependency of children's DC on all three of these predictors, namely (i) F, (ii) IMD: index of multiple deprivation, and (iii) WH: water hardness—as a proxy for calcium concentration; in England. The results showed that all three predictors are statistically significantly ($p < 0.05$) associated with DC, with, separately, increased fluoride, increased water hardness, and decreased deprivation being associated with lower DC. A key novel finding is that the DC ~ F relationship is quantitatively less pronounced (by about 24%) when WH is included as a predictor—thus the oral health and financial benefits of water fluoridation based on models not considering water calcium may overestimate or underestimate those benefits depending upon water calcium (or WH as a proxy). Moreover, segmented analyses showed that, potentially and partially due to WH's influence, the DC ~ F relationship is dependent upon F concentration, with the dependence much stronger for drinking water $F < 0.10$ mg/L than for $F > 0.37$ mg/L, a concentration considerably lower than the widely reported optimal F, i.e., (0.7–1.0) mg/L. Any modelling of expected costs and benefits for fluoridation should explicitly include consideration of water calcium (or WH as proxy) and the non-first-order linear DC ~ F relationship.

Keywords Dental caries · Water fluoridation · Calcium · Deprivation · Inequalities

✉ David A. Polya
david.polya@manchester.ac.uk

Mohammad Mehrabi
mohammad.mehrabi@manchester.ac.uk

Yang Han
yang.han@manchester.ac.uk

Deborah Moore
deborah.moore24@nhs.net

Matthew J. Ascott
matta@bgs.ac.uk

Anne-Marie Glenny
a.glenny@manchester.ac.uk

1 Department of Earth and Environmental Sciences, School of Natural Sciences, Faculty of Science and Engineering, The University of Manchester, Manchester M13 9PL, UK

2 Department of Mathematics, School of Natural Sciences, Faculty of Science and Engineering, The University of Manchester, Manchester M13 9PL, UK

3 Public Health Directorate, NHS England (North West), Liverpool, UK

4 British Geological Survey, Nicker Hill, Keyworth, Nottingham NG12 5GG, UK

5 Division of Dentistry, School of Medical Sciences, Faculty of Biology, Medicine and Health, The University of Manchester, Manchester M13 9PL, UK

Published online: 18 May 2026

Abbreviations

DC	Dental caries
MLR	Multiple linear regression
LSOA	Lower-layer super output area
LAD	Local authority district
DMF-S	Decayed, missing and filled tooth surfaces
WH	Water hardness in supplied drinking water
F	Fluoride concentration in supplied drinking water
IMD	Index of multiple deprivation
NHS	National Health Service
UA	Unitary authorities
SVM	Support vector machine
BGS	British Geological Survey
ANN	Artificial neural network
ANOVA	Analysis of variance
RSE	Residual standard error
ρ	Pearson correlation coefficient
R^2	Coefficient of determination
AIC	Akaike information criterion
BIC	Bayesian information criterion

Introduction

Dental caries (DC) is not only the most common oral condition in children (Bernabe et al. 2025), affecting 60–90% of schoolchildren worldwide (Mehta and Bhalla 2014), but also the most prevalent non-communicable disease (NCD) globally (World Health Organization 2025). Apart from the obvious direct detrimental impacts of DC on the individuals presenting with DC, severe DC in children can also have further detrimental impacts on families (e.g. feeling stressed and disruption of normal activities) (Abed et al. 2020). In England, notwithstanding its descending prevalence in the last decades, DC still impacts a large part of the population, notably around a quarter of 5-year-olds (Roberts et al. 2023).

Whilst highly prevalent, dental caries is also known to be among the most preventable of diseases, notably through limiting the consumption of free-sugars, and good dental hygiene incorporating fluoride toothpaste (World Health Organization 2025) both of which practices can be promoted through public health programmes. In the 1940s, drinking water fluoridation was suggested as a cost-effective method of reducing tooth decay (Bruvo et al. 2008; Moore et al. 2021; Whelton et al. 2019). It is often stated that the effect of water fluoridation is particularly beneficial in populations of lower socio-economic status (Krisdapong et al. 2014; Pattussi et al. 2001; Tinanoff et al. 2019). McGrady et al. (2012) concluded that water fluoridation was an effective measure in reducing the social class gradient between deprivation and caries experience. However, a recent systematic review failed to find evidence of water fluoridation reducing socioeconomic status dependent disparities in caries (Iheozor-Ejiofor et al. 2024). In the UK, Nyakutsikwa et al. (2021) investigated the variation of fluoride for lower-layer super output areas (LSOAs) in England and created a dataset covering the period 2009 to 2020. According to their findings, the coverage of 'optimal fluoridation' (≥0.7 mg/L) in the country ranged from 6.3% of LSOAs (in 2016) to 10.9% of LSOAs (in 2014). Following this, Nyakutsikwa et al. (2022) compared the census characteristics of these optimally fluoridated populations with non-fluoridated ones. They found that optimally fluoridated communities tend to be more economically deprived, more urban, and slightly younger on average.

Calcium in drinking water is another factor that, according to many studies, plays an important role in improving tooth and oral health (Bruvo et al. 2008; Huang et al. 2018). Lin et al. (2014), for example, demonstrated that high calcium and high calcium/phosphorus ratio in drinking water were associated with lower primary DCs in schoolchildren, whilst Tanaka et al. (2012) found a similar relationship between the mothers' calcium intake during pregnancy and children's DC. Bruvo et al. (2008) reported the significant combined effect of calcium and fluoride on the number of decayed, filled, and missing tooth surfaces (DMF-S). These two components explained 45% of the DMF-S variations among 52,057 15-year-old schoolchildren in Denmark. Arvin et al. (2018) successfully constructed a linear model to explore the dependency of DMF-S on the concentration of drinking water calcium and fluoride, as well as family income in Denmark. They found that all three factors are adversely proportional to ln(DMF-S). Similar conclusions have been derived from studies in other parts of the world (Akuno et al. 2019; Costa et al. 2012; Iheozor-Ejiofor et al., 2015; Pizzo et al. 2007).

Although there are several studies of the relationship between DC and various predictive factors in England (Balmer et al. 2012; Jones and Worthington 1999, 2000; McGrady et al. 2012; Moore et al. 2024a), to the best of our knowledge, there is no study which has systematically explored and quantified the relationship between DC and drinking water calcium across England. This might be, in part, because calcium per se, is not a drinking water constituent that is required to be routinely analysed by water suppliers and so drinking water calcium data for public water supplies in England is relatively sparse. However, there is widespread data for water hardness (WH, in mg/L), which being the sum of calcium (Ca^{2+}, in mg/L) and magnesium (Mg^{2+}, in mg/L) concentrations—as per Eq. (1)—might be used as a proxy for calcium (Elphick et al. 2011; Ghosh 2024).

$$\mathrm{WH} = 2.5\ [\mathrm{Ca}^{2+}] + 4.1\ [\mathrm{Mg}^{2+}] \tag{1}$$

Accordingly, this study investigates the association between DC prevalence in five-year-olds and three factors, namely water hardness (WH) as a proxy for calcium, fluoride (F) concentration, and index of multiple deprivation (IMD) through multiple linear regression (MLR) modelling. We test the hypothesis that WH is a significant predictor of DC in England and that incorporation of WH into DC predictive models significantly alters the relationship of DC and other known factors, notably fluoride concentration and socio-economic status.

Materials and Methods

Methodology

A schematic of the study methodology is shown in Fig. 1. In the first phase, a dataset was created from different resources (see Sect. "Study Area and Spatial Units") where DC is the target parameter hypothesised to be influenced by WH, F, and IMD. In the next phase, the dependency of the DC on these three predictors was explored by (i) simple trend and statistical analysis and (ii) applying an MLR model within the R environment (R Core Team 2011).

Study Area and Spatial Units

This study focuses on quantifying the combined effect of key drinking water parameters, notably fluoride concentration and water hardness (as a proxy for calcium), and socioeconomic deprivation on DC in England. The main geographical division system used in this study was the LSOA. LSOAs are areas with similar population sizes (approximately 1500 residents/650 households). This study used the 2011 LSOAs (n = 32,844) downloaded from the UK Data Service website (UKdataservice). To create the numerical dataset, the points that geographically represent the center of LSOAs were used for data extraction. For some variables and areas, data were not available by LSOA and were instead imputed from data available for other administrative levels, notably districts and/or unitary authorities (UAs). Figure 2 shows the LSOAs and their representative points in England.

Dataset

The dataset analyzed during this research was composed of DC as the target variable and WH, IMD, and F as predictors. The spatial distribution, mapped using ArcGIS Pro (v 3.3.0), of these variables across England is shown in Fig. 3. The sources of these data are outlined in more detail below.

Dental Caries Data

DC data, specifically the indicator 'the percentage of 5-year-olds with experience of visually obvious dental decay

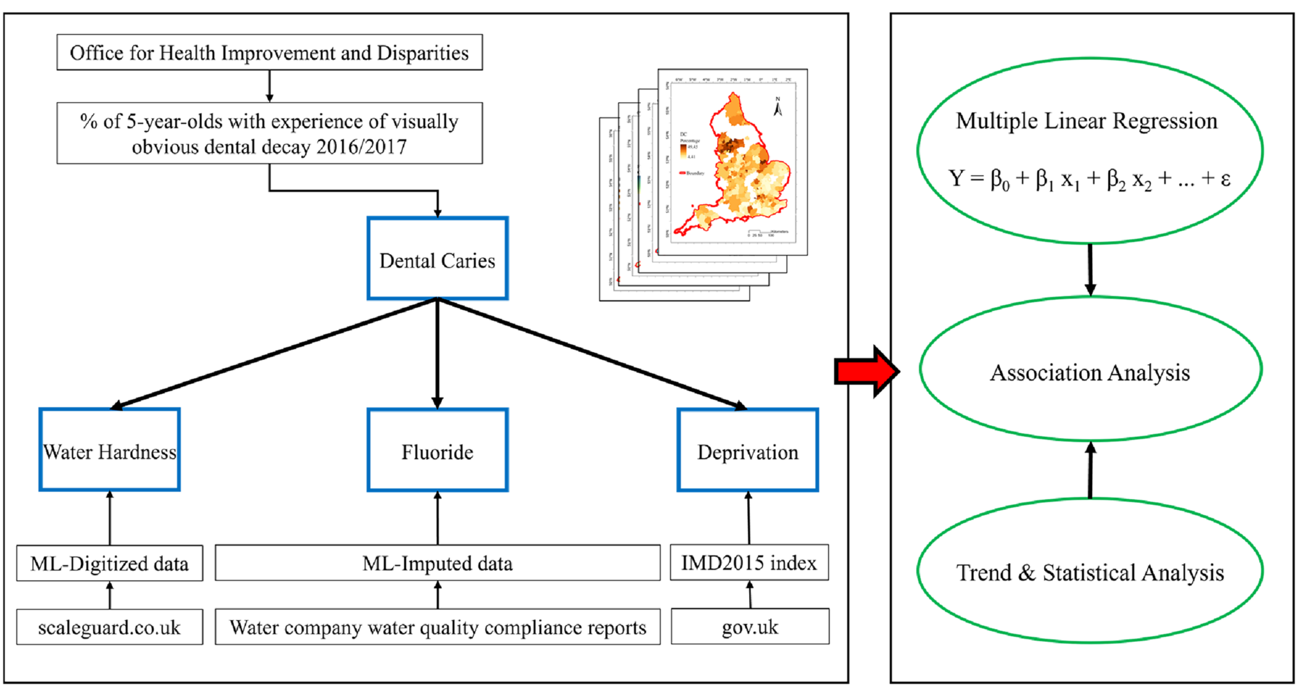

Fig. 1 Schematic of study methodology

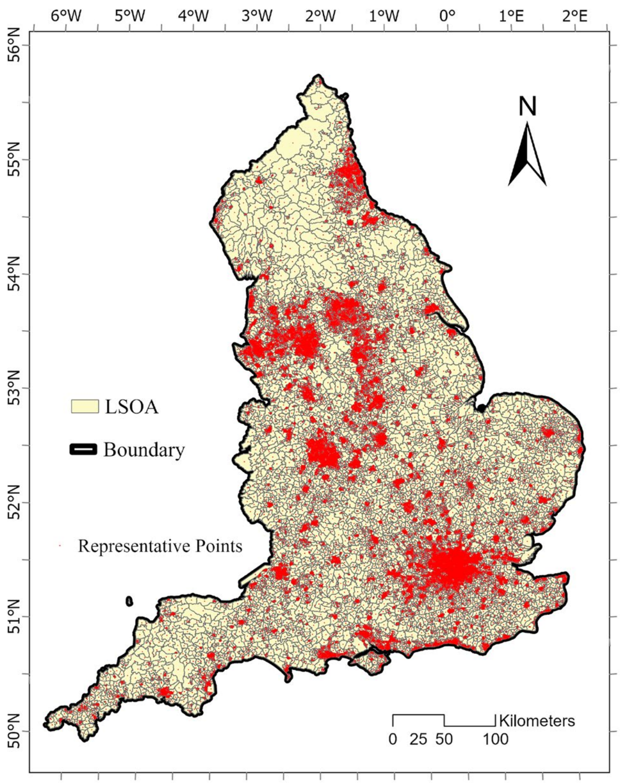

Fig. 2 LSOA (2011) system in England and representative points, produced by ArcGIS Pro [Source: UK Data Service (UKdataservice, 2011)]. Each red point represents (the geometric centre of) an LSOA

in 2016/2017' were obtained from the Office for Health Improvement and Disparities (Office for Health Improvement and Disparities 2023). These data were collected (Office for Health Improvement and Disparities 2023) via a population-based stratified 2-stage random sample of schools, then schoolchildren, according to a single national protocol with trained and calibrated examiners. The numeric data was downloaded for the whole of England at the Districts and UAs scale (See Fig. 3a).

Water Hardness Data

In this study, the much more widely reported WH for the year 2013 was used as a proxy for calcium, for which data for public drinking water supplies in England [See Fig. 3b] is substantially incomplete. The data of WH was acquired using a machine learning model that digitized a map that illustrates the public water supply hardness in mg/L as Calcium in England (scaleguard.co.uk 2024). Data acquisition process included.

(i) Downloading and importing a high-quality image into ArcGIS Pro,
(ii) Georeferencing the image to geographically fit the study area,
(iii) Performing image classification using a support vector machine (SMV) model in ArcGIS Pro,
(iv) Performing manual quality checks in some parts with a high density of LSOA data extraction points.

The output was a raster layer with categorical WH values. Apart from areas with no information and no public supply, six WH classes were Soft (0–50) mg/L, Moderately Soft (51–100) mg/L, Slightly Hard (101–150) mg/L, Moderately Hard (151–200) mg/L, Hard (201–300) mg/L, and Very Hard (>300) mg/L (See Fig. 3c). In the numerical dataset, these classes are represented by the values of 1, 2, 3, 4, 5, and 6, respectively.

Fluoride Data

Fluoride concentration data for public water supplies for the year 2015 were acquired by downloading water quality compliance reports from water supplier websites by a systematic postcode search as described previously by Bowyer et al. (2025). Missing values were imputed using machine learning and geographical interpolation models as follows:

(i) The 2014 Fluoride map of England was obtained from a previous study (Nyakutsikwa et al. 2021),
(ii) A machine learning model—artificial neural network (ANN)—was trained to predict 2015 Fluoride data (using 2014 Fluoride data as a predictor). The ANN was then applied to impute the missing values of the 2015 Fluoride data (details in the Supplementary Materials Table S1),
(iii) While the ANN model could impute most missing data, there were still gaps in the data, due to the missing values in the predictor (i.e., 2014 Fluoride map),
(iv) To fill the remaining gaps, Natural Neighbors interpolation technique was employed to create the final 2015 Fluoride dataset.
(v) Eventually, the dataset was validated based on the prediction results ($R^2 = 0.87$—see Eq. (5), and mean square error = 0.0077 mg/L), and also visual checks with the 2015 map of fluoride data from a previous study (Roberts et al. 2020).

Socioeconomic Inequality Data

In this study, deprivation is considered a social factor that can influence public dental health, similar to family income in earlier work (Arvin et al. 2018). The deprivation status of the LSOAs was represented by IMD data in 2015 (See Fig. 3e), which takes into account seven deprivation

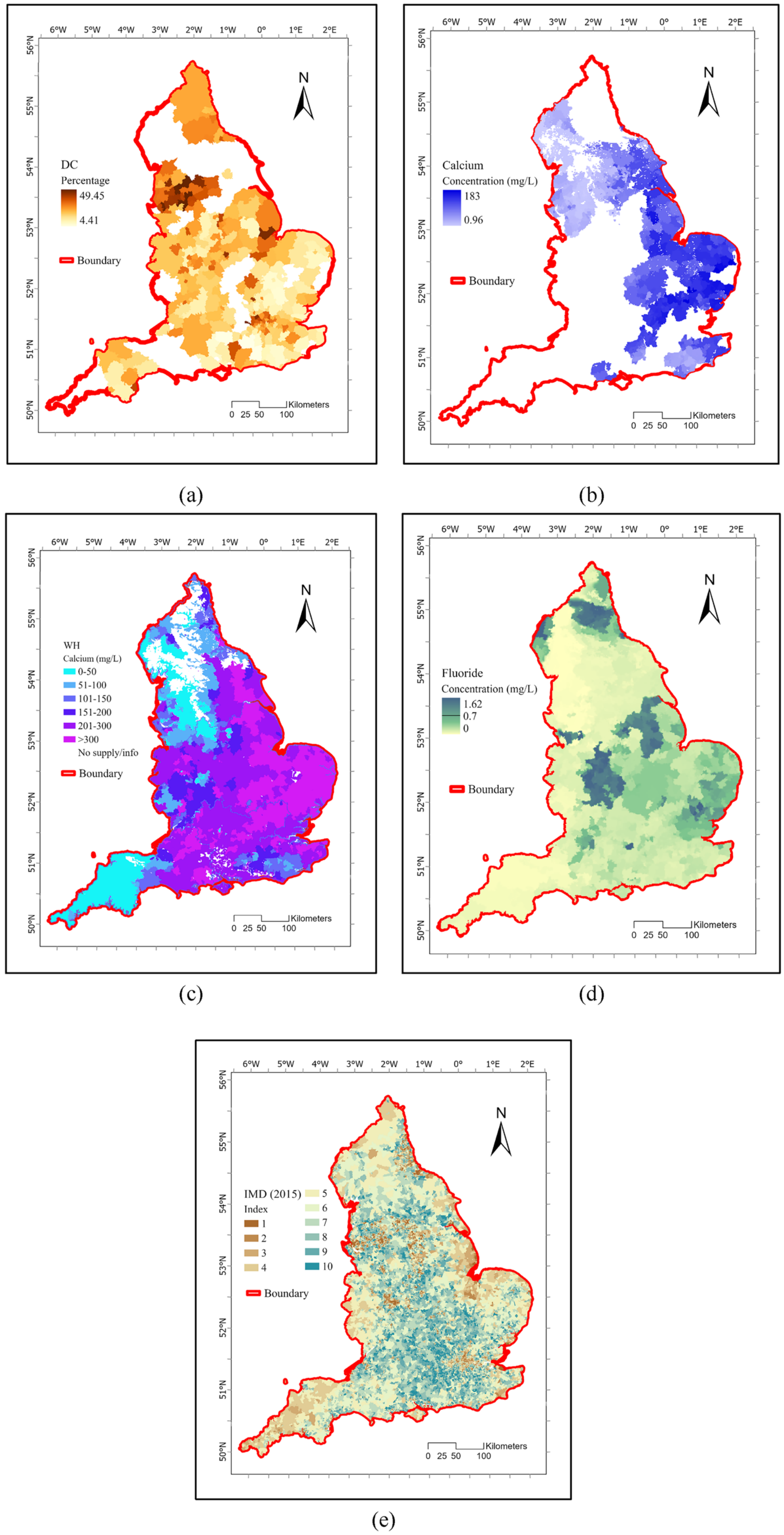

Fig. 3 Distribution of **a** DC (Dental Caries; expressed as the percentage of 5-year-olds with experience of visually obvious dental decay in 2016/2017—source: [Office for Health Improvement and Disparities 2023)], **b** Calcium [Calcium concentration of Drinking Water—source: after Ascott et al (2018)], **c** WH [Water Hardness of Drinking Water—source: (scaleguard.co.uk 2024)] in 2013, **d** Fluoride [Fluoride concentration of Drinking Water—source:after Ascott et al (2018)], and **e** IMD [Index of Multiple Deprivation—source: (www.gov.uk2015)] for England in 2015 (with 1 and 10 indicating the most and least deprived LSOAs respectively), produced by ArcGIS Pro

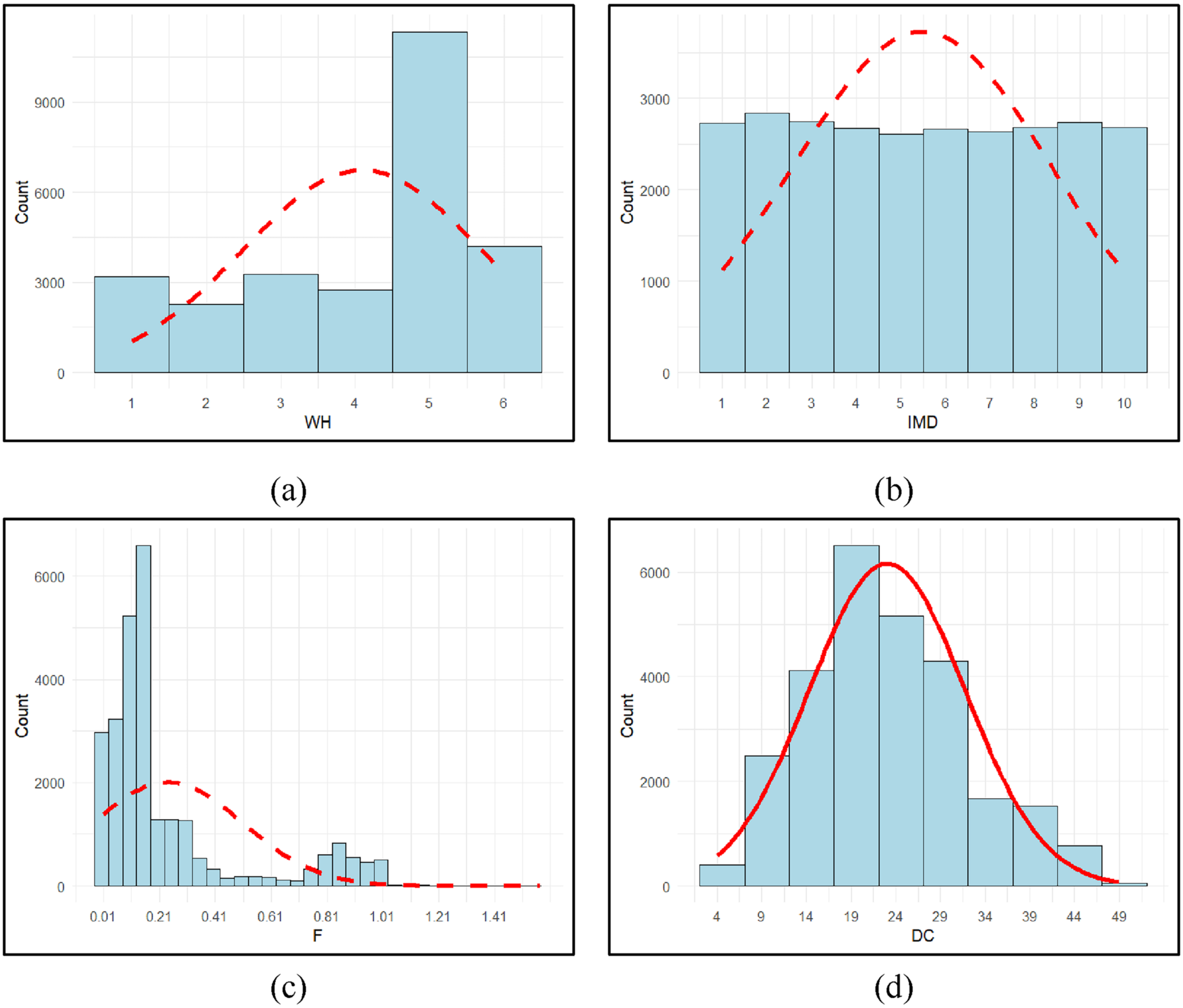

Fig. 4 Histogram of distribution of LSOA-level data for **a** WH, **b** IMD, **c** F, **d** DC across England, produced by R. See text for detailed sources. Red curves show the best-fit normal distributions with the same mean and standard deviation of the data. The distribution of the target variable (DC) is close to normal, whereas as those of the predictor variables, WH, IMD and F are not

measures concerning income, employment, education, skills and training, health and disability, crime, housing and services, and living environment. IMD decile values range between 1 and 10, addressing the most and least deprived LSOAs, respectively. The IMD data for LSOAs was downloaded from the UK government services and information website (www.gov.uk 2015).

Table 1 Descriptive statistics of the dataset

Index	DC (%)	WH (–)	IMD (–)	F (mg/L)
Mean	23.45	4.09	5.47	0.24
Standard Deviation	8.73	1.60	2.89	0.27
Sample Variance	76.29	2.55	8.33	0.07
Minimum	4.41	1.00	1.00	0.01
Maximum	49.45	6.00	10.00	1.57

Descriptive Statistics

After the collection and spatial pre-processing of the DC records and predictors (i.e., WH, IMD, and F), the final dataset is composed of 26,971 records. Histograms of the frequency distribution of WH, IMD, F and DC are shown in Fig. 4. As shown in Fig. 4-(a–d), unlike DC which has a nearly normal distribution, the predictor variables, WH, IMD, and F, are not normally distributed, albeit that normality is not a requirement of MLR (Bradley 1960). A summary of distribution descriptive statistics is presented in Table 1. The mean DC is 23%, with values in (LAD-scale) individual LSOAs ranging from 4 to 50%. For the predictors, WH, IMD, and F, have means of 4.09, 5.47, and 0.24 mg/L, respectively with ranges of [1, 6], [1, 10], and [0.01, 1.57] mg/L, respectively.

The dataset correlation matrix is given in Table 2. DC is negatively correlated with all of WH, IMD, and F with Pearson correlation coefficients (ρ, see Eq. (4)) of −0.41, −0.37, and −0.18, respectively, corresponding to moderate, low, and poor inverse correlations, respectively (Mukaka 2012; Schober et al. 2018) indicating the utility of a multiple regression modelling approach.

Model

This study employed MLR (Faraway 2016; Montgomery et al. 2021) to establish objectively the association between the response variable, DC, and multiple predictors, viz. WH, IMD and F, including, for various models, interaction terms between WH, IMD, and F as shown in Eq. (2).

$$\begin{aligned} DC =& \beta_0 + \beta_1 WH + \beta_2 IMD + \beta_3 F + \beta_4 WH \times F \\ &+ \beta_5 WH \times IMD + \beta_6 IMD \times F + \beta_7 WH \times F \times IMD + \varepsilon \end{aligned} \tag{2}$$

where β_0 is the intercept, β_i (i=1–7) represent distinct regression coefficients, and ε represents the model's residual standard error (RSE). A total of 16 models were investigated by fitting various combinations of regression coefficients, β_i, as shown in Table 3.

Further, we implemented the above MLR model in an F-segmented format to further investigate DC~F relationship (Wagner et al. 2002). In this process, based on F concentrations considered as breaking points (BPs), different models were fit to the left and right sides of each BP, yielding a more flexible model that showed F concentrations at which DC associations exhibit significant changes.

Quality Indicators

Five quality indicators, namely RSE, ρ, coefficient of determination (R^2), Akaike information criterion (AIC), and Bayesian information criterion (BIC) were used for model quality assessment. These indicators were calculated according to Eqs. (3, 4, 5, 6, 7):

$$\mathrm{RSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n - p}} \tag{3}$$

$$\rho = \frac{\sum_{i=1}^{n} (y_i - \overline{y})(\hat{y}_i - \overline{y_i})}{\sqrt{\sum_{i=1}^{n} (y_i - \overline{y})^2}\sqrt{\sum_{i=1}^{n} (\hat{y}_i - \overline{y_i})^2}} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{5}$$

$$\mathrm{AIC} = -2\log L + 2k \tag{6}$$

$$\mathrm{BIC} = -2\log L + k\ln(n) \tag{7}$$

where, y_i = observed value and $\hat{y}_i$ = predicted value, $\overline{y}$ = mean of the observed values, $\overline{y_i}$ = mean of the predicted values, n = number of observations, p = number of estimated parameters (including intercept), k = number of estimated parameters plus one (error term), and logL = log-likelihood of the model [details in Ref. (Kuha 2004)].

BIC is used to determine the most parsimonious of models being tested, with a reduction of greater than 2 units typically indicative of a materially improved model. In this study, we further applied the F-test (James et al. 2013; Neter et al. 1983) using analysis of variance (ANOVA) to compare the MLR models with different predictors, to determine whether or not the addition of new predictor(s) made a significant improvement to the model's fit, with a $p < 0.05$ taken to indicate a significant difference between the two compared models.

Table 2 Correlation matrix of the dataset

Parameters	DC	WH	IMD	F
DC	**1.00**			
WH	−0.41 ***	**1.00**		
IMD	−0.37 **	0.18 **	**1.00**	
F	−0.18 **	0.13 **	−0.04 *	**1.00**

*** Moderate correlation, ** Poor correlation, * Negligible correlation (Mukaka 2012; Schober et al. 2018)

Results

Models and Trends

Results of MLR modelling of DC with different linear combinations of single predictors (Models 1–7) and with further interaction terms (Models 8–16) are shown in Table 3. The ANOVA results of F-tests of all nested models are presented in Figures S1 and S2. Regarding the models' residuals, although formal tests did not indicate normality of residual DCs (possibly due to the large number of samples, i.e., 26,971), residuals exhibited near-zero kurtosis and skewness, reflecting practically no relevant departure from normality (See Figure S3). Whilst preferred, many studies have shown that a normal distribution of the target variable residuals is not a strict requirement for linear regression models, especially in large sample size settings (Knief and Forstmeier 2021; Schmidt and Finan 2018). In Models 1–15, the significantly (as indicated by 95% confidence

Table 3 Comparison of MLR models of dental caries (DC) as a function of water hardness (WH), index of multiple deprivation (IMD), and water fluoride (F) for LSOAs in England

No	Predictors	Model coefficients for indicated predictive variable								MLR model quality indicators				
		β_0 Intercept	β_1 WH	β_2 IMD	β_3 F	β_4 WH·IMD	β_5 WH·F	β_6 IMD·F	β_7 WH·IMD·F	ε (RSE)	ρ	R^2	AIC	BIC
1	F	24.82 ± 0.13	–	–	−5.78 ± 0.38	–	–	–	–	8.60	0.18	0.03	192,588	192,612
2	IMD	29.47 ± 0.21	–	−1.10 ± 0.03	–	–	–	–	–	8.14	0.36	0.13	189,632	189,657
3	WH	32.71 ± 0.26	−2.26 ± 0.06	–	–	–	–	–	–	7.95	0.41	0.17	188,373	188,398
4	IMD, F	31.11 ± 0.22	–	−1.13 ± 0.03	−6.32 ± 0.35	–	–	–	–	7.96	0.41	0.17	188,441	188,474
5	WH, F	33.33 ± 0.26	−2.18 ± 0.06	–	−4.13 ± 0.35	–	–	–	–	7.87	0.43	0.19	187,856	187,889
6	WH, IMD	36.48 ± 0.28	−1.97 ± 0.06	−0.90 ± 0.03	–	–	–	–	–	7.52	0.51	0.26	185,394	185,427
7	WH, IMD, F	37.33 ± 0.28	−1.86 ± 0.06	−0.94 ± 0.03	−4.81 ± 0.33	–	–	–	–	7.41	0.53	0.28	184,607	184,648
8	WH, IMD, F, WH·IMD	38.21 ± 0.48	−2.09 ± 0.11	−1.11 ± 0.08	−4.83 ± 0.33	0.04 ± 0.02	–	–	–	7.41	0.53	0.28	184,589	184,638
9	WH, IMD, F, WH·F	39.00 ± 0.32	−2.32 ± 0.07	−0.95 ± 0.03	−14.18 ± 0.89	–	2.45 ± 0.22	–	–	7.35	0.54	0.29	184,124	184,174
10	WH, IMD, F, IMD·F	38.39 ± 0.32	−1.87 ± 0.06	−1.13 ± 0.04	−8.99 ± 0.65	–	–	0.83 ± 0.11	–	7.38	0.53	0.29	184,398	184,447
11	WH, IMD, F, WH·IMD, WH·F	40.23 ± 0.5	−2.64 ± 0.12	−1.19 ± 0.08	−14.39 ± 0.9	0.06 ± 0.02	2.50 ± 0.22	–	–	7.34	0.54	0.29	184,088	184,146
12	WH, IMD, F, WH·IMD, IMD·F	38.91 ± 0.48	−2.01 ± 0.11	−1.24 ± 0.08	−8.91 ± 0.66	0.03 ± 0.02	–	0.81 ± 0.11	–	7.38	0.53	0.29	184,392	184,450
13	WH, IMD, F, WH·F, IMD·F	39.56 ± 0.33	−2.28 ± 0.07	−1.08 ± 0.04	−16.08 ± 0.97	–	2.19 ± 0.22	0.57 ± 0.11	–	7.33	0.54	0.30	184,030	184,088
14	WH, IMD, F, WH·IMD, IMD·F, WH·F	40.49 ± 0.51	−2.54 ± 0.13	−1.26 ± 0.08	−16.11 ± 0.97	0.05 ± 0.02	2.25 ± 0.22	0.53 ± 0.11	–	7.33	0.54	0.30	184,009	184,075
15	WH, IMD, F, WH·IMD, IMD·F, WH·F, WH·IMD·F	40.79 ± 0.56	−2.63 ± 0.14	−1.33 ± 0.1	−17.73 ± 1.59	0.07 ± 0.02	2.70 ± 0.42	0.90 ± 0.31	−0.10 ± 0.08	7.33	0.54	0.30	184,005	184,078
16	WH, IMD, Segmented F, WH·IMD, IMD·F, WH·F, WH·IMD·F	41.90 ± 0.55	−0.94 ± 0.17	−1.13 ± 0.09	−130.59 ± 5.92 (188.42 ± 12.67*) (F–0.1) (−73.81 ± 11.54*) (F–0.15) (13.04 ± 2.99*) (F–0.37)	0.04 ± 0.02	0.57 ± 0.42	0.91 ± 0.30	-0.13 ± 0.07	7.07	0.59	0.34	182,078	182,201

*In Model 16, for the coefficient β_3, the values ± 12.67, ± 11.54, and ± 2.99 do not represent coefficient CIs (due to the F BPs being estimates themselves) but rather were calculated as ± 1.96 × SE(β_3)

limits) negative coefficients for the predictive variables WH, F, and IMD show that higher drinking water WH and F and improved socioeconomic status are all associated with an improvement in dental health as indicated by lower DC prevalence.

Of the simple linear models (Models 1–7), Model 7 has the largest ρ (0.53) and R^2 (0.28), as well as the lowest RSE (7.41), AIC (184607), and BIC (184648) and hence Eq. (8) below represents the best predictive MLR model of DC involving just WH, F and IMD as simple first-order linear predictive variables:

$$\begin{aligned} \mathrm{DC} = {} & (37.33 \pm 0.28) + (-1.86 \pm 0.06)\,\mathrm{WH} \\ & + (-0.94 \pm 0.03)\,\mathrm{IMD} + (-4.81 \pm 0.33)\,\mathrm{F} \end{aligned} \tag{8}$$

The relative importance of the predictive variables in predicting DC can be assessed by observing the ratios of the relevant β coefficients in Eq. (8). That $\beta_1/\beta_3 = 0.39$ indicates that, on average, a 1 category increase (e.g. 3—Slightly Hard to 4—Moderately Hard) increase in WH or a 0.39 mg/L increase in F would be expected to achieve the same improvement in DC outcome. Similarly, that $\beta_2/\beta_3 = 0.19$ and $\beta_2/\beta_1 = 0.50$ indicates that, on average, an increase in IMD category of 2 (i.e. 2 decile reduction in relative area deprivation) would have the same impact on DC outcome as a 2 × 0.19 mg/L increase in F or a 1 category increment in WH.

However, the magnitude of the association between DC and F (Fig. 5a) and, to a much lesser extent, between DC and WH (Fig. 5b) varies with IMD category. This is particularly pronounced for F, where it is clear that the positive association of higher drinking water fluoride with lower DC is much higher for low IMD groups than it is for high IMD groups—in other words, fluoridation might be argued to have a greater positive impact on the dental health of populations of lower socioeconomic status than of populations with higher socioeconomic status. It is evident, therefore, that consideration of WH-IMD-F interaction terms is required for a more accurate DC ~ WH + IMD + F model.

Interactive Effects of Predictors

Models 8–15 in Table 3 represent Model 7 variably incorporating one of the interaction terms (WH·F, WH·IMD, and IMD·F). The coefficient of WH·IMD (+0.04) indicates that the impact of WH on reducing DC is lower for less deprived LSOAs. The positive sign of the WH·F coefficient (+2.45) implies that WH and F can considerably reduce each other's independent influence on reducing DC. It, therefore, calls for establishing a balance between WH and F levels in public health strategies that aim at minimizing DC. Similarly, for IMD·F, the coefficient (+0.83) suggests that the protective influence of fluoride is not uniform across LSOAs with different socio-economic conditions.

Fluoride Concentration-Dependence of DC-F Association

Model 16 corresponds to a segmented version of Model 15 with F-based BPs determined different segments for the MLR. Different models (with 1, 2 or 3 BPs with different initial estimates of BPs) were tested, and it was observed that the inclusion of 3 BPs at 0.10, 0.15, 0.37 mg/L F created the most accurate segmented model.

Model 16, as rendered by Eq. (9) was found to be significantly better than the other models in Table 3, according to all the fit indicators of RSE (7.07), ρ (0.59), R^2 (0.34), AIC (182,078), and BIC (182,201).

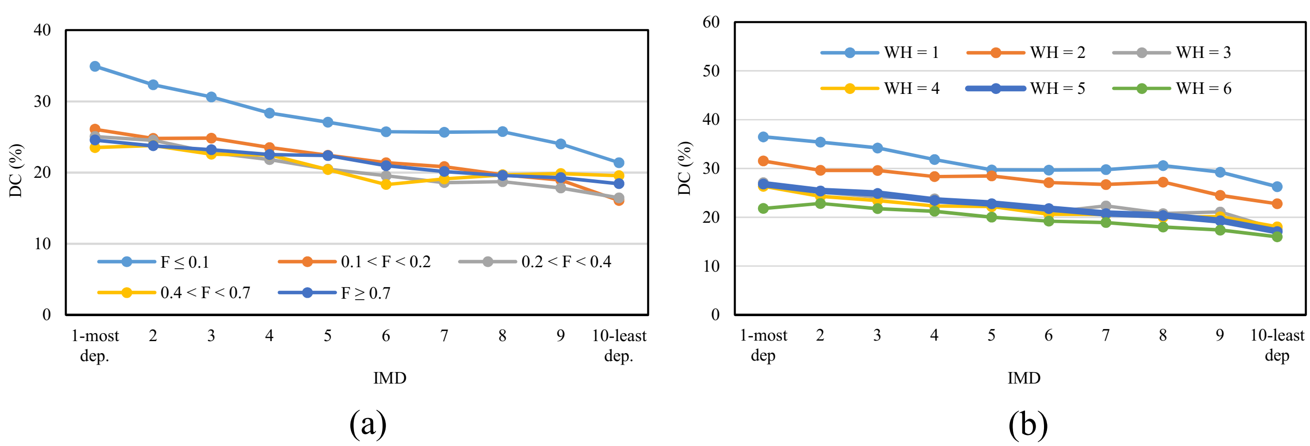

Fig. 5 Mean DC for each category value (1–10) of IMD for various ranges of **a** drinking water F; and **b** drinking water WH (as a proxy for Ca) where values of 1, 2, 3, 4, 5, and 6 represent WH levels of Soft (0–50) mg/L, Moderately Soft (51–100) mg/L, Slightly Hard (101–150) mg/L, Moderately Hard (151–200) mg/L, Hard (201–300) mg/L, and Very Hard (> 300) mg/L, respectively

$$
\begin{aligned}
&\text{For } F \leq 0.10\ \text{mg/L}: \\
&\quad DC = (41.90 \pm 0.55) + (-130.59 \pm 5.92)\,F \\
&\qquad + (-0.94 \pm 0.17)\,WH + (-1.13 \pm 0.09)\,IMD \\
&\qquad + (0.57 \pm 0.42)\,F{\cdot}WH + (0.91 \pm 0.30)\,F{\cdot}IMD \\
&\qquad + (0.04 \pm 0.02)\,WH{\cdot}IMD + (-0.13 \pm 0.07)\,F{\cdot}WH{\cdot}IMD \\
&\text{For } 0.10\ \text{mg/L} < F \leq 0.15\ \text{mg/L}: \\
&\quad DC = (41.90 \pm 0.55) + (-130.59 \pm 5.92)\,F \\
&\qquad + (188.42 \pm 12.67)\,(F - 0.1) + (-0.94 \pm 0.17)\,WH \\
&\qquad + (-1.13 \pm 0.09)\,IMD + (0.57 \pm 0.42)\,F{\cdot}WH \\
&\qquad + (0.91 \pm 0.30)\,F{\cdot}IMD + (0.04 \pm 0.02)\,WH{\cdot}IMD \\
&\qquad + (-0.13 \pm 0.07)\,F{\cdot}WH{\cdot}IMD \\
&\text{For } 0.15\ \text{mg/L} < F \leq 0.37\ \text{mg/L}: \\
&\quad DC = (41.90 \pm 0.55) + (-130.59 \pm 5.92)\,F \\
&\qquad + (188.42 \pm 12.67)\,(F - 0.1) + (-73.81 \pm 11.54)\,(F - 0.15) \\
&\qquad + (-0.94 \pm 0.17)\,WH + (-1.13 \pm 0.09)\,IMD \\
&\qquad + (0.57 \pm 0.42)\,F{\cdot}WH + (0.91 \pm 0.30)\,F{\cdot}IMD \\
&\qquad + (0.04 \pm 0.02)\,WH{\cdot}IMD + (-0.13 \pm 0.07)\,F{\cdot}WH{\cdot}IMD \\
&\text{For } F > 0.37\ \text{mg/L}: \\
&\quad DC = (41.90 \pm 0.55) + (-130.59 \pm 5.92)\,F \\
&\qquad + (188.42 \pm 12.67)\,(F - 0.1) + (-73.81 \pm 11.54)\,(F - 0.15) \\
&\qquad + (13.04 \pm 2.99)\,(F - 0.37) + (-0.94 \pm 0.17)\,WH \\
&\qquad + (-1.13 \pm 0.09)\,IMD + (0.57 \pm 0.42)\,F{\cdot}WH \\
&\qquad + (0.91 \pm 0.30)\,F{\cdot}IMD + (0.04 \pm 0.02)\,WH{\cdot}IMD \\
&\qquad + (-0.13 \pm 0.07)\,F{\cdot}WH{\cdot}IM
\end{aligned}
\tag{9}
$$

The relationship between DC* (DC corrected by subtracting the fitted WH and IMD contributions (including interactions) to visualize the marginal effect of fluoride) and F, according to the optimal Model 16, is illustrated in Fig. 6. This clearly shows that the relationship between DC* and F is not a simple first order linear relartionship—the dependence of DC* on F is, instead, strongly dependent on F concentration—with a strong negative dependence of DC* on F for F concentrations less than 0.10 mg/L, but a much weaker negative dependence for F concentrations higher than 0.37 mg/L whilst for F concentrations between 0.10 mg/L and 0.15 mg/L the dependence of DC* on F is actually significantly positive.

Discussion

Effects of Calcium Inclusion in Models

The effect of inclusion of WH in models of DC ~ F relationships should be highlighted. Firstly, the significant coefficient of WH (-1.86 ± 0.06) in Model 7 demonstrates the independent contribution of WH to explaining DC. Secondly, inclusion of WH as a predictive variable improves the accuracy of the model (Model 7 cf. Model 4, F-test results ($p < 2e-16$) along with the quality indicators in Table 3). Thirdly, incorporation of WH as a predictive variable diminishes the strength of F's correlation with DC by around 24% (β_3: −4.81 ± 0.33 cf. −6.32 ± 0.35) and of IMD's correlation with DC by around 17% (β_2: −0.94 ± 0.03 cf. −1.13 ± 0.03).

From an economic perspective, earlier studies have convincingly demonstrated that water fluoridation in England has the potential to marginally reduce individuals' dental treatment costs. Moore et al. (2024b), analyzing 2010–2020 records of patients aged ≥ 12 years, showed that annual

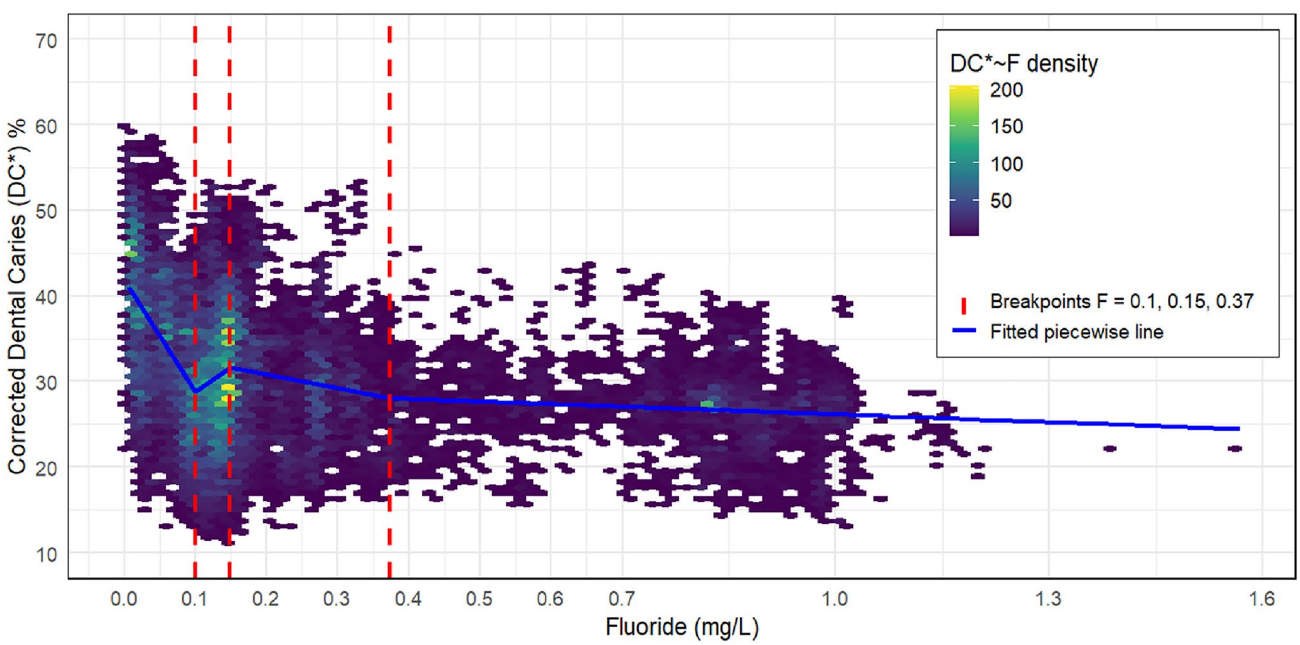

Fig. 6 Segmented MLR fit (Model 16). Note that, while all predictive factors (WH, IMD, F, and all interaction terms) were included in Model 16, DC in this graph was corrected for the impact of WH and IMD (by subtracting the fitted WH and IMD contributions, including interactions) for better visualization. This graph illustrates that the DC* ~ F relationship varies across F concentrations, having the strongest negative dependence of DC* on F for F concentrations below 0.10 mg/L

National Health Service (NHS) dental treatment costs for optimally fluoridated patients in England were 5.5% lower (by £22.26 per person, 95% CI £21.43, £23.09) than for non-optimally fluoridated patients. These were average effects across England and have included a range of WH levels. However, the present study illustrates that WH (as a proxy for calcium) is an important effect modifier of the relationship between F exposure and DC prevalence. WH should therefore be reported and considered as an important contextual factor in studies on the dental health effects of water fluoridation. For decision-makers considering new fluoridation programmes, the findings of this study suggest that the impact of a new programme would be expected to vary according to WH, such that reductions in caries prevalence would likely be greater in a soft water area, than in a comparably deprived hard water area.

Further, based on the demonstrated significant association of DC with lower WH, it can be suggested that the higher rate of DC in some regions (most notably, the North West) is not only due to insufficient drinking water fluoride, and deprivation, (Weston-Price et al. 2018) but can also be significantly partly attributed to the softness of water (i.e., low WH and insufficient calcium in community water, see Fig. 3).

Some studies have shown severe consequences for simultaneous imbalanced exposures to fluoride and calcium (e.g., high fluoride and low calcium for animals Simon et al. 2014, 2016)). This, and the potential adverse effects on DC resulting from low WH demonstrated in this and other studies (Tang et al. 2021) suggests that cost–benefit analyses of water softening programmes (e.g. (Van der Bruggen et al. 2009)) also need to be re-evaluated in the light of these findings and consideration of other health outcomes associated with WH (e.g. eczema (Lopez et al. 2022)).

Additional Considerations on Fluoridation

The present study found that the impact of water F on dental caries prevalence was greater in more deprived areas, that is LSOAs with lower IMD. This is in line with other recent ecological studies using area-based, aggregate outcome data (Disparities, 2022; Hobbs et al. 2020). This is also consistent with the findings of Henein and Landes (2022) who demonstrated a significant association between socioeconomic status, water fluoridation, and dental interventions for children in England, and observed that in the most deprived populations (IMD = 1), there is a considerable difference between the proportions of active interventional treatments in fluoridated and non-fluoridated local authorities (0.188 and 0.243, respectively). Likewise, in New Zealand, Hobbs et al. (2020) observed at an area-level that the rate of hospitalisations in children due to dental caries was reduced to a greater extent in census area units with higher socioeconomic disadvantage.

In contrast, studies which have collected individual-level outcome data have failed to find that water fluoridation has a greater preventive effect in more deprived individuals (Goodwin et al. 2022; Iheozor-Ejiofor et al. 2024; Moore et al. 2024b). These different findings may be a classic example of an epidemiological ‘ecological fallacy’, whereby inferences based on group-level data cannot be directly transferred to individuals. As so eloquently explained by Rose (2001), the major determinants of differences in health *between* populations are environmental conditions (e.g. water fluoride levels). In contrast, the major determinants of differences in the health of individuals *within* a given population are those factors which vary at the individual level, such as access to personal resources and resulting behaviours (e.g. ability to afford toothpaste, healthy food).

F concentrations between 0.7 mg/L and 1 mg/L have been repeatedly reported as optimal F concentrations for community water fluoridation (Disparities, 2022). This target is intended to provide the best balance between caries prevention and avoidance of dental fluorosis (Spencer and Do 2016). Many studies have cautioned the current approaches of determining optimal F (Spencer and Do 2016) and have accordingly recommended the selection of the optimal F concentration to be more flexible with respect to the location (Brouwer et al. 1988) and time (Iheozor-Ejiofor et al. 2024) of interest. Indeed, this research (see Figs. 5 and 6) shows that the fluoridation level that yields the most dramatic reduction in dental caries prevalence is much lower than F = 0.7 mg/L with a substantially weakened protective effect of increasing F above 0.37 mg/L. This may reflect the availability of fluoride in the form of toothpaste, tablets, and rinses today, resulting in the protective role of community water fluoridation becoming less pronounced recently. Indeed, updating the optimal fluoridation from (0.7, 1.2) ppm to 0.7 ppm in 2015 by the USA was done in light of people receiving fluoride from other sources (besides drinking water) now (Health and Fluoridation, 2015). In line with this, Davies et al. (2017) revealed that fluoride availability in the form of children’s toothpaste (with a minimum of 1000 ppm fluoride) was one of the most significant reasons behind the decline in caries levels in 5-year-olds in England.

Notwithstanding all this, target fluoridation concentration is generally not the major driver of the operational costs of fluoridation schemes and nor of the often larger capital expenditure costs. However, we believe that more detailed dose–response and cost–benefit analyses that take account of WH are required towards science-informed decision-making as to whether or not investment in new fluoridation schemes represents a best value for improving public health.

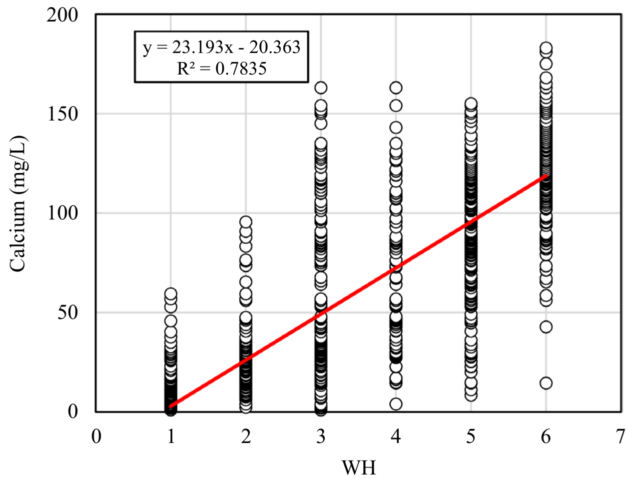

Fig. 7 Correlation between drinking water calcium and modelled WH (WH values 1≥6 indicate Soft≥Very Hard hardness classes)

Uncertainties and Limitations

Uncertainties and limitations of the findings of this study include those related to the input data and to the model:

(i) DC was represented by 'the percentage of 5-year-olds with experience of visually obvious dental decay'. As with any measurement, there is potential for errors of misclassification in the clinical assessment of decay, although the survey examiners are calibrated to a standard threshold.

(ii) Spatial heterogeneity can be another source of uncertainty. When using geographical data with specific divisions, the factors are calculated as an average for the whole geographical unit; hence variabilities may be considered in this regard. Referring to Fig. 3, the map of IMD was depicted at the LSOA-level covering the whole country, whereas there were missing records for DC whose map was created based on the district division system. Further regarding data, such studies could also benefit from auxiliary spatial data (e.g., spatial accessibility to healthcare services influenced by population distribution, healthcare resourcing, and transportation infrastructure), which may also play a role in oral health outcomes and dental care utilization, as highlighted in studies on healthcare accessibility (Chen et al, 2023).

(iii) Although WH is a well-known proxy for calcium concentration and in this study are highly correlated ($R^2=0.78$; see Fig. 7, a statistically significant correlation with p-value ≈ 0) utilizing WH as a proxy for calcium might result in a conservative (i.e. under-estimation) estimation of the correlation of calcium with DC in this study.

(iv) The distribution of LSOA level F concentrations was imputed using machine learning and whilst that for WH was digitized from an image (see Sect. "Study area and spatial units"). Regarding digitization, while the accuracy of the model implies the general quality of digitization, the model can encounter some difficulties in small and dense areas with abrupt changes of the digitizable values. In such cases, manual checks in critical spots can be adopted (as was done in this study) to ensure the precision of the digitized map. Future studies could address these limitations toward an improved MLR model.

(v) Drinking water quality data were obtained from specific time-points, whereas such quality may vary over time. Although, in particular, Moore et al. (2020) found that fluoride in artificially fluoridated supplies in England had a higher temporal variation than water supplies with naturally elevated fluoride, Roberts et al. (2020) showed that public water supply data for the period 2005–2014 could be used as an effective proxy for 1995–2004 public water supply fluoride concentrations. Bowyer et al. (2025) provide a further discussion of the relative time-averaged constancy of drinking water quality in England.

(vi) While the results of the employed MLR were significant for association analysis, the best-fitted model achieved ρ=0.59. This modest fit suggest that there may be other significant predictors of DC that have not been considered here; and/or that the nature of the mathematical relationship between DC and the WH, IMD and F predictive variables is more complicated than indicated by the relatively simple models used—for example, irrespective of other confounding factors, the relationship between DC and drinking water quality might reasonably be expected to be in the form of a skewed upside down U as there is widely thought to be an optimal value for drinking water F, below which the protective effect is sub-optimal and above which, ultimately F becomes damaging to teeth, through fluorosis, rather than protective. Future studies could usefully explore, therefore, dose–response models that conform more closely to this theoretically mechanistically expected behavior. Further, sophisticated artificial intelligence models with appropriate expert oversight (e.g. using stacking machine learning combined with appropriate feature selection models (Mehrabi et al. 2025)) might also be of utility for the more robust prediction of DC

Conclusions

The prevalence of children's dental caries (DC) in England is a function not only of drinking water fluoride concentration and social deprivation but also of water hardness (WH) (used as a proxy for calcium concentration). Further, the association between DC and F is dependent upon F concentration, with the dependence much stronger for drinking water F < 0.10 mg/L than for F > 0.37 mg/L. Both of these results should be explicitly taken into account in cost–benefit modelling for new drinking water fluoridation proposals and suggest that the relatively poor dental health in children noted in northern regions, notably the North West, may not be uniquely attributable to sub-optimal drinking water fluoride but also to the softness of the drinking water supplied.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12403-026-00782-z.

Acknowledgements Mohammad Mehrabi acknowledges a University of Manchester Faculty of Science and Engineering Dean's Doctoral Scholarship. The views expressed in this paper are those of the authors and not necessarily those of any of their affiliated institutions including NHS England. We thank two anonymous reviewers for comments that helped us improve the clarity of the paper.

Author Contributions Conceptualization and design were performed by Mohammad Mehrabi, David A. Polya, Deborah Moore, Yang Han. Material preparation and data collection were performed by Mohammad Mehrabi, David A. Polya, Matthew J. Ascott. Software and Analysis were performed by Mohammad Mehrabi and Yang Han. Visualization and writing—original draft preparation were performed by Mohammad Mehrabi. Writing—review and editing was performed by Mohammad Mehrabi, Yang Han, Deborah Moore, Matthew J. Ascott, Anne-Marie Glenny, David A. Polya. Supervision was performed by Yang Han and David A. Polya. All authors read and approved the final manuscript.

Funding This research received no external funding.

Data Availability The material used in this work can be available upon reasonable request from corresponding author.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish MJA publishes with the permission of the Director, British Geological Survey (NERC).

References

Abed R, Bernabe E, Sabbah W (2020) Family impacts of severe dental caries among children in the United Kingdom. Int J Environ Res Public Health 17:109

Akuno M, Nocella G, Milia E, Gutierrez L (2019) Factors influencing the relationship between fluoride in drinking water and dental fluorosis: a ten-year systematic review and meta-analysis. J Water Health 17:845–862

Arvin E, Bardow A, Spliid H (2018) Caries affected by calcium and fluoride in drinking water and family income. J Water Health 16:49–56

Ascott,M.J., Stuart, M.E., Gooddy, D.C., Marchant, B.P., Talbot, J.C., Surridge, B.W.J. and Polya, D.A. (2018) Provenance of drinking water revealed through compliance sampling. Environmental Science: Processes and Impacts, 21, 1052–1064. https://doi.org/10.1039/C8EM00437D

Balmer R, Toumba J, Godson J, Duggal M (2012) The prevalence of molar incisor hypomineralisation in Northern England and its relationship to socioeconomic status and water fluoridation. Int J Paediatr Dent 22:250–257

Bernabe E, Marcenes W, Abdulkader RS, Abreu LG, Afzal S, Alhalaiqa FN, Al-Maweri S, Alsharif U, Anyasodor AE, Arora A (2025) Trends in the global, regional, and national burden of oral conditions from 1990 to 2021: a systematic analysis for the Global Burden of Disease Study 2021. Lancet 405:897–910

Bowyer RC, Schillereff DN, Ascott MJ, Giles L, García MP, Lachance G, Lochlainn MN, Steves CJ, Gooddy DC (2025) Personalised estimates of dosage within a population-based cohort suggest limited evidence that drinking water chemistry modulates health outcomes. Sci Total Environ 999:180309

Bradley JV (1960) Distribution-free statistical tests. United States Air Force

Brouwer I, De Bruin A, Dirks OB, Hautvast J (1988) Unsuitability of World Health Organisation guidelines for fluoride concentrations in drinking water in Senegal. Lancet 331:223–225

Bruvo M, Ekstrand K, Arvin E, Spliid H, Moe D, Kirkeby S, Bardow A (2008) Optimal drinking water composition for caries control in populations. J Dent Res 87:340–343

Chen, L., Chen, T., Lan, T., Chen, C., & Pan, J. (2023). The contributions of population distribution, healthcare resourcing, and transportation infrastructure to spatial accessibility of health care. INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 60, 00469580221146041. https://doi.org/10.1177/00469580221146041

Costa SM, Martins CC, Bonfim MdLC, Zina LG, Paiva SM, Pordeus IA, Abreu MH (2012) A systematic review of socioeconomic indicators and dental caries in adults. Int J Environ Res Public Health 9:3540–3574

Davies G, Neville J, Jones K, White S (2017) Why are caries levels reducing in five-year-olds in England? Br Dent J 223:515–519

Disparities TOfHIa (2022) Water fluoridation - Health monitoring report for England 2022

Elphick JR, Bergh KD, Bailey HC (2011) Chronic toxicity of chloride to freshwater species: effects of hardness and implications for water quality guidelines. Environ Toxicol Chem 30:239–246
Faraway JJ (2016) Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models. Chapman and Hall/CRC
Ghosh T (2024) Groundwater hydro-geochemical inferences and eXplainable Artificial Intelligence augmented groundwater quality prediction in arid and semi-arid segment of Rajasthan, India. Groundw Sustain Dev 26:101272
Goodwin M, Emsley R, Kelly MP, Kelly M, Sutton M, Tickle M, Walsh T, Whittaker W, Pretty IA, Pretty I (2022) Evaluation of water fluoridation scheme in Cumbria: the CATFISH prospective longitudinal cohort study. Public Health Res 10:1–186
Health UDo, Fluoridation HSFPoCW (2015) US Public Health Service recommendation for fluoride concentration in drinking water for the prevention of dental caries. Public Health Rep 130:318–331
Henein C, Landes D (2022) NHS dental activity: a population marker for the effectiveness of community water fluoridation in children in England. Brit Dent J. https://doi.org/10.1038/s41415-021-3822-1
Hobbs M, Wade A, Jones P, Marek L, Tomintz M, Sharma K, McCarthy J, Mattingley B, Campbell M, Kingham S (2020) Area-level deprivation, childhood dental ambulatory sensitive hospitalizations and community water fluoridation: evidence from New Zealand. Int J Epidemiol 49:908–916
Huang Y, Wang J, Tan Y, Wang L, Lin H, Lan L, Xiong Y, Huang W, Shu W (2018) Low-mineral direct drinking water in school may retard height growth and increase dental caries in schoolchildren in China. Environ Int 115:104–109
Iheozor-Ejiofor Z, Walsh T, Lewis SR, Riley P, Boyers D, Clarkson JE, Worthington HV, Glenny A-M, O'Malley L (2024) Water fluoridation for the prevention of dental caries. Cochrane Database Syst Rev. https://doi.org/10.1002/14651858.CD010856.pub3
Iheozor-Ejiofor Z, Worthington HV, Walsh T, O'Malley L, Clarkson JE, Macey R, Alam R, Tugwell P, Welch V, Glenny AM (2015) Water fluoridation for the prevention of dental caries. Cochrane Database Syst Rev
James G, Witten D, Hastie T, Tibshirani R (2013) An introduction to statistical learning: with applications in R. Springer
Jones C, Worthington H (1999) The relationship between water fluoridation and socioeconomic deprivation on tooth decay in 5-year-old children. Br Dent J 186:397–400
Jones C, Worthington H (2000) Water fluoridation, poverty and tooth decay in 12-year-old children. J Dent 28:389–393
Knief U, Forstmeier W (2021) Violating the normality assumption may be the lesser of two evils. Behav Res Methods 53:2576–2590
Krisdapong S, Somkotra T, Kueakulpipat W (2014) Disparities in early childhood caries and its impact on oral health–related quality of life of preschool children. Asia Pac J Public Health 26:285–294
Kuha J (2004) AIC and BIC: comparisons of assumptions and performance. Sociol Methods Res 33:188–229
Lin H-S, Lin J-R, Hu S-W, Kuo H-C, Yang Y-H (2014) Association of dietary calcium, phosphorus, and magnesium intake with caries status among schoolchildren. Kaohsiung J Med Sci 30:206–212
Lopez DJ, Singh A, Waidyatillake NT, Su JC, Bui DS, Dharmage SC, Lodge CJ, Lowe AJ (2022) The association between domestic hard water and eczema in adults from the UK Biobank cohort study. Br J Dermatol 187:704–712
McGrady MG, Ellwood RP, Maguire A, Goodwin M, Boothman N, Pretty IA (2012) The association between social deprivation and the prevalence and severity of dental caries and fluorosis in populations with and without water fluoridation. BMC Public Health 12:1–17
Mehrabi M, Polya DA, Han Y (2025) Machine learning models of the geospatial distribution of groundwater quality: a systematic review. Water 17:2861
Mehta A, Bhalla S (2014) Assessing consequences of untreated carious lesions using pufa index among 5–6 years old school children in an urban Indian population. Indian J Dent Res 25:150–153
Montgomery DC, Peck EA, Vining GG (2021) Introduction to linear regression analysis. Wiley
Moore D, Allen T, Birch S, Tickle M, Walsh T, Pretty IA (2021) How effective and cost-effective is water fluoridation for adults? Protocol for a 10-year retrospective cohort study. BDJ Open 7:3
Moore D, Goodwin M, Pretty IA (2020) Long-term variability in artificially and naturally fluoridated water supplies in England. Community Dent Oral Epidemiol 48:49–55
Moore D, Nyakutsikwa B, Allen T, Lam E, Birch S, Tickle M, Pretty IA, Walsh T (2024b) How effective and cost-effective is water fluoridation for adults and adolescents? The LOTUS 10-year retrospective cohort study. Community Dent Oral Epidemiol. https://doi.org/10.1111/cdoe.12930
Moore D, Nyakutsikwa B, Allen T, Lam E, Birch S, Tickle M, Pretty IA, Walsh T (2024) Effect of fluoridated water on invasive NHS dental treatments for adults: the LOTUS retrospective cohort study and economic evaluation. Public Health Res 12:1–147
Mukaka MM (2012) A guide to appropriate use of correlation coefficient in medical research. Malawi Med J 24:69–71
Neter J, Wasserman W, Kutner MH (1983) Applied linear regression models. Richard D. Irwin
Nyakutsikwa B, Allen T, Walsh T, Pretty I, Birch S, Tickle M, Moore D (2022) Who are the 10%? Characteristics of the populations and communities receiving fluoridated water in England. Community Dent Health 39:247–253
Nyakutsikwa B, Walsh T, Pretty I, Moore D (2021) Water fluoride concentrations in England, 2009–2020. Community Dental Health
Office for Health Improvement and Disparities (2023) Fingertips | Public health data. https://fingertips.phe.org.uk/search/percentage%20of%205%20years#page/8/gid/1/pat/6/par/E12000001/ati/501/are/E06000047/iid/93563/age/34/sex/4/cat/-1/ctp/-1/yrr/1/cid/4/tbm/1/page-options/tre-ao-1. Accessed 15 Oct 2024
Pattussi MP, Marcenes W, Croucher R, Sheiham A (2001) Social deprivation, income inequality, social cohesion and dental caries in Brazilian school children. Soc Sci Med 53:915–925
Pizzo G, Piscopo MR, Pizzo I, Giuliana G (2007) Community water fluoridation and caries prevention: a critical review. Clin Oral Investig 11:189–193
R CoreTeam (2011) A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria
Roberts DJ, Massey V, Morris J, Verlander NQ, Saei A, Young N, Makhani S, Wilcox D, Davies G, White S (2023) The effect of community water fluoridation on dental caries in children and young people in England: an ecological study. J Public Health 45:462–469
Roberts DJ, Morris J, Wood A, Verlander N, Leonardi G, Fletcher T (2020) Use of public water supply fluoride concentration as an indicator of population exposure to fluoride in England 1995–2015. Environ Monit Assess 192:1–16
Rose G (2001) Sick individuals and sick populations. Int J Epidemiol 30:427–432
scaleguard.co.uk (2024) Hard Water Areas. https://www.scaleguard.co.uk/hard-water-areas.html. Accessed 15 Oct 2024
Schmidt AF, Finan C (2018) Linear regression and the normality assumption. J Clin Epidemiol 98:146–151
Schober P, Boer C, Schwarte LA (2018) Correlation coefficients: appropriate use and interpretation. Anesth Analg 126:1763–1768
Simon M, Beil F, Rüther W, Busse B, Koehne T, Steiner M, Pogoda P, Ignatius A, Amling M, Oheim R (2014) High fluoride and low calcium levels in drinking water is associated with low bone mass,

reduced bone quality and fragility fractures in sheep. Osteoporos Int 25:1891–1903

Simon MJ, Beil FT, Riedel C, Lau G, Tomsia A, Zimmermann EA, Koehne T, Ueblacker P, Rüther W, Pogoda P (2016) Deterioration of teeth and alveolar bone loss due to chronic environmental high-level fluoride and low calcium exposure. Clin Oral Investig 20:2361–2370

Spencer AJ, Do LG (2016) Caution needed in altering the 'optimum'fluoride concentration in drinking water. Community Dent Oral Epidemiol 44:101–108

Tanaka K, Miyake Y, Sasaki S, Hirota Y (2012) Dairy products and calcium intake during pregnancy and dental caries in children. Nutr J 11:1–8

Tang C, Rygaard M, Rosshaug PS, Kristensen JB, Albrechtsen H-J (2021) Evaluation and comparison of centralized drinking water softening technologies: effects on water quality indicators. Water Res 203:117439

Tinanoff N, Baez RJ, Diaz Guillory C, Donly KJ, Feldens CA, McGrath C, Phantumvanit P, Pitts NB, Seow WK, Sharkov N (2019) Early childhood caries epidemiology, aetiology, risk assessment, societal burden, management, education, and policy: global perspective. Int J Paediatr Dent 29:238–248

UKdataservice (2011) Accessed 15 Oct 2024 https://borders.ukdataservice.ac.uk/easy_download_data.html?data=England_lsoa_2011

Van der Bruggen B, Goossens H, Everard P, Stemgée K, Rogge W (2009) Cost-benefit analysis of central softening for production of drinking water. J Environ Manage 91:541–549

Wagner AK, Soumerai SB, Zhang F, Ross-Degnan D (2002) Segmented regression analysis of interrupted time series studies in medication use research. J Clin Pharm Ther 27:299–309

Weston-Price S, Copley V, Smith H, Davies G (2018) A multi-variable analysis of four factors affecting caries levels among five-year-old children; deprivation, ethnicity, exposure to fluoridated water and geographic region. Community Dent Health 35:217–222

Whelton H, Spencer A, Do L, Rugg-Gunn A (2019) Fluoride revolution and dental caries: evolution of policies for global use. J Dent Res 98:837–846

World Health Organization (2025) Sugars and dental caries: WHO technical note, May 2025

www.gov.uk (2015) Index of Multiple Deprivation. https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015. Accessed 15 Oct 2024