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The relationship between altitude and BMI varies across low- and middle-income countries

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Abstract

Objectives: Studies suggest that living at high altitude decreases obesity risk, but this research is limited to single-country analyses. We examine the relationship between altitude and body mass index (BMI) among women living in a diverse sample of low- and middle-income countries.

Materials and Methods: Using Demographic and Health Survey data from 1 583 456 reproductive age women (20–49 years) in 54 countries, we fit regression models predicting BMI and obesity by altitude controlling for a range of demographic factors—age, parity, breastfeeding status, wealth, and education.

Results: A mixed-effects model with country-level random intercepts and slopes predicts an overall -0.162 kg/m^2 (95% CI -0.220, -0.104) reduction in BMI and lower odds of obesity (OR 0.90, 95% CI 0.87, 0.95) for every 200 m increase in altitude. However, countries vary dramatically in whether they exhibit a negative or positive association between altitude and BMI (34 countries negative, 20 positive). Mixed findings also arise when examining odds of obesity.

Discussion: We show that past findings of declining obesity risk with altitude are not universal. Increasing altitude predicts slightly lower BMIs at the global level, but the relationship within individual countries varies in both strength and direction.

1 | INTRODUCTION

Human biology follows several ecogeographic patterns (Katzmarzyk & Leonard, 1998; Ruff, 2002); altitude is one of the best researched of these geographic variables (Beall, 2007; Bigham et al., 2009; Frisancho, 2013; Little et al., 2013; Obert et al., 1994; Scheinfeldt et al., 2012; Simonson et al., 2010; Stinson, 1982). A growing body of research has found that altitude predicts differences in body size (Table S1), with the most well-known paper suggesting that obesity risk increases at lower elevations in the United States (Voss et al., 2013). For this reason, some researchers have proposed that exposure to hypoxic conditions or extended stays at high altitude might represent novel therapeutic interventions to reduce obesity (Kayser & Verges, 2013; Palmer & Clegg, 2014; Quintero et al., 2010). Others suggest that altitude represents an important, overlooked source of population-level variation in obesity (Díaz-Gutiérrez et al., 2016; Voss et al., 2013; Woolcott et al., 2014) and associated chronic diseases (Thiersch et al., 2017; Woolcott et al., 2014). Multivariate tests of this relationship in adults derive almost exclusively from research in upper-middle- and high-income nations (Table S1). However, most of the world's high-altitude population lives in low- and middle-income countries (LMICs), and the socioeconomic marginalization of mountain communities in those contexts is often acute (Romeo et al., 2020). A few studies from LMICs, namely Peru and Ecuador, have shown an inverse relationship between altitude and measures of body mass index (BMI), although the relationship appears to vary by place and sex/gender (Woolcott et al., 2016; Pérez-Galarza, et al., 2021). Finally, Yang et al. (2015) studied the relationship between BMI and altitude in Korea and found no significant association. Collectively, these studies make it unclear whether, or to what extent, the association between altitude and body size exists globally.

In this study, we expand understanding of the relationship between altitude and body size by testing for an association between BMI, obesity risk, and elevation in a global sample of reproductive age women from 54 LMICs. We also assess the relationship between BMI, obesity, and altitude within each individual country. The wide range of elevations included in this analysis and the variety of countries surveyed allow us to examine the association between altitude and body size in a diverse set of social and ecological environments.

2 | BACKGROUND

Explanations for the proposed relationship between altitude and body size can be characterized as either ecogeographic or socioeconomic. The most popular ecogeographic explanation centers around hypoxia. Increases in elevation yield a logarithmic drop in atmospheric pressure; consequently, oxygen partial pressure in the blood decreases and hypoxia increases (Paralikar & Paralikar, 2010). Hypoxia could lead to population-level differences in BMI via hypoxia-inducible factor-1 (HIF-1) and its downstream effects on leptin signaling, basal metabolic rate, and glucose metabolism (Ambrosini et al., 2002; Palmer & Clegg, 2014; Quintero et al., 2010).

However, several other environmental factors are also plausible contributors. Temperature is known to predict BMI, and temperature drops with increasing altitude (Hruschka, Hadley, et al., 2015; Katzmarzyk & Leonard, 1998; Ruff, 2002). Higher elevations are also characterized by greater ultraviolet radiation (Gorman et al., 2017) and more challenging terrains and lower productivity which could contribute to lower BMIs. Studies have shown greater infectious disease burdens at lower altitudes (Clegg et al., 1972; Gelaw et al., 2019), and infectious disease is linked with weight loss.

Socioeconomic explanations are tied to the high rates of poverty, food insecurity, and underinvestment in infrastructure (e.g., healthcare, sanitation, supply lines) observed in many mountain communities, particularly those in rural areas (Romeo et al., 2020). In this vein, seasonal food scarcity and low wage economy participation have been linked with nutritional differences in high-altitude areas (Leonard, 1989). And socioeconomic measures appear to account for at least some of the differences in physical growth and size observed between high- and low-altitude communities (Little et al., 2013; Obert et al., 1994; Stinson, 1982).

The association between altitude and body size in different contexts could be further modified by sociocultural factors that vary with elevation. This possibility is apparent in the most widely cited paper on altitude and body size, which used only a small number of Colorado residents as its high-altitude sample (≥3000 m) and drew a substantial portion of its lowest altitude population from the southern United States (Voss et al., 2013). It seems likely that the average Colorado resident varies from those living in southern US states on a number of sociocultural characteristics that might influence BMI (e.g., ideal body size, food preferences and dietary norms, or physical activity patterns) in addition to socioeconomic ones (e.g., wealth, education, food stamp reliance, food deserts, transportation options).

Thus, a varied set of factors could contribute to the proposed link between altitude and body size. However, most large-scale population research on this topic comes from high-income countries, making it unclear to what extent those findings indicate something fundamental about human biogeography. To address this idea, we used mixed-effects regression to explore the relationship between altitude and body size in a diverse sample 54 LMICs. If a negative association is found in most settings, then this would lend support to previous suggestions that elevation and body size are fundamentally linked (Díaz-Gutiérrez et al., 2016; Voss et al., 2013; Woolcott et al., 2014). However, if a negative relationship is not observed—and that too despite the multiple factors thought to yield lower BMIs at high altitude—this may challenge the universality of the association.

3 | MATERIALS AND METHODS

3.1 | Data and variables

The data used here come from the Demographic and Health Surveys (DHS) (www.measuredhs.com), nationally representative surveys conducted in low- and middle-income countries about a range of health-related topics. We included surveys from all countries and years (1992–2020) for which standard DHS were available at the time of download and for which altitude and the other desired variables were recorded for adult, reproductive age women (20–49 years) (see Figure S1 for map). The World Bank income classifications for each country in a given survey year totaled 13 upper-middle-income countries, 54 lower-middle-income countries, and

122 low-income countries (Table S2). Most countries included data from more than one survey year, and several countries had different income classifications in different years.

Two variables were used to control for SES: education and an absolute household wealth index. Educational achievement was measured using a four-point scale: no education, primary, secondary, or higher. The household wealth index was calculated using a method that facilitates cross-national comparisons of household wealth in purchasing parity dollars (Hruschka, Gerkey, & Hadley, 2015). This approach converts the DHS relative wealth index into a measure of absolute wealth using mean wealth per capita and the Gini coefficient in each country during a given survey year. This measure was validated against both World Bank poverty headcounts (consumption expenditures) and anthropometric measures; it was found to be a better predictor of women's BMI both between and within countries than the original relative wealth indices from the DHS (Hruschka, Hadley, et al., 2015).

Four additional variables known to be associated with BMI in low- and middle-income countries were included: urban or rural residence, breastfeeding status, parity, and age. Urban or rural residence was included as a categorical variable. The definitions of urban and rural may vary slightly between countries because the DHS rely on local administrative classifications. These classifications are usually based on population size as determined during local censuses. Breastfeeding status was included as a dichotomous variable, but pregnant women were excluded (Hruschka & Hagaman, 2015). Parity was included as a categorical variable: 0 births, 1–2 births, 3–4 births, and more than 4 births.

Three geographic and environmental variables were included in the analysis: altitude, latitude, and temperature. Altitude measurements were taken directly from the DHS Program, which reports cluster-level elevation as either: (1) the altitude indicated by a digital elevation model (DEM) for the larger commune to which the cluster belongs and (2) the altitude indicated by a GPS receiver during data collection. Where both DEM and GPS altitudes were reported for a given cluster, the DEM-based estimates were prioritized during analysis. 99.5% of the altitude data were DEM-based estimates. In order to anonymize data, the DHS Program includes anywhere from 0 to 10 km of error in its reported GPS coordinates. Fifteen countries recorded elevations that were lower than possible based on the lowest altitudes reported for the country by the CIA World Factbook (2016). The mean discrepancy between the lowest recorded and lowest possible altitudes for each of those 15 countries was 28.2 m (range 1 to 200 m). In each case, the impossible elevation was changed to the lowest elevation (as applicable) reported for that country (The World Factbook, 2016). These countries were not dropped because the discrepancies were so small as to be unlikely to yield physiologically meaningful differences in the underlying socioeconomic (e.g., education, income, food insecurity) and ecogeographic variables of interest (e.g., hypoxia, temperature, infectious disease). Only one country (Nigeria) had a single cluster with an elevation substantially higher than possible (>1400 m higher than possible) (The World Factbook, 2016); the individuals in that cluster were dropped because the discrepancy between reported altitude and technically possible altitude was large enough to conceivably yield physiological differences.

Different high-altitude cut-offs are used across studies, from as low as 500 m to as high as 3500 m. In acclimatized populations, declines in oxygen saturation tend to begin around 1500 m with substantial drops closer to 2500 m (Rojas-Camayo et al., 2018). In this study, we use ≥1500 m as the minimum cut-off for high altitude but also report results for additional cut-offs at ≥2500 and ≥3500 m.

To control for latitude and temperature, we included the absolute value of the cluster-level latitude reported by the DHS Program in regression analyses. Clusters with coordinates recorded as (0,0) were removed from the sample as this location is not plausible. Where the DHS Program provided cluster-level monthly temperature, the annual average was calculated and included in regression models. Where the DHS Program provided cluster-level GPS coordinates but not cluster-level temperature, the closest weather station within 100 km listed by the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climatology Network (GHCN) was identified in R using the meteo_nearby_stations() function from the *rnoaa* package (Chamberlain, 2018). For each station, we calculated the average annual temperature of the most recent year that daily average temperatures were recorded at least 75% of the time (temperatures available from 1941 to 2020). These annual means were then used for the applicable clusters. Where no nearby weather stations were available, the mean cluster-level temperature of the closest cluster within 100 km was used. We dropped any clusters without coordinates, a nearby weather station, or a nearby cluster for which temperature was known.

Trained DHS field staff collected the height and weight measurements at the respondent's house; these were used to calculate BMI. We created a dichotomous variable for obesity, defined as a BMI ≥30 kg/m^2. The final sample consisted of 54 countries and 1 583 456 women. All statistical analyses were conducted in R.

3.2 | Descriptive statistics

Descriptive statistics were calculated for the full sample in addition to the subsamples living at <500, ≥1500, ≥2500, and ≥ 3500 m. To visualize the unadjusted relationship between altitude and body size, we plotted country average BMI by country average elevation (Figure 1A).

3.3 | Full-sample regression models

To determine whether a linear model was appropriate for the global sample, we ran a mixed-effects regression predicting BMI that specified altitude as a 20-level categorical variable. Elevations between 0 and 3600 m were split into 200 m increments. Because altitudes <0 and ≥3600 m are uncommon, the lowest altitude interval included all elevations <0 m and the highest altitude interval included all elevations ≥3600 m. The lowest altitude interval (<0 m) was used as the reference level for the categorical altitude variable in this linear regression. The model included country-level random intercepts for altitude (i.e., the intercept for altitude was allowed to vary by country) in addition to fixed effects for breastfeeding status, parity, age, wealth, education, urban or rural residence, absolute latitude, and temperature. The effect sizes for each of the 20 altitude intervals from that model were then plotted against altitude (Figure 1B). A linear pattern between those effect sizes and altitude (i.e., the altitude interval they each represent) would suggest that the relationship between altitude and BMI is linear when adjusting for variables known to predict body size.

We then examined the relationship between altitude and BMI in a mixed-effects model with altitude treated as a continuous variable. Altitude was scaled such that the reported coefficients and odds ratios each reflect the result of a 200 m increase in altitude. Correlated random intercepts and random slopes were included at the country level—that is, the intercept for altitude and the slope between altitude and BMI were allowed to vary by country. We included breastfeeding status, parity, age, wealth, education, urban or rural residence, absolute latitude, and temperature as fixed effects. We calculated Wald confidence intervals.

We modeled obesity risk using a mixed-effects logistic regression with altitude treated as a continuous variable. For ease of interpretation, altitude was scaled such that the reported coefficients and odds ratios each reflect the result of a 200 m increase in altitude. Correlated random intercepts and random slopes were included at the country level—that is, the intercept for altitude and the association between altitude and BMI were allowed to vary by country. Breastfeeding status, parity, age, wealth, education, urban or rural residence, absolute latitude, and temperature were included as fixed effects. Odds ratios for obesity risk were calculated using the formula: exp(coefficient). We used Wald confidence intervals.

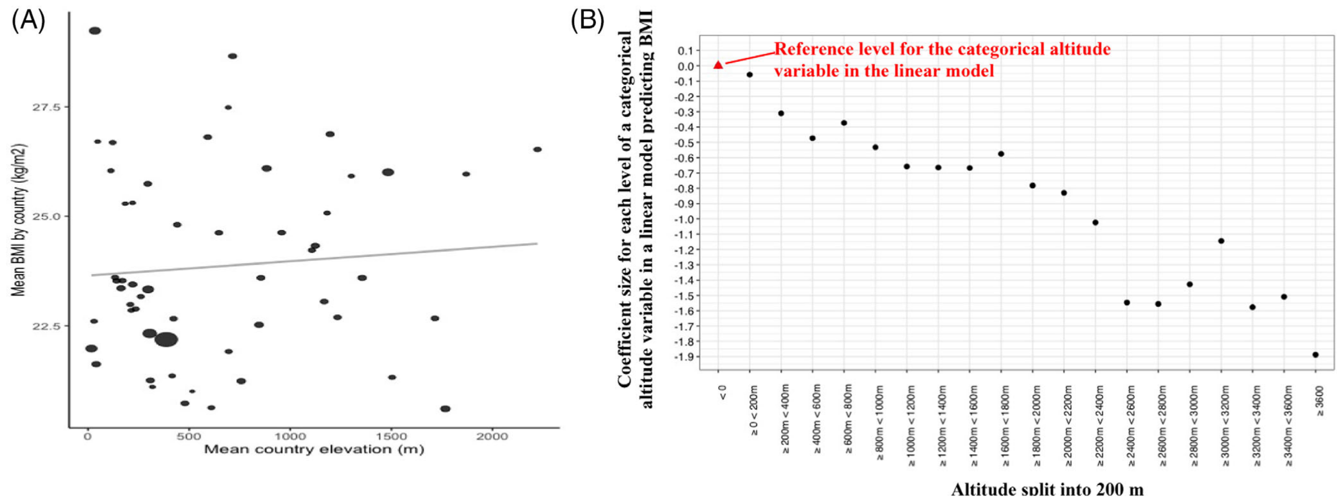

FIGURE 1 (A) Average country-level BMI by average country-level elevation. The size of the point indicates the sample size from each country (the largest point is India). The Pearson's correlation for the trend is .08 ($p = .52$). (B) Beta coefficients for each level of a categorical altitude variable taken from a mixed-effects linear model predicting BMI. The categorical altitude variable was created by splitting altitude into 200 m increments between 0 and 3600 m, with minimum category <0 m and maximum category ≥3600 m. The model included country-level random intercepts in addition to fixed effects for breastfeeding status, parity, age, wealth, education, urban or rural residence, absolute latitude, and temperature.

3.4 | Country-specific regression models

To describe between-country differences in the relationship between altitude and BMI, we fit simple linear regressions for each of the 54 countries. These models controlled for breastfeeding status, parity, age, wealth, urban or rural residence, education level, absolute latitude, and temperature. For each country, altitude was scaled such that the reported effect sizes reflect predictions for a 200 m increase in elevation. We calculated Wald confidence intervals.

To understand differences in the relationship between altitude and obesity between countries, we fit simple logistic regressions for each of the 54 countries. These models adjusted for breastfeeding status, parity, age, wealth, urban or rural residence, education level, absolute latitude, and temperature. For each country, we scaled altitude so that reported effect sizes reflect a 200 m increase in elevation. We used Wald confidence intervals.

3.5 | Ethics statement

All analyses were performed on de-identified responses, and all respondents provided their informed consent to trained members of the Demographic and Health Surveys teams.

4 | RESULTS

4.1 | Descriptive statistics

The mean age was 32.7 (SD = 8.4), and the mean BMI was 23.3 kg/m^2 (SD = 4.9) (Table 1). Only 9.0% were obese. Over half (64.0%) lived in rural areas. Less than two-thirds had completed at least primary education, with around a third (32.0%) completing secondary education; a further 10.0% had completed higher education. The average cluster temperature was 23.5°C (SD = 4.7). The average cluster-level absolute latitude was 18.4° (9.4).

4.2 | Full-sample regression models

There was no association between mean country BMI and mean country elevation (Figure 1A). At the individual level, in an OLS regression with no covariates other than elevation, BMI was positively associated with elevation (estimate: 0.034, $p < .001$) but this result was influenced heavily by India; removing India from the model reversed the elevation estimate to −0.002 ($p < .001$); given the large variability in altitude within countries, analyses at the country level are likely minimally informative.

In contrast, in a linear mixed-effects model controlling for breastfeeding status ($b = -0.41$), parity ($b_{1\text{–}2\ \text{births}} = 0.93$, $b_{3\text{–}4\ \text{births}} = 1.1$, $b_{5+\ \text{births}} = 0.80$), age ($b = 0.10$), wealth ($b = 1.33$), rural dwelling ($b = -0.67$), education level ($b_{\text{primary}} = 0.82$, $b_{\text{secondary}} = 0.97$, $b_{\text{higher}} = 0.52$), absolute latitude ($b = -.03$), and temperature ($b = -0.13$), the coefficient size for each level of a 20-level categorical altitude variable (200 m intervals) predicting BMI trends downward when plotted against altitude (Figure 1B). In a second linear mixed-effects model predicting BMI, a 200 m increase in a continuous altitude variable was associated with −0.162 kg/m^2 decrease in BMI (95% CI −0.220, −0.104) (Table 2). As a result, an individual living at ≥3600 m would be predicted to have a BMI at least 2.92 kg/m^2 lower than an individual living at sea level.

In a logistic mixed-effects model with all covariates and predicting obesity, each 200 m increase in a continuous altitude variable was associated with lower odds of obesity (OR 0.90, 95% CI 0.87, 0.94) (Table 3).

4.3 | Country-specific regression models

In simple linear models controlling for breastfeeding status, parity, age, wealth, urban or rural, education level, absolute latitude, and temperature and predicting BMI, altitude was negatively associated with BMI in 34 countries and positively associated with BMI in 20 countries (Table S2). The strongest associations between altitude and BMI in each direction were Bangladesh ($b = 4.265$; 95% CI 3.588, 4.942) and Guyana ($b = -1.499$; 95% CI −2.227, −0.77) (Table S2A). Both countries had limited altitude ranges as their highest altitude observations were less <100 m and <1000, respectively. Among countries with altitudes ≥1500 m, altitude was negatively associated in 21 and positively associated in 13 (Figure 2A). For these countries, the strongest positive association was in Cameroon ($b = 0.295$; 95% CI 0.201, 0.389), while the strongest negative association was in Honduras ($b = -0.245$; 95% CI −0.334, −0.157). The predicted difference in BMI between the lowest and highest altitudes recorded in Cameroon would be 3.43 kg/m^2; in Honduras, the predicted difference would be −2.63 kg/m^2.

India, Nepal, Ethiopia, Kenya, Peru, Bolivia, Guatemala, Colombia, Kyrgyzstan, Lesotho, and Tajikistan had the highest overall elevations in this sample, with each including observations around 3000 m. Controlling for breastfeeding status, parity, age, wealth, urban or rural, education level, absolute latitude, and temperature, the relationship between altitude and BMI was negative in Peru ($b = -0.088$; 95% CI −0.099, −0.077), Bolivia ($b = -0.154$; CI −0.207, −0.102), Colombia ($b = -0.080$;

TABLE 1 Descriptive statistics for individual- and cluster-level variables used in regression analyses.

	Total ($n = 1\,583\,456$)	<1500 m ($n = 1\,091\,543$)	≥1500 m < 2500 m ($n = 116\,758$)	≥2500 m < 3500 m ($n = 26\,937$)	≥3500 m ($n = 15\,381$)
Age					
Min	20	20	20	20	20
Max	49	49	49	49	49
Mean (SD)	32.7 (8.4)	32.8 (8.4)	32.4 (8.5)	33.3 (8.5)	33.6 (8.5)
Breastfeeding					
Yes	424 828 (27%)	294 879 (27%)	32 335 (28%)	5787 (21%)	3462 (23%)
No	1 158 628 (73%)	795 870 (73%)	84 423 (72%)	21 150 (79%)	11 919 (77%)
Parity					
0 births	220 990 (14%)	144 649 (13%)	22 384 (19%)	4573 (17%)	2385 (16%)
1–2 births	550 995 (35%)	382 289 (35%)	38 426 (33%)	9721 (36%)	5075 (33%)
3–4 births	445 156 (28%)	311 402 (29%)	29 605 (25%)	6639 (25%)	4064 (26%)
>4 births	366 315 (23%)	252 409 (23%)	26 343 (23%)	6004 (22%)	3857 (25%)
Location					
Urban	569 241 (36%)	393 715 (36%)	37 110 (32%)	11 400 (42%)	6527 (42%)
Rural	1 014 215 (64%)	697 034 (64%)	79 648 (68%)	15 537 (58%)	8854 (58%)
Education Level					
None	547 610 (35%)	432 166 (40%)	31 899 (27%)	5209 (19%)	1624 (11%)
Primary	367 598 (23%)	215 561 (20%)	38 335 (33%)	8975 (33%)	6218 (40%)
Secondary	505 202 (32%)	337 485 (31%)	33 875 (29%)	7399 (27%)	4543 (30%)
Higher	163 046 (10%)	105 537 (10%)	12 649 (11%)	5354 (20%)	2996 (19%)
BMI					
Min	12.01	12.01	12.02	13.07	13.26
Max	59.98	59.98	59.61	58.99	50.70
Mean (SD)	23.3 (4.9)	23.2 (4.9)	23.3 (4.5)	24.5 (4.3)	25.2 (3.9)
Obesity					
Normal	1 433 508 (91%)	986 913 (90%)	106 887 (92%)	24 190 (90%)	13 638 (89%)
Obese	149 948 (9%)	103 836 (10%)	9871 (8%)	2747 (10%)	1743 (11%)
Altitude					
Min	−377	−377	1500	2500	3501
Max	5951	499.9	2499	3499	5951
Mean (SD)	540.4 (705.9)	173.3 (143.5)	1856.1 (274.8)	2897.8 (295.9)	3909.7 (292.0)
Temperature					
Min	−9.8	8.0	−1.6	−4.8	−9.8
Max	31.1	31.1	29.3	20.8	20.5
Mean (SD)	23.5 (4.7)	25.5 (2.8)	16.4 (3.6)	11.7 (4.2)	7.7 (3.5)
Latitude					
Min	−30.6	−28.7	−30.6	−29.9	−21.9
Max	48.4	48.4	42.8	42.8	38.2
Mean (SD)	18.4 (9.4)	19.0 (8.7)	15.7 (12.6)	13.6 (8.8)	15.8 (5.8)

CI −0.132, −0.028), Guatemala ($b = -0.183$; CI −0.250, −0.117), Kenya ($b = -0.206$; CI −0.264, −0.147), Lesotho ($b = -0.192$; CI −0.373, −0.011), and India ($b = -0.201$; CI −0.212, −0.191). It was positive for those living in Ethiopia ($b = 0.074$; CI 0.041, 0.107) and Nepal ($b = 0.102$; CI 0.071, 0.133). In Kyrgyzstan ($b = 0.071$; CI

TABLE 2 Estimates (SE) from a mixed-effect linear regression predicting BMI in a combined sample of 54 countries.

	BMI
Intercept	16.086*** (0.234)
Altitude[a]	−0.162*** (0.030)
Breastfeeding	−0.415*** (0.009)
1–2 births	0.927*** (0.011)
2–3 births	1.080*** (0.013)
≥4 births	0.796*** (0.015)
Rural	−0.668*** (0.008)
Age (centered)	0.104*** (0.001)
Latitude[b]	−0.030*** (0.001)
Temperature	−0.127*** (0.003)
Primary education	0.816*** (0.010)
Secondary education	0.971*** (0.010)
Higher education	0.515*** (0.015)
Wealth index	1.328*** (0.006)
Observations	1 583 456

Note: Altitude is treated as a continuous variable but is scaled to 200 m for ease of interpretation (i.e., the coefficient for altitude represents the change in BMI for a 200 m increase in altitude). Country-level correlated random intercepts and random slopes were included for altitude; thus, the altitude X BMI relationship was allowed to vary by country.

[a]Scaled to 200 m.

[b]Absolute value.

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

TABLE 3 Odds ratios (95% CI) from a mixed-effect logistic regression predicting obesity in a combined sample of 54 countries.

	Obesity
Intercept	0.001*** (0.001, 0.002)
Altitude[a]	0.90*** (0.87, 0.95)
Breastfeeding	0.71*** (0.70, 0.72)
1–2 births	1.56*** (1.52, 1.60)
2–3 births	1.84*** (1.80, 1.89)
≥4 births	1.79*** (1.74, 1.84)
Rural	0.70*** (0.69, 0.71)
Age (centered)	1.06*** (1.06, 1.06)
Latitude[b]	0.99*** (0.99, 0.99)
Temperature	0.97*** (0.97, 0.98)
Primary education	1.62*** (1.59, 1.65)
Secondary education	1.64*** (1.61, 1.67)
Higher education	1.19*** (1.16, 1.22)
Wealth index	1.79*** (1.77, 1.81)
Observations	1 583 456

Note: Altitude is treated as a continuous variable but is scaled to 200 m for ease of interpretation (i.e., the coefficient for altitude represents the change in BMI for a 200 m increase in altitude). Country-level correlated random intercepts and random slopes were included for altitude; thus, the altitude X BMI relationship was allowed to vary by country.

[a]Scaled to 200 m.

[b]Absolute value.

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

−0.081, 0.223) and Tajikistan ($b = -0.022$; CI −0.110, 0.066), there were slight trends toward positive and negative associations, respectively. In logistic models controlling breastfeeding status, parity, age, wealth, urban or rural, education level, absolute latitude, and temperature and predicting obesity, increasing altitude was associated with lower odds of obesity in 34 countries and increased odds of obesity in 20 countries (Table S2B).

5 | DISCUSSION

This analysis found a negative linear trend between BMI and altitude at the global level, after controlling for a range of socioeconomic factors. Increases in altitude also predicted reduced obesity risk when all countries were examined together. However, in contrast to expectation, there was substantial variability across countries: The

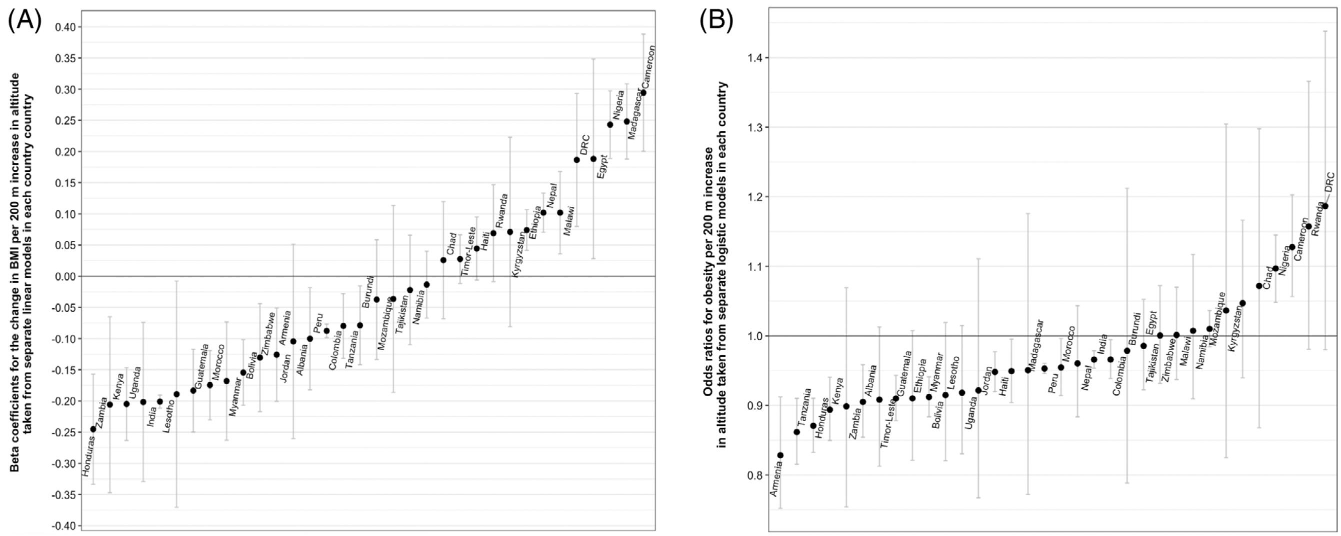

FIGURE 2 (A) Beta coefficients predicting change in BMI per each 200 m increase in a continuous altitude variable; each coefficient was taken from separate, country-specific simple linear regressions. Coefficients are plotted in ascending order by size. All models controlled for breastfeeding status, parity, age, wealth, urban or rural residence, education level, absolute latitude, and temperature. Only countries with high-altitude observations (≥1500 m) are shown (see Table S2A for all countries). (B) Odds ratios predicting obesity risk per each 200 m increase in altitude; each odds ratio was taken from separate, country-specific logistic regressions. Odds ratios are plotted in ascending order by size. All models controlled for breastfeeding status, parity, age, wealth, urban or rural residence, education level, absolute latitude, and temperature. Only countries with high-altitude observations (≥1500 m) are shown (see Table S2B for all countries).

effect sizes varied, and many countries exhibited positive relationships between altitude and body size. Because variation exists despite the multiple factors thought to contribute to lower BMIs at high altitude (e.g., hypoxia, temperature, economic marginalization), this complicates suggestions that the proposed relationship represents something fundamental about human biogeography (Díaz-Gutiérrez et al., 2016; Voss et al., 2013; Woolcott et al., 2014).

The degree of variation is made clear when the effect sizes relating altitude to BMI are compared with those relating altitude to wealth. The direction of the association between wealth and BMI was nearly unanimous: positive in 51 out of 54 countries. Only Moldova, Jordan, and Kyrgyzstan exhibited (small) inverse associations between wealth and BMI, and this fits with an analysis of DHS data by Subramanian et al. (2011). They found the size of the slopes between wealth and BMI in these three countries to be among the smallest (1st, 6th, and 7th smallest of 54 countries, respectively; and negative for Moldova) (Subramanian et al., 2011). In contrast to wealth, the association between altitude and BMI in this study was negative in 34 countries and positive in 20.

In LMICs, higher SES has historically predicted larger BMIs (Popkin et al., 2012; Templin et al., 2019). However, this has begun to change as populations in LMICs transition to diets increasingly reflective of those in high-income countries—more fat, sugar, animal products, refined carbohydrates, and other highly processed foods (Popkin et al., 2012; Templin et al., 2019). The DHS sample used here covers a nearly 30-year span (1992–2020) and includes low-, lower-middle-, and upper-middle-income countries. Yet despite the range of time periods, income levels, and sociocultural and ecological environments considered, the direction of the relationship between wealth and BMI in this sample was far more consistent than for altitude and BMI.

On the other hand, the variable and sometimes negligible relationship observed between BMI and altitude could stem from the relative lack of resources available to women in this sample. In contrast to the United States, where obesity rates hover around 40% (Hales et al., 2017) and where a negative association exists between altitude and obesity (Voss et al., 2013), obesity is low in most countries included here (9.5%).

Notably, no single country in this sample contained the full range of possible altitudes. As such, cultural, genetic, and socioeconomic factors characteristic of particular countries or regions and unrelated to high-altitude living could underlie the negative relationship observed globally (Beall, 2007). For example, most individuals in the lowest altitude increment (<0 m) come from Jordan and Egypt, which are both known for extremely high obesity rates (WHO, 2014). And, indeed, Jordan and Egypt had the two highest mean BMIs in this sample at 28.7 and 29.2 kg/m^2, respectively.

5.1 | Limitations

This study faced a variety of sampling constraints, including large absolute sample size differences between countries and across the range of altitudes examined. Though more geographically and ethnically diverse than previous studies, our sample was biased toward low-latitude populations. The majority of the world's population falls within the range of latitudes represented here (−30.6° to 48.4°), but our mean absolute latitude (18.4°) falls within the two tropics. The relationship between altitude and atmospheric pressure is not uniform across the globe; it varies with latitude (West et al., 1983). This means that the severity of hypoxia at high altitude could be modified by one's proximity to the poles.

A number of countries with markedly high or low average elevations were not represented in this study. Several absent Asian countries, including Pakistan, Mongolia, and China, have both high average elevations (The World Factbook, 2016) and low- to mid-range BMIs (WHO, 2014). In contrast, many smaller island nations, such as Palau, Antigua and Barbuda, and the Marshall Islands, have both low average elevations (The World Factbook, 2016) and very high BMIs (WHO, 2014). Unfortunately, these and similar countries were missing from the final dataset such that the negative relationship observed globally might be stronger were they included.

In addition, except for temperature and two generalized measures of SES (household wealth index and education), we were unable to assess the relevance of more proximate factors for the proposed relationship. This includes ecological variables like oxygen partial pressure and ultraviolet light radiation but also local measures of SES like occupation, subsistence mode, or wage economy participation. In this vein, while the wide range of cultural contexts analyzed is a strength of this study, it also limits the depth of analysis possible. The diversity of local foodways and dietary norms present in 54 different countries make it similarly difficult to select or develop a single measure for any of these factors. The variables included in this analysis were ultimately chosen because they are reasonably comparable across contexts.

Finally, one potential explanation for positive associations between altitude and BMI is an increased risk of stunting at higher altitudes. Specifically, if stunting is more likely at higher altitudes, women at higher altitudes will be shorter. Since BMI is calculated as weight divided by height squared and then if weight is kept constant, women at higher altitude would have a higher BMI. To assess this possibility, we examined the association of women's adult height with altitude in countries where there was a positive association between altitude and BMI. Contrary to the stunting explanation, the association between altitude and height in those countries was slightly positive.

6 | CONCLUSIONS

Overall, our results suggest that the relationship between altitude and body size is not straightforward. Although there is a negative trend between altitude and body size at the global level, the direction and size of this association varies within individual countries. Future research should pursue more in-depth analyses in LMICs to better understand why the association appears to exist in some contexts but not others. More direct and context-specific measures of the ecogeographic and social variables thought to link altitude and body size are needed.

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CONFLICT OF INTEREST STATEMENT
The authors have no conflicts of interest to report.

DATA AVAILABILITY STATEMENT
The data used in this study are available from the Demographic and Health Surveys (DHS) Program at https://dhsprogram.com/data/. Code available upon request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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