DOI: 10.1111/saje.12354

ORIGINAL ARTICLE

Ruggedness and child health outcomes: Evidence from Burundi, Cameroon, Ethiopia and Nigeria

Carolyn Chisadza[1] | Matthew Clance[1] | Fritz van der Merwe[2] | Eleni Yitbarek[1]

[1]Department of Economics, University of Pretoria, Hatfield, South Africa

[2]Consultant and University of Pretoria, Pretoria, South Africa

Correspondence
Carolyn Chisadza, Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa.
Email: carolyn.chisadza@up.ac.za

Abstract

This paper examines the effect of terrain ruggedness on child stunting in Burundi, Cameroon, Ethiopia and Nigeria. Using a cross-section analysis with data from the Demographic and Health Surveys (DHS) and a measure that captures variation in the terrains of the countries, we find that the more difficult it is to traverse the terrain in Burundi, Cameroon and Nigeria, the higher the likelihood of child stunting. However, this association is not consistent for Ethiopia until we account for the Oromia region, which has the capital city Addis Ababa. These results remain robust with the inclusion of socio-economic factors related to child health (*e.g.* maternal health, maternal education and household income), demographic factors (*e.g.* gender of child), other geographical factors (*e.g.* rainfall patterns and malaria prevalence) and survey and region effects. The results suggest that there are complementary factors to geography that may contribute to poor child health outcomes, such as the quality of infrastructure and the ability to access healthcare services. Given that child health is a key development outcome, understanding such spatial variations associated with child health inequalities can assist in designing effective intervention programmes and allocating resources where they are most needed.

KEYWORDS

Africa, geography, ruggedness, stunting

JEL CLASSIFICATION

R12, I12, O57

1 | INTRODUCTION

Sustainable Development Goal (SDG) 3 highlights the global importance of ensuring healthy lives and promoting well-being at all ages, including the reduction of infant and child mortality. As such, a central question in the development literature has been and continues to focus on understanding the factors underlying child health outcomes. The research surrounding child health is of paramount importance given that early years of child development have long-term consequences on human capital accumulation, including decreased physical growth, lower educational attainment, lower cognition, decreased workforce productivity and lower wages (Hoddinott et al., 2013; Li et al., 2009). In general, social determinants, such as socio-economic status (*e.g.* family income, parental education, parental occupation, place of residence, ethnicity and/or religious background) and adverse childhood experiences (*e.g.* abuse, bullying or neglect) have been key determinants in explaining differences in child health outcomes, such as birth weight, obesity, stunting or mental health (Pickett et al., 2022). According to Spencer (2003, 2018), children are particularly vulnerable to adverse effects of socio-economic status and poverty, with increased risk the longer the child is exposed to worsening social conditions.

Although the empirical evidence on the social determinants of child health is quite established, more evidence linking geography and child health outcomes is emerging (Gayawan et al., 2016; Yourkavitch et al., 2018), highlighting an important avenue to explore. For example, Pezzulo et al. (2016) find that, across 27 sub-Saharan African countries, geospatial factors can explain up to 60% of the variance in child mortality compared with the usual demographic and socio-economic determinants. Previous literature has included geographical dummies (*e.g.* urban, rural, province or region), but such dummies were of limited policy relevance as they did not identify the geographical characteristics of an area that explained the differences in child health outcomes. In addition, several studies have used different measures to capture the effects of spatial geography on health outcomes, such as distance to the nearest city, distance to the nearest main road or distance to the nearest healthcare facility (Pezzulo et al., 2016; Tounkara et al., 2022; Weiss et al., 2020). In recent times, software innovations and the availability of improved geospatial data have allowed researchers to examine interlinkages between more nuanced geographical factors (such as weather patterns, land elevation or natural disaster events) and development outcomes (Headey et al., 2017; Ouma et al., 2021). However, the evidence with these later measures of geography pertaining to child health outcomes is still limited, which presents an opportunity to make a meaningful contribution to this emerging literature.

We investigate the effects of terrain ruggedness on child health outcomes. Terrain ruggedness is defined as an area of land with rough, irregular surface covered with rocks, trees, caverns, caves and cliff walls, which can make productive farming difficult or certain locations inaccessible. We propose that terrain ruggedness is associated with stunting outcomes in children. Using measures of land variations and geolocated Demographic and Health Surveys (DHS) data from 4 African countries, namely Burundi, Cameroon, Ethiopia and Nigeria, we find positive associations between terrain ruggedness and stunting.

We focus our study on terrain ruggedness because this type of measure captures land variations, which may provide a plausible mechanism for inaccessibility to healthcare services or agricultural suitability leading to poor health outcomes. We also focus on stunting as the preferred child health outcome because stunting reflects long-term, life-threatening health outcomes (Dewey & Begum, 2011; Feinstein, 2003). Although stunting and wasting frequently co-exist, wasting mainly reflects a short-term inadequacy of dietary intake. The existing empirical evidence suggests that stunting during early childhood has long-term adverse effects on human capital accumulation (Beegle & Christiaensen, 2019). Stunted children may never reach their full possible height and have suboptimal brain development, which can persist into adulthood and negatively affect their outcomes, such as lower educational attainment and economic productivity (Conti et al., 2010; Heckman, 2006). Estimates suggest that the penalty (per capita income losses) for stunting ranges from 5% to 7% in low- and middle-income countries (Galasso & Wagstaff, 2019). Stunting is also a cyclical process because stunted mothers tend to have stunted children, creating an intergenerational cycle of poverty and reduced human capital accumulation that is difficult to break (Harper et al., 2003). Notably, there is limited catch-up for stunted children from the consequences of poor childhood health and schooling outcomes (Beegle & Christiaensen, 2019).

The choice for our sample of countries is mainly determined by the differences in topography between the four countries (discussed in detail in Section 3.1) and their similar high prevalence of stunting within their respective regions.[1] Eastern, Central and Western Africa currently contribute to the high rate of child stunting in sub-Saharan Africa (Skoufias et al., 2019; World Health Organization, 2019). Moreover, within these regions, recent DHS-based studies show that Burundi and Ethiopia have the highest stunting rates in Eastern Africa, Cameroon in Central Africa and Nigeria in Western Africa (Ekholuenetale et al., 2020; Quamme & Iversen, 2022). These country characteristics make them interesting case studies to explore our hypothesis.

Although our findings show that terrain ruggedness in Burundi, Cameroon and Nigeria is positively associated with child stunting, the results are however not consistent for Ethiopia. The insignificant results are somewhat surprising for Ethiopia, given that the country's terrain is predominantly mountainous. The implications of the findings are twofold: first, there are factors that may be working in tandem with terrain ruggedness that can contribute to adverse results on child health outcomes, such as a history of conflict that may create insecurity for people, or the quality of infrastructure necessary for ease of mobility and public goods delivery (Ouma et al., 2021). Second, Ethiopia's mountainous areas may have grouped populations in more centralised clusters such that the provision of public goods is relatively accessible; hence, child health outcomes may not be directly affected by terrain ruggedness (Jimenez-Ayora & Ulubaşoğlu, 2015).

The findings from this study not only highlight the importance of policy interventions that will provide access to inaccessible areas in order to promote inclusive growth but also that the policies should take into account unique features of the country that may exacerbate the adverse effects of geography on child health outcomes, such as poor infrastructure. Our results indicate that to reduce the effect of terrain ruggedness on health outcomes, national policymakers should focus on the distributions of public infrastructures, such as roads that facilitate trade and access to health services, and local interventions should focus on increasing the nutritional diversity that can offset the adverse effects of terrain ruggedness (Headey et al., 2017).

2 | LITERATURE REVIEW

Our study straddles two disciplines in the development literature, health and geography. Evidence indicates that health has been a historically important source of differences in economic growth across countries (Gallardo-Albarrán, 2018). Therefore, understanding the factors that affect population health outcomes, in our case child health, is a central issue in research and policymaking. Previous literature highlights the importance of various socio-economic factors that contribute to child health outcomes. For example, Akombi et al. (2019) find that low maternal education, poor households and households located in rural areas and in the North East and North West regions (*i.e.* where the terrorist group Boko Haram typically operates) contribute to an increase in stunting, wasting and underweight among children under 5 years in Nigeria. Similarly, Pappachan and Choonara (2017) and Angdembe et al. (2019) highlight that wealth, malnutrition, mother's health and education, and poor access to healthcare services are associated with child mortality in India and inequalities in stunting in Nepal, respectively. Evidence by Quansah et al. (2016) also shows that social factors influencing child health outcomes, such as mortality and nutritional status in Ghana, include maternal education, family income and rural–urban disparities. This existing literature, however, fails to take into account geographical characteristics as a contributing factor to child health outcomes.

In the geography literature, it is widely accepted that geography can have important consequences for economic development in general (Engerman et al., 2002; Fang & Ying, 2016; Nunn & Puga, 2012; Xu et al., 2021). For example, countries that are located in tropical climates have poor growth outcomes, in relation to countries from temperate regions, as they are prone to diseases that may have adverse

[1]Including all African countries in the analysis may attenuate the effects of ruggedness on child stunting as several countries with vastly different cultures, economies and terrain would be grouped together, making it challenging to compare their results and may not yield informative insights. We report the results in Table A4 for a sample of 16 countries. The findings indicate that, on average, ruggedness is positively associated with stunting in sub-Saharan Africa.

consequences on the health of productive labour, animals and crops (Acemoglu et al., 2001; Dell et al., 2012). Countries that are also located near coasts outperform inland countries because of the ease of transporting goods and services (Sachs et al., 2001). Moreover, evidence suggests that agricultural productivity is a major issue in areas with irregular terrain, which is tough to cultivate, difficult to draw water for irrigation, making it costly to produce cash crops and impossible to transport the goods to the markets (Forsido et al., 2021; Headey et al., 2017). As a result, populations living in areas with rugged terrain tend to have lower incomes and poorer health (Allen et al., 2005). Other studies, such as Nunn & Puga (2012), find that residing in areas with rugged terrain (caves, mountains, valleys, forestry) proved an advantage because it provided lookout posts and hiding places from slave raiders and other tribes that were raiding villages for slaves. As a result, ruggedness in Africa had an indirect and positive effect on contemporaneous incomes, especially in West Africa where slave trade was most prevalent.

Although previous literature treated studies from these two disciplines as separate bodies of evidence, more recent studies have started drawing associations between geography and population health outcomes, showing that geographical access to healthcare is an important signal for the quality of health systems (Wigley et al., 2020). Evidence by Porter (2002) and Headey et al. (2017) shows that rural areas are characterised by poor nutrition outcomes than urban areas in sub-Saharan Africa, mainly driven by inequalities in wealth, education and infrastructure services. Other studies by Ouma et al. (2021) and Tounkara et al. (2022) highlight that variations in geographical access to care can help identify vulnerable populations at greater risk for preventable diseases. For example, Tounkara et al. (2022) find that women in Mali residing far from the referral healthcare facility are relatively more likely to succumb to maternal mortality than women living in close access to the facility.

However, within this existing literature, evidence is mainly focussed on general population health outcomes, with few studies examining the direct link between geographical factors and child health outcomes. A few examples include a study by Balk et al. (2004) that estimates the risk of infant and child mortality using individual, household and geographical factors. They find that the risk of infant mortality tends to be higher in rural than in urban areas and increases with distance from the coast. A related study by Okwaraji et al. (2012), for a rural area in Ethiopia, finds that children who lived more than 1.5 h from a healthcare facility had a greater risk of mortality than children who lived less than 1.5 h from the healthcare facility. In addition, Forsido et al. (2021) examine undernutrition and associated factors for children under 2 years of age in Ethiopia. They find that children who live in lowland areas were more prone to wasting than those from midland and highland areas. They attribute this result to the lowland district being relatively further from the capital and having a less diverse agricultural sector. van der Merwe et al. (2022) also find that climate change (increasing temperatures and decreasing precipitation) leads to a higher probability of malnutrition (stunting and underweight) among children under 5 years in Nigeria.

Although the above studies are related to ours, we deviate from the commonly used geographical factors, such as land use, weather patterns, distances to the nearest healthcare facilities, coasts or roads, and introduce a measure of terrain ruggedness to capture the variations in the landscape. This measure indicates the ease or difficulty of mobility for people within the area or for services to reach them. In essence, this measure of ruggedness provides us with a possible channel to explain why distance to the nearest road or healthcare facility may be difficult to access. Moreover, there is still limited evidence linking geographical factors to child health outcomes specifically. The literature tends to focus either on the common social determinants of child health (Pappachan & Choonara, 2017; Quansah et al., 2016) or on geographical access to healthcare and associations with population health in general, not child health specifically. We contribute to the existing literature by proposing that terrain ruggedness can be associated with poor child health outcomes. According to Weiss et al. (2020), around 8.9% (646 million) of the global population cannot access healthcare within an hour by motorised transport, and about 43% (3.16 billion) cannot access healthcare facility by foot within an hour. These statistics are quite alarming and highlight the urgent need to find sustainable measures to address the inequality in health outcomes.

3 | MATERIAL AND METHODS

3.1 | Data

We use data from the DHS, a publicly available comprehensive nationally representative survey dataset for Burundi, Cameroon, Ethiopia and Nigeria.[2] DHS collects data on women at reproductive age (age 15–49), their household and their children under 5 years of age living in residential households. In all DHS surveys, detailed information is collected on household demographics, anthropometric measurements for children under 5 years of age and housing conditions. This study uses the two most recent DHS surveys that contain data on child anthropometric and GPS-tagged household data for the four countries. For Burundi, we combined the surveys that are collected in 2010 and 2016. For Cameroon, we used 2011 and 2018 surveys; for Ethiopia, we used 2011 and 2016 surveys; and for Nigeria, we combined 2008 and 2013 surveys.

Georeferencing of the households within the surveys enables us to merge the household data with the elevation map for the four countries using Quantum Geographic Information Systems (QGIS). When measuring the terrain ruggedness, we capture irregularities, such as valleys, mountains, vegetation and rocky areas, that contribute to the ease or difficulty of mobility of people and goods and services. Terrain ruggedness can also affect agricultural practices. The 1-arc-second elevation data were downloaded from the earth explorer website (USGS) and compiled into 3-arc-second mosaics.[3] The vector ruggedness measure (VRM) and terrain ruggedness measure (TRI) are calculated using the QGIS, and both will be used as comparable measures of variability in terrain ruggedness. For the remainder of the article, we will refer to 'variability in terrain ruggedness' as ruggedness. The VRM measure is described as incorporating the heterogeneity of both slope and aspect of the country's terrain (Sappington et al., 2007, p. 1420). VRM is calculated by measuring the dispersion of the vectors perpendicular to grid cells (pixels 3×3) where the cells are coded with a slope and aspect value.[4]

Each cluster is geo-located in the DHS survey but with error to make it impossible to specifically identify an individual.[5] To create a measure of the relative ruggedness of the area around a cluster, we create a buffer with a 5-km radius around each cluster and calculate the standard deviation of VRM and TRI within each buffer.[6]

The VRM values are low in both evenly flat and evenly steep areas, but larger in a highly variable and rugged terrain, which is the primary reason we choose to use it in the regression analysis. The VRM value varies between zero and one where zero indicates even terrain and one indicates a very diverse terrain in slope and aspect. The TRI, on the other hand, only considers height differences without considering slope and aspect in the calculation, but we include it because other researchers in the field have used it (Jimenez-Ayora & Ulubaşoğlu, 2015; Nunn & Puga, 2012).[7] We consider the standard deviation of VRM within the 5-km buffer zone a good measure of the variability in unevenness of terrain directly related to a cluster and similarly for the standard deviation of TRI, but less dynamic. Additionally, geographically unique features of each country are more easily discernible in the TRI raster maps in Figures 1–4.

Burundi is a land-locked country bordered by Rwanda to the North, the Democratic Republic of Congo to the west and Tanzania to the east. The terrain of the country is largely hilly and mountainous dropping to a plateau in the east, as indicated in Figure 1. The lowest elevation is at 772 m in Lake

[2]https://dhsprogram.com/

[3]Accessed July 2019. We started with 1-arc-second elevation but subsequently re-sampled to restructure images to 3-arc-second using System for Automated Geoscientific Analyses (SAGA) (Conrad et al., 2015). This was done to reduce file size and computing time but still retain a spatial resolution of 90 m.

[4]The programs QGIS and SAGA were used to calculate our VRM and TRI measures.

[5]Each cluster within DHS surveys is offset randomly up to 5 km in rural areas and 2 km in urban areas. Only 1% of the sample is offset up to 10 km.

[6]The buffer guarantees that 99% of the clusters are associated (within) with our calculations. In addition, we ran a simulation (with 1000 iterations) that excluded 5% of the sample, and the results remained unchanged. Finally, for robustness, we also created 2-km buffers for urban households and 5-km buffers for rural households; the results remained unchanged. We report the results in Tables A2 and A3.

[7]In Economics, authors have usually averaged the TRI measure at the country level to compare across countries.

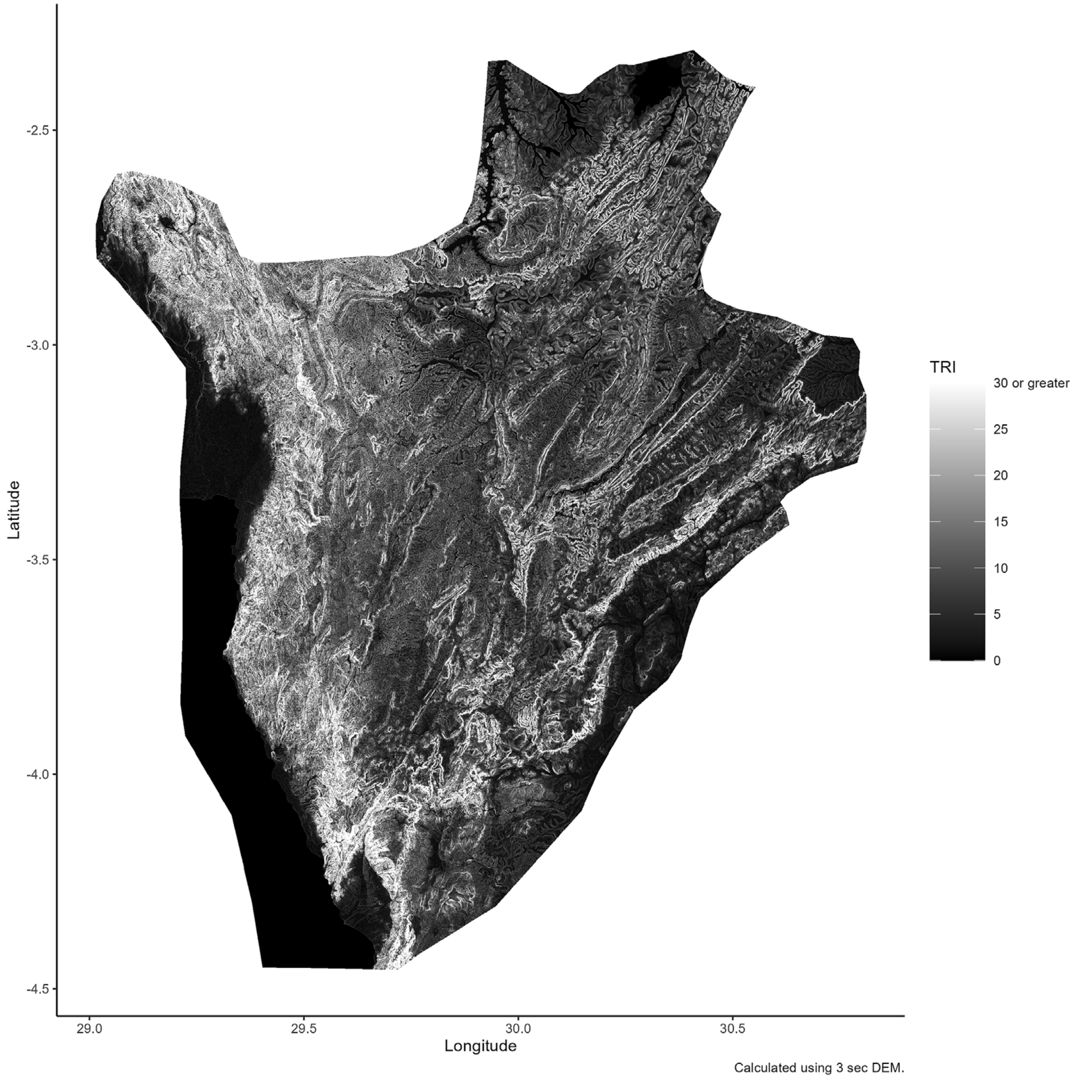

FIGURE 1 Map of Burundi Terrain. This graph shows the terrain in Burundi measured by TRI. The lighter shades indicate places where the terrain is more rugged or sloped, whereas the darker shades indicate moderate to low terrain ruggedness.

Tanganyika, whereas the highest point is at 2670 m on Mount Heha (https://www.worldatlas.com/maps/burundi).

Cameroon features various geographical regions, such as mountains, deserts, coastal plains, savanna and rainforests. The low South Cameroon Plateau has an average elevation of 500–600 m with dense tropical rainforest. The southwest of Cameroon is an irregular chain of mountains, hills and plateaus that contains some of the country's most fertile soils, notably around volcanic Mount Cameroon where the elevation reaches 4070 m, the highest in West Africa. To the north, the land slopes into a savanna plain (see Figure 2). Cameroon's lowest point is the Atlantic Ocean at 0 m (https://www.worldatlas.com/maps/cameroon).

Ethiopia, on the other hand, is part of the East African Plateau with elevations that range from 125 m below sea level to about 4000 m above sea level (Asefa et al., 2020). The national capital of Addis Ababa is located in the centre of the country on the edge of the central plateau. Years of erosion have

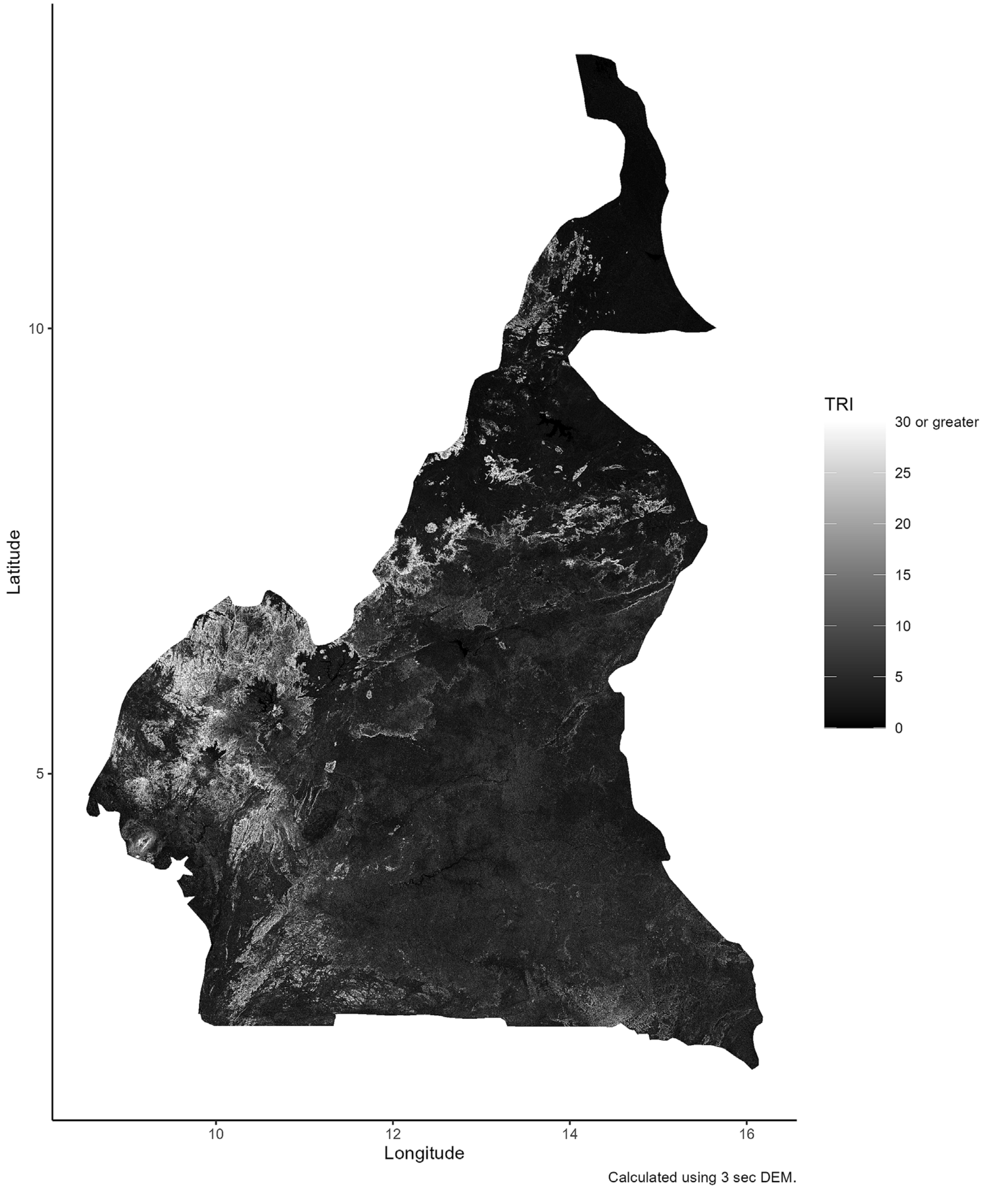

FIGURE 2 Map of Cameroon Terrain. This graph shows the terrain in Cameroon measured by TRI. The lighter shades indicate places where the terrain is more rugged or sloped, whereas the darker shades indicate moderate to low terrain ruggedness.

produced steep and wide valleys unsuitable for navigation. The highlands that comprise much of the country are divided by the Great Rift Valley into the north-western highlands and the south-eastern highlands. The north-western highlands are considerably more extensive and rugged, whereas in the southeast, the land is rocky desert and sparsely populated (see Figure 3). To the southwest of Addis Ababa, the plateau is also rugged but its elevation is slightly lower than in its northern section (http://countrystudies.us/ethiopia/40.htm).

Nigeria is mostly made up of flat plains in the south and some elevated areas and mountains in the north (Shiru et al., 2019), as shown in Figure 4. The elevation pattern of Nigeria mostly consists of a gradual rise from the coastal plains to the northern savanna regions, generally reaching an elevation of 600–700 m. The lowest elevation is 0 m near the Atlantic Ocean in the south, whereas the higher elevations reaching about 2000 m are found in isolated areas of the Jos Plateau and in parts of the north-eastern highlands. The eastern and western sections of the coastal plain are separated by the Niger Delta, much of which is swampland, separated by numerous islands. Much of the population of southern Nigeria is located in these eastern and western coastal plains and in some of the contiguous areas of the coast and the lower Niger Basin (http://countrystudies.us/nigeria/32.htm).

Our unit of analysis are children who are between the ages of 0 and 59 months. After removing potential erroneous measurements in children's anthropometric data,[8] our dataset contains approximately 113,294 children between 0 and 59 months (Burundi with 19,647; Cameroon with 19,810; Ethiopia with 20,052 and Nigeria with 53,785), with potential observations loss from missing values for other relevant variables included in the estimations. We construct an indicator variable for stunting following the World Health Organisation (WHO) standards for all children under 5 years of age. First, we calculate height-for-age (HAZ) scores. The *z*-scores represent the number of standard deviations by which the child's anthropometric measurements deviate from WHO's median child growth standard. Second, a *z*-score cut-off point of −2 is used to generate a binary indicator for stunting, a long-term child malnutrition status measure (De Onis & Blössner, 2003; World Health Organization, 1995).

Table 1 presents the summary statistics of variables used in our analysis. The prevalence of stunting among children is relatively high in Nigeria (38.7%) compared with the average percentage of stunting within Western Africa at 29.2% (World Health Organization, 2019). Similarly, Burundi and Ethiopia have stunting prevalence of 51.9% and 38.8%, respectively, which are significantly higher than the average percentage of stunting in Eastern Africa at 35.2% (World Health Organization, 2019). Another interesting observation is that the Eastern African countries have relatively higher means of terrain ruggedness measures (TRI) within the 5-km radius of the households surveyed, with Ethiopia reporting the highest, followed by Burundi. On the other hand, Nigeria and Cameroon report moderately lower means of ruggedness (TRI), suggesting that these countries have relatively flat terrains compared with the other two countries. These similarities in the prevalence of stunting and yet differences in geographical attributes indicate that there is variation in our sample of countries that we can exploit in the analysis.

3.2 | Methodology

We examine the association between ruggedness and child growth proxied by stunting. First, we estimate the effects in pooled cross-section data of each country accounting for children characteristics, which provides descriptive population-level evidence. However, these estimates are confounded by factors such as the mother's access to health services during pregnancy, access to infrastructure, and other household characteristics that may be correlated with child growth. To account for these concerns, we then estimate a standard fixed effects ordinary least squares regression model of ruggedness on child anthropometric outcomes for stunting, controlling for both spatially and temporally invariant factors to exploit conditionally exogenous variation in terrain ruggedness.

Our main regression equation is an ordinary least squares regression model of the form:

$$stunting_{ij} = \beta ruggedness_j + \gamma X_{ij} + \delta + \alpha + \xi_{ij}$$

[8]We exclude children with incomplete or questionable anthropometry data from the analysis following World Health Organisation (WHO)'s recommendations. For example, unlikely values for HAZ are those greater than 6 standard deviations above or below the median *z* score of the reference population according to the WHO flagging convention (World Health Organization, 2010).

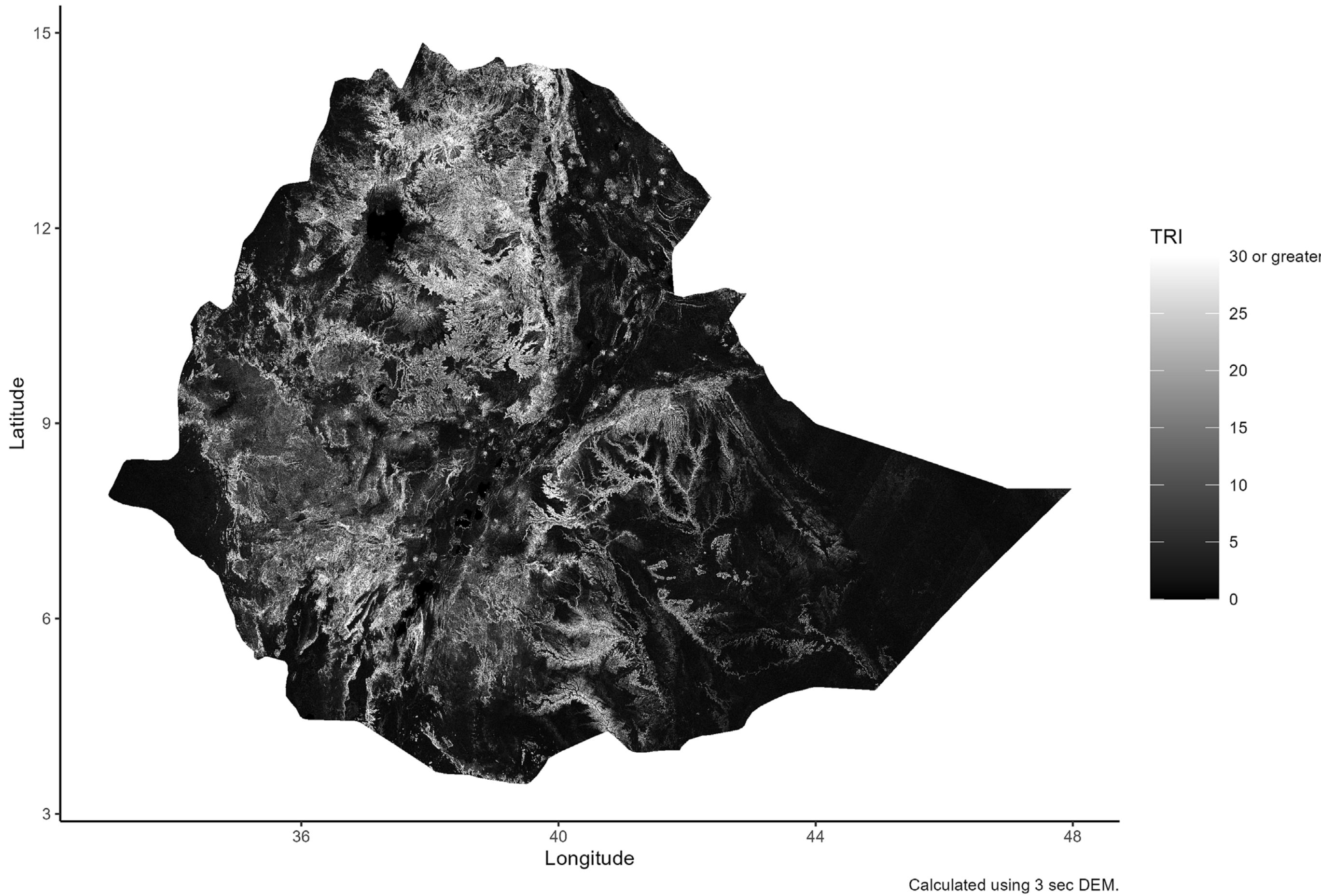

FIGURE 3 Map of Ethiopia Terrain. This graph shows the terrain in Ethiopia measured by TRI. The lighter shades indicate places where the terrain is more rugged or sloped, whereas the darker shades indicate moderate to low terrain ruggedness.

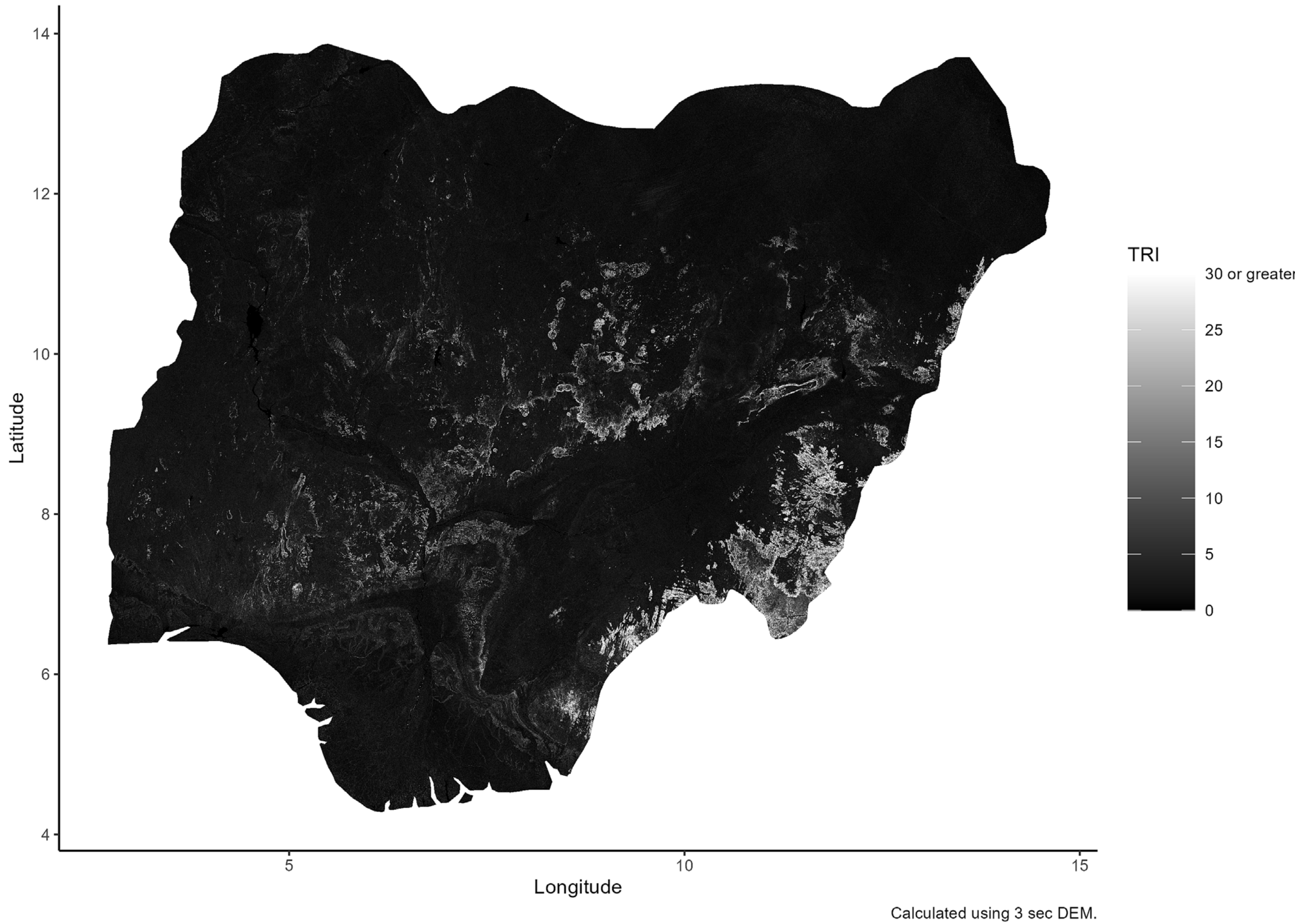

FIGURE 4 Map of Nigeria Terrain. This graph shows the terrain in Nigeria measured by TRI. The lighter shades indicate places where the terrain is more rugged or sloped, whereas the darker shades indicate moderate to low terrain ruggedness.

TABLE 1 Descriptive statistics by country.

Columns by: Country	Burundi	Cameroon	Ethiopia	Nigeria	Total
n (%)	19,647 (17.3)	19,810 (17.5)	20,052 (17.7)	53,785 (47.5)	113,294 (100.0)
Primary variables					
Stunting, *n* (%)					
No, *n* (%)	4569 (48.1)	6806 (70.9)	11,009 (61.2)	28,146 (61.3)	50,530 (60.9)
Yes, *n* (%)	4923 (51.9)	2800 (29.1)	6974 (38.8)	17,744 (38.7)	32,441 (39.1)
Vector ruggedness measure, mean (sd)	0.262 (0.019)	0.287 (0.013)	0.280 (0.020)	0.268 (0.023)	0.272 (0.022)
Terrain ruggedness measure, mean (sd)	3.930 (1.416)	2.840 (4.767)	6.057 (3.764)	1.960 (2.110)	3.181 (3.351)
km of roads, mean (sd)	18.304 (10.822)	20.927 (32.791)	13.966 (45.116)	14.775 (25.656)	16.319 (29.792)
Demographic variables					
Medical distance problem, *n* (%)					
Yes, *n* (%)	7881 (40.1)	6065 (42.9)	12,962 (64.7)	19,129 (35.7)	46,037 (42.9)
No, *n* (%)	11,761 (59.9)	8087 (57.1)	7081 (35.3)	34,447 (64.3)	61,376 (57.1)
Time to water, mean (sd)	28.140 (31.324)	20.243 (30.885)	53.852 (80.602)	19.428 (27.849)	27.213 (44.956)
Maternal height in centimetres, mean (sd)	155.561 (6.291)	160.510 (6.404)	157.659 (6.692)	158.119 (6.769)	158.024 (6.765)
Child's age in months, mean (sd)	28.693 (17.306)	27.612 (17.292)	28.877 (17.445)	27.727 (17.267)	28.064 (17.319)
Gender of child, *n* (%)					
Male, *n* (%)	9911 (50.4)	9876 (49.9)	10,208 (50.9)	27,136 (50.5)	57,131 (50.4)
Female, *n* (%)	9736 (49.6)	9934 (50.1)	9844 (49.1)	26,649 (49.5)	56,163 (49.6)
Diarrhoea in last 2 weeks, *n* (%)					
No, *n* (%)	15,136 (77.3)	16,116 (83.5)	17,240 (86.8)	47,503 (89.5)	95,995 (85.9)
Yes, *n* (%)	4437 (22.7)	3182 (16.5)	2614 (13.2)	5585 (10.5)	15,818 (14.1)
Fever in last 2 weeks, *n* (%)					
No, *n* (%)	12,856 (65.7)	15,284 (79.0)	16,505 (83.2)	45,417 (85.6)	90,062 (80.6)
Yes, *n* (%)	6719 (34.3)	4068 (21.0)	3333 (16.8)	7621 (14.4)	21,741 (19.4)
Primary education, *n* (%)					
No, *n* (%)	11,446 (58.3)	12,339 (62.3)	14,979 (74.7)	42,193 (78.4)	80,957 (71.5)
Yes, *n* (%)	8201 (41.7)	7471 (37.7)	5073 (25.3)	11,592 (21.6)	32,337 (28.5)
Secondary education, *n* (%)					
No, *n* (%)	17,484 (89.0)	12,905 (65.1)	19,022 (94.9)	40,238 (74.8)	89,649 (79.1)
Yes, *n* (%)	2163 (11.0)	6905 (34.9)	1030 (5.1)	13,547 (25.2)	23,645 (20.9)
More than secondary education, *n* (%)					
No, *n* (%)	19,424 (98.9)	19,010 (96.0)	19,498 (97.2)	50,671 (94.2)	108,603 (95.9)
Yes, *n* (%)	223 (1.1)	800 (4.0)	554 (2.8)	3114 (5.8)	4691 (4.1)
Iron supplements, *n* (%)					
No, *n* (%)	17,991 (91.8)	16,683 (86.7)	18,143 (92.0)	48,173 (90.8)	100,990 (90.5)
Yes, *n* (%)	1597 (8.2)	2566 (13.3)	1572 (8.0)	4856 (9.2)	10,591 (9.5)
Breastfeeding, *n* (%)					
No, *n* (%)	3130 (15.9)	851 (4.3)	3149 (15.7)	1692 (3.2)	8822 (7.8)
Yes, *n* (%)	16,509 (84.1)	18,940 (95.7)	16,893 (84.3)	51,838 (96.8)	104,180 (92.2)

TABLE 1 (Continued)

Columns by: Country	Burundi	Cameroon	Ethiopia	Nigeria	Total
Middle income, *n* (%)					
No, *n* (%)	15,837 (80.6)	15,294 (77.2)	16,979 (84.7)	43,085 (80.1)	91,195 (80.5)
Yes, *n* (%)	3810 (19.4)	4516 (22.8)	3073 (15.3)	10,700 (19.9)	22,099 (19.5)
High income, *n* (%)					
No, *n* (%)	11,618 (59.1)	12,986 (65.6)	13,299 (66.3)	35,847 (66.6)	73,750 (65.1)
Yes, *n* (%)	8029 (40.9)	6824 (34.4)	6753 (33.7)	17,938 (33.4)	39,544 (34.9)
Urban, *n* (%)					
Rural, *n* (%)	16,344 (83.2)	11,362 (57.4)	16,577 (82.7)	37,176 (69.1)	81,459 (71.9)
Urban, *n* (%)	3303 (16.8)	8448 (42.6)	3475 (17.3)	16,609 (30.9)	31,835 (28.1)
Average precipitation, mean (sd)	99.581 (12.633)	139.229 (52.465)	82.766 (34.403)	109.724 (51.936)	108.339 (47.906)
Malaria prevalence, mean (sd)	0.123 (0.066)	0.228 (0.103)	0.005 (0.005)	0.327 (0.106)	0.221 (0.152)
Soil suitability, mean (sd)	4.151 (0.951)	2.642 (1.349)	3.513 (1.701)	2.288 (1.065)	2.874 (1.431)
Exposure to UV radiation, mean (sd)	1.6e+04 (467.480)	1.6e+04 (2272.112)	0e+04 (1264.018)	1.7e+04 (1841.195)	1.7e+04 (2195.108)

where stunting is the dependent variable that takes a value of one if a child is stunted and zero otherwise and subscripts i and j represent the child and cluster, respectively. The ruggedness in the area of a cluster is captured by *ruggedness* variable. The vector X is child-specific controls for mother characteristics (mother's education, mother's height, mother's access to iron supplement during pregnancy and breastfeeding), children characteristics (childbirth order, child sex, age, the prevalence of fever and diarrhoea), household characteristics (household wealth index, whether household is in an urban area) and other geographical factors (the average of rainfall over the past 3 years to account for changes in weather patterns,[9] whether distance to the nearest health centre is a challenge to access health services, time to the nearest water resource, prevalence of malaria in the countries [Pfeffer et al., 2018], soil suitability for agriculture[10] and exposure to ultraviolet radiation[11]). We also include the kilometres of motorways and primary and secondary roads within a 5-km radius of GPS coordinates to capture the quality of infrastructure within each cluster.

To remove spatial forms of bias, we include dummies for the sub-national region δ (administrative level 1), such that average spatial differences at the sub-national scale are accounted for. These regions are identified in the survey for each country and are standardised across survey waves.[12] Likewise, to account for temporal bias, we include survey dummies α, capturing average country-level trends in anthropometrics. Given the likelihood for within-group correlation of the residuals, we adjust the standard errors for potential clustering. We report standard errors, in parenthesis, adjusted for two-way clustering of households by GPS location (latitude and longitude) (ElHaj et al., 2023). Potential dependence based on spatial proximity may also be present in the sample, so we calculate and report Conley (1999) standard errors, in square brackets, adjusted for spatial correlation. These methods produce relatively similar standard errors.[13]

[9]Climatic Research Unit (CRU-TS-4.03), University of East Anglia.
[10]https://gaez.fao.org/
[11]https://worldclim.org/data/worldclim21.html
[12]The survey waves for Burundi changed how the administrative regions were identified between the 2010 and 2016 survey. The 2010 survey used an aggregated version of the 2016 administrative level 1 version, so we matched the GPS locations in the cluster in survey 2010 to the administrative level 1. This was to ensure consistency in the regression that uses regional fixed effects. For Ethiopia, we included Addis Ababa (the capital city), and Harari with the Oromia regional state, which the DHS waves originally separated. The results are similar if we do not combine these areas.
[13]We also clustered standard errors by strata (*i.e.* adjusted by geographic region and by urban/rural areas within each region). The standard errors are similar to two-way clustering by location and the Conley standard errors. Results are available on request from the authors.

4 | RESULTS

4.1 | Regression results

The ruggedness coefficient measures how much the stunting rate of children under 5 years is affected by a change in the roughness or complexity of the terrain surface. The coefficient measures the correlation between the probability of a child under 5 years being stunted for a 1% change in the standard deviation of VRM within the 5-km buffer, which refers to variability in terrain in the immediate area of the survey respondent. A positive correlation indicates that when the terrain becomes harder to traverse, the likelihood of children experiencing stunting also increases. For example, a 1% change in the standard deviation of ruggedness increases the likelihood of child stunting by 0.34% for Burundi in Table 2, column 1. Larger magnitudes for coefficients indicate a higher effect in the country. In Table 2, we observe that the more difficult the terrain is to navigate, the higher the likelihood of child stunting across all four countries, although Ethiopia is statistically insignificant.

In Table 3, we include region effects and find that the positive effects of ruggedness on child stunting remain consistent and statistically significant for Cameroon and Nigeria, although Burundi loses significance. The effects, however, become muted for Ethiopia, with a negative coefficient. This result may be in line with Headey et al. (2017), who find that after controlling for socio-economic status and health infrastructure services, remoteness has no further explanatory power on nutrition variations between rural and urban areas. We explore Ethiopia's results further in Section 5.

For robustness check, we use a similar model as Equation 1 where our main explanatory variable is now the TRI measure instead of the VRM measure of ruggedness. Table 4 reports the results. The overall conclusions remain unchanged as in our previous findings. Ruggedness, using the alternative measure, is positively associated with child stunting in Burundi, Cameroon and Nigeria but is negative and not significant in Ethiopia.

From the household control variables that are statistically significant, we find that children residing in urban areas have a lower chance of being stunted. Urban areas typically have access to improved sanitation and wealth. According to Headey et al. (2017), most nutritional disadvantages can be explained by differences in wealth and human capital across rural and urban areas in sub-Saharan Africa (Headey et al., 2017), as well as access to water and sanitation (Agha, 2000; Hussain et al., 1999). The maternal characteristics that are consistent and statistically significant indicate that maternal education and maternal height are negatively associated with stunting. Maternal education is highlighted as an important contributor to child survival through better knowledge on nutritional benefits and modern health services (Arendt et al., 2021; Le & Nguyen, 2020). Maternal height reflects the mother's health status which has been shown to be strongly correlated with child health outcomes (Porwal et al., 2021; Subramanian et al., 2009).

From the child characteristics, we find that the age of the child and diarrhoea are positively associated with stunting. Research has shown that children aged 24–59 months are at a higher risk of stunting compared with the lower age group of 6–23 months (Kismul et al., 2018; Nshimyiryo et al., 2015). Illnesses, such as diarrhoea, can lead to malnutrition, delayed growth and mortality in children (Mulatya & Mutuku, 2020; Rice et al., 2000). On the other hand, girl children have a lower chance of being stunted relative to boys who have a higher risk of mortality during neonatal period than female peers (Berhane et al., 2020). Boys are also more likely to become stunted because of nutritional deficiencies that they may be exposed to than females, for example, preferences in feeding practices (Nshimyiryo et al., 2015; Wamani et al., 2007). The geographical factors are inconsistent and mostly statistically insignificant.

5 | DISCUSSION

Our findings indicate that terrain ruggedness and child stunting are positively associated for Burundi, Cameroon and Nigeria, whereas Ethiopia is not in line with our expectations. One mechanism that may

TABLE 2 Ruggedness variation and stunting using the vector ruggedness measure (survey effects included).

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Log ruggedness	0.342***	0.591***	−0.002	0.182***
	(0.116)	(0.222)	(0.081)	(0.052)
	[0.102]	[0.219]	[0.085]	[0.053]
Log km of roads	0.003	−0.001	−0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
	[0.002]	[0.002]	[0.001]	[0.001]
Gender of child	−0.085***	−0.059***	−0.028***	−0.037***
	(0.010)	(0.013)	(0.008)	(0.004)
	[0.009]	[0.013]	[0.008]	[0.004]
Child's age in months	0.006***	0.002***	0.006***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]
Birth order number	0.004*	0.002	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.001)
	[0.002]	[0.003]	[0.002]	[0.001]
Diarrhoea in last 2 weeks	0.036***	0.031	0.062***	0.044***
	(0.012)	(0.020)	(0.012)	(0.008)
	[0.012]	[0.020]	[0.012]	[0.008]
Fever in last 2 weeks	0.023**	0.002	0.016	0.012*
	(0.011)	(0.017)	(0.010)	(0.007)
	[0.011]	[0.017]	[0.010]	[0.007]
Maternal height in centimetres	−0.016***	−0.010***	−0.011***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.000)
	[0.001]	[0.001]	[0.001]	[0.000]
Primary education	0.016	−0.009	−0.021**	−0.020**
	(0.012)	(0.023)	(0.010)	(0.008)
	[0.012]	[0.023]	[0.010]	[0.008]
Secondary education	−0.089***	−0.032	−0.062***	−0.059***
	(0.021)	(0.024)	(0.018)	(0.009)
	[0.022]	[0.023]	[0.017]	[0.009]
More than secondary education	−0.154***	−0.070**	−0.103***	−0.118***
	(0.036)	(0.033)	(0.023)	(0.012)
	[0.036]	[0.033]	[0.022]	[0.012]
Iron supplements	0.015	−0.008	0.010	0.003
	(0.020)	(0.020)	(0.014)	(0.008)
	[0.020]	[0.018]	[0.014]	[0.008]
Breastfeeding	0.061***	0.051*	−0.092***	−0.043***
	(0.015)	(0.026)	(0.011)	(0.013)
	[0.014]	[0.026]	[0.011]	[0.013]
Middle income	−0.033**	−0.056**	−0.047***	−0.035***
	(0.015)	(0.022)	(0.011)	(0.008)
	[0.015]	[0.022]	[0.011]	[0.008]
High income	−0.131***	−0.119***	−0.070***	−0.088***
	(0.014)	(0.026)	(0.011)	(0.009)
	[0.014]	[0.025]	[0.011]	[0.009]

(Continues)

TABLE 2 (Continued)

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Urban	−0.072***	−0.004	−0.070***	−0.021**
	(0.020)	(0.022)	(0.016)	(0.009)
	[0.020]	[0.022]	[0.015]	[0.008]
Average precipitation	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.000)	(0.000)	(0.000)
	[0.001]	[0.000]	[0.000]	[0.000]
Difficulty to medical centre	0.004	0.008	0.008	0.009
	(0.012)	(0.017)	(0.009)	(0.006)
	[0.011]	[0.016]	[0.009]	[0.006]
Time to water source	0.000	0.000	0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]
Malaria prevalence	0.016	0.028	−0.005	0.037***
	(0.020)	(0.020)	(0.010)	(0.008)
	[0.019]	[0.020]	[0.011]	[0.008]
Soil suitability	0.035	0.008	0.023**	−0.008
	(0.027)	(0.022)	(0.011)	(0.008)
	[0.023]	[0.022]	[0.011]	[0.008]
Exposure to UV radiation	−0.908**	0.275***	0.022	0.682***
	(0.391)	(0.104)	(0.117)	(0.064)
	[0.379]	[0.106]	[0.120]	[0.067]
Survey FE	Yes	Yes	Yes	Yes
Region FE	No	No	No	No
Number of observations	8377	4219	16,527	43,793
R-squared	0.170	0.087	0.108	0.102

Note: Coefficients reported. We report two standard errors below each coefficient The first in parentheses are standard errors adjusted for two-way clustering by location. The second in square brackets are the Conley (1999) standard errors adjusted for spatial correlation.
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

account for these findings is that ruggedness can affect the mobility of people to access healthcare services, resulting in poor child health outcomes. For example, in Nigeria, the percentage of population (0–19 years) living within 2 h of a health facility with a paediatric facility ranged from less than 2% to 30.5% depending on the region (Abd salam El Vilaly et al., 2021). These statistics highlight the significant differences in geographical access to health services, with over 70% of the Nigerian population lacking access. Moreover, difficulty to access the nearest healthcare facility has been found to be positively associated with increased stunting by Okwaraji et al. (2012) and Weiss et al. (2020).

Second, ruggedness can pose a risk to food security, which can also lead to poor child health outcomes. Populations residing in regions with steep terrain may have a less diverse agricultural sector because farming is difficult and transport costs are high (Balk et al., 2004; Headey et al., 2017; Forsido et al., 2021; Ouma et al., 2021). Another mechanism to explain the poor child health outcomes is the association between ruggedness and quality of infrastructure. For example, a rugged area may have poor health outcomes precisely because ruggedness limits infrastructure access or development. According to Makanga et al. (2017), short travel times to the nearest healthcare facilities during dry seasons can be significantly increased in wet seasons due to poor road infrastructure.

We explore our findings further by conducting a mediation analysis, which tests if the effects of ruggedness on stunting work through one of the mechanisms discussed above, namely road infrastructure

TABLE 3 Ruggedness variation and stunting using the vector ruggedness measure (survey and region effects included).

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Log ruggedness	0.147	0.579***	−0.043	0.126**
	(0.140)	(0.224)	(0.089)	(0.052)
	[0.128]	[0.208]	[0.089]	[0.053]
Log km of roads	0.001	−0.002	−0.001	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)
	[0.002]	[0.002]	0.001[]	[0.001]
Gender of child	−0.085***	−0.059***	−0.029***	−0.037***
	(0.010)	(0.013)	(0.008)	(0.004)
	[0.009]	[0.013]	[0.008]	[0.004]
Child's age in months	0.006***	0.002***	0.006***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]
Birth order number	0.005**	0.002	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.001)
	[0.002]	[0.003]	[0.002]	[0.001]
Diarrhoea in last 2 weeks	0.036***	0.033	0.061***	0.050***
	(0.012)	(0.020)	(0.012)	(0.008)
	[0.012]	[0.020]	[0.012]	[0.008]
Fever in last 2 weeks	0.021*	0.003	0.015	0.017**
	(0.011)	(0.017)	(0.010)	(0.007)
	[0.011]	[0.017]	[0.010]	[0.007]
Maternal height in centimetres	−0.016***	−0.010***	−0.010***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.000)
	[0.001]	[0.001]	[0.001]	[0.000]
Primary education	0.011	−0.011	−0.020**	−0.016**
	(0.012)	(0.024)	(0.010)	(0.008)
	[0.012]	[0.023]	[0.010]	[0.008]
Secondary education	−0.091***	−0.036	−0.060***	−0.053***
	(0.021)	(0.024)	(0.018)	(0.009)
	[0.022]	[0.024]	[0.017]	[0.009]
More than secondary education	−0.150***	−0.080**	−0.097***	−0.111***
	(0.037)	(0.033)	(0.022)	(0.012)
	[0.038]	[0.033]	[0.023]	[0.012]
Iron supplements	0.014	−0.017	−0.000	0.003
	(0.020)	(0.019)	(0.014)	(0.008)
	[0.020]	[0.018]	[0.014]	[0.008]
Breastfeeding	0.065***	0.059**	−0.086***	−0.044***
	(0.015)	(0.026)	(0.011)	(0.013)
	[0.014]	[0.026]	[0.011]	[0.013]
Middle income	−0.031**	−0.058***	−0.049***	−0.033***
	(0.015)	(0.022)	(0.011)	(0.008)
	[0.015]	[0.022]	[0.011]	[0.008]
High income	−0.126***	−0.122***	−0.069***	−0.091***
	(0.014)	(0.027)	(0.011)	(0.009)
	[0.014]	[0.026]	[0.011]	[0.009]

(Continues)

TABLE 3 (Continued)

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Urban	−0.067***	0.011	−0.051***	−0.015*
	(0.022)	(0.022)	(0.017)	(0.008)
	[0.020]	[0.022]	[0.016]	[0.008]
Average precipitation	0.001	0.000	−0.001***	−0.000
	(0.002)	(0.001)	(0.000)	(0.000)
	[0.002]	[0.001]	[0.000]	[0.000]
Difficulty to medical centre	0.004	0.018	0.013	0.012*
	(0.012)	(0.016)	(0.009)	(0.006)
	[0.011]	[0.016]	[0.009]	[0.006]
Time to water source	0.000*	0.000	0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]
Malaria prevalence	0.033	0.051**	−0.011	0.019**
	(0.036)	(0.023)	(0.011)	(0.008)
	[0.033]	[0.022]	[0.011]	[0.009]
Soil suitability	0.024	−0.019	0.007	−0.003
	(0.028)	(0.024)	(0.011)	(0.008)
	[0.023]	[0.024]	[0.012]	[0.008]
Exposure to UV radiation	−0.214	−0.353	−0.532***	0.261**
	(0.852)	(0.286)	(0.171)	(0.108)
	[0.807]	[0.284]	[0.183]	[0.109]
Survey FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Number of observations	8377	4219	16,527	43,793
R-squared	0.175	0.097	0.114	0.106

Note: Coefficients reported. We report two standard errors below each coefficient The first in parentheses are standard errors adjusted for two-way clustering by location. The second in square brackets are the Conley (1999) standard errors adjusted for spatial correlation.
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

TABLE 4 Ruggedness variation and stunting using the terrain ruggedness measure (TRI).

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Log ruggedness	0.000	0.037***	−0.014	0.006
	(0.018)	(0.013)	(0.008)	(0.006)
	[0.014]	[0.014]	[0.008]	[0.006]
Demographic controls	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Number of observations	8377	4219	16,527	43,793
R-squared	0.175	0.098	0.114	0.106

Note: Coefficients reported. We report two standard errors below each coefficient The first in parentheses are standard errors adjusted for two-way clustering by location. The second in square brackets are the Conley (1999) standard errors adjusted for spatial correlation.
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

and difficulty in getting to the nearest health centre. We conduct the mediation analysis based on the Baron and Kenny (1986) approach, which is adjusted by Iacobucci, Saldanha and Deng (2007) for use with structural equation modelling.[14] Mediation analysis tests a hypothetical causal link where one variable X (independent variable) affects a second variable M (mediator variable) and, in turn, M affects a third variable Y (outcome variable) (Agler & De Boeck, 2017). Mediators describe the indirect effect, basically the how or why of a relationship between two other variables or the process through which an effect occurs. For example, countries with higher incomes have lower adult mortality rates but this effect may be explained by the mediating influence of having access to better healthcare. In addition, increases in rainfall lower stunting, but this effect may be explained through increased agricultural yield and hence better nutrition (Nsabimana & Mensah, 2020; Mendiratta, 2015; Cornwell & Inder, 2015). For our mediator variables, we use whether distance to the nearest health centre is a challenge to access health services, as well as the number of motorways and primary and secondary roads within a 5-km radius within each cluster.

The Sobel *z*-test is statistically insignificant across Burundi, Cameroon and Nigeria suggesting that these mediator variables explain a small proportion of the effects of ruggedness on stunting. The RIT score, which shows the ratio of the indirect to total effects, indicates that about 1% of the effect of ruggedness on stunting is mediated by either road infrastructure or difficulty to the nearest health centre. The RID score confirms these findings as the ratio of the indirect to direct effects also indicates minimal mediation. We do however find some significant mediation for Ethiopia, particularly with difficulty in getting to the nearest health centre. About 102% of the effect of ruggedness on stunting can be explained by difficulty to the nearest health centre, whereas 10% of the effect of ruggedness on stunting can be explained by road infrastructure.

These findings highlight the importance of the availability of good quality road infrastructure, which can make inaccessible locations due to terrain ruggedness relatively more accessible and/or reduce travel times to the nearest healthcare facility made longer by terrain ruggedness. The weak and insignificant mediation effects may in fact signal a paucity of road infrastructure within our sample of countries, presenting an opportunity for effective targeted policies. According to the road quality index recorded by the World Economic Forum, these four countries averaged very low scores individually between 2006 and 2019. Furthermore, a recent report by African Development Bank also highlights the slow progress in infrastructure development, using the Africa Infrastructure Development Index, which is based on four major components: transport, electricity, Information and Communications Technology (ICT) and water and sanitation (Lufumpa et al., 2020). All four countries have low infrastructure development rankings, with Ethiopia falling in the bottom 10 performers for 2020 (Nigeria ranked 24, Cameroon 28, Burundi 39 and Ethiopia ranked 48 out of 54 African countries).

Overall, our findings for Burundi, Cameroon and Nigeria are in line with expectations that ruggedness can contribute to poor child health outcomes. The results, however, appear counterintuitive for Ethiopia. Ethiopia is considered to be quite rugged comparatively, based on the geographical descriptions provided in Section 3.1, and the statistical evidence highlighted in Table 1 by the TRI ruggedness measure. We would therefore expect Ethiopia to have relatively more significant adverse effects on child health outcomes given the country's geography. Because we observe in our analysis in Table 3 that the inclusion of the region effects attenuated the positive effects of ruggedness on child stunting in Ethiopia, as well as the mediation analysis in Table 5 that highlights accessibility to health centre as a mechanism, we therefore explore the country's results further by examining the individual regions within the country. We find that Oromia, a regional state in Ethiopia, which also has the capital city Addis Ababa, is contributing to the insignificant child health outcomes. Table 6 reports the results for Ethiopia controlling for region effects and separately interacting the Oromia region with ruggedness. We now find that the coefficient for Ethiopia is positively associated with child stunting in relation to the Oromia region, which is negatively associated with child stunting and statistically significant.

[14]We use the Zhao et al. (2010) approach as a robustness check for the mediation analysis. The findings are consistent with the Baron and Kenny approach. The results are available on request.

TABLE 5 Mediation analysis with difficulty to the nearest health centre and road infrastructure as mediators.

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Difficulty to nearest health centre				
Sobel *z*-test	−0.465	−0.524	−2.477**	−1.396
Step 1 (ruggedness to health centre)	−0.051	−0.385**	−0.347***	−0.048
Step 2 (health centre to stunting	0.013	0.008	0.002***	0.013***
Step 3 (ruggedness to stunting)	-	-	0.015	-
RIT (indirect/total effect)	0.002	0.005	1.023	0.003
RID (indirect/direct effect)	0.002	0.005	0.506	0.003
Outcome of mediation	None	None	Complete	None
Road infrastructure				
Sobel *z*-test	1.319	−0.554	−1.244	−0.884
Step 1 (ruggedness to road infrastructure)	1.265**	4.434***	0.962*	−3.210***
Step 2 (road infrastructure to stunting)	0.003	−0.001	−0.001	0.000
Step 3 (ruggedness to stunting)	-	-	-	-
RIT (indirect/total effect)	0.011	0.007	0.101	0.009
RID (indirect/direct effect)	0.011	0.007	0.092	0.009
Outcome of mediation	None	None	None	None

Note: Coefficients reported. If either (or both) coefficient for Step 1 or Step 2 is not significant, there is no mediation. If both coefficients for Step 1 and Step 2 are significant, there is partial mediation. If the coefficient for Step 3 is significant, but the Sobel *z*-test is insignificant, there is partial mediation. If both the coefficient for Step 3 and the Sobel *z*-test are significant, there is partial mediation. If the coefficient for Step 3 is insignificant but the Sobel z-test is significant, there is complete mediation.
**$p < 0.05$, and ***$p < 0.01$.

TABLE 6 Ruggedness variation and stunting using the vector ruggedness measure: Oromia region vs Ethiopia.

	(1) Stunting	(2) Stunting
Log ruggedness	0.050	0.015
	(0.083) [0.087]	(0.090) [0.090]
Oromia region	−0.706**	−0.576*
	(0.338) [0.344]	(0.340) [0.346]
Oromia region	−0.542**	−0.514*
x log ruggedness	(0.270) [0.275]	(0.272) [0.276]
Demographic controls	Yes	Yes
Survey FE	Yes	Yes
Region FE	No	Yes
Number of observations	16,527	16,527
R-squared	0.109	0.114

Note: Coefficients reported. We report two standard errors below each coefficient The first in parentheses are standard errors adjusted for two-way clustering by location. The second in square brackets are the Conley (1999) standard errors adjusted for spatial correlation.
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

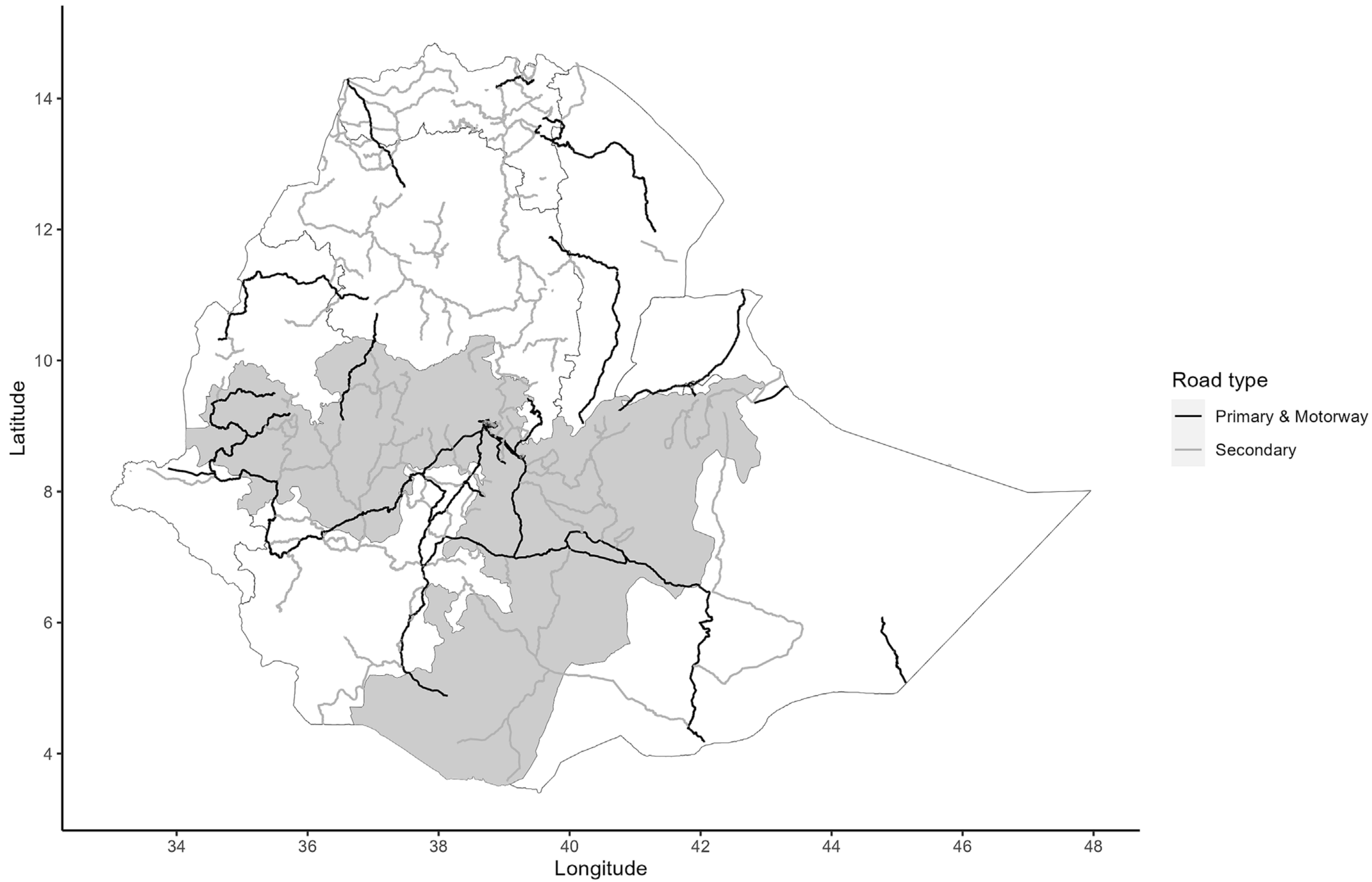

FIGURE 5 Map of Ethiopia Roads—Oromia Region. This graph shows the motorway, primary and secondary roads (if they exist) listed by OpenStreetMap data as created by World Food Program. The data can be found at https://geonode.wfp.org/layers. The region borders are superimposed on the map with the Oromia region highlighted.

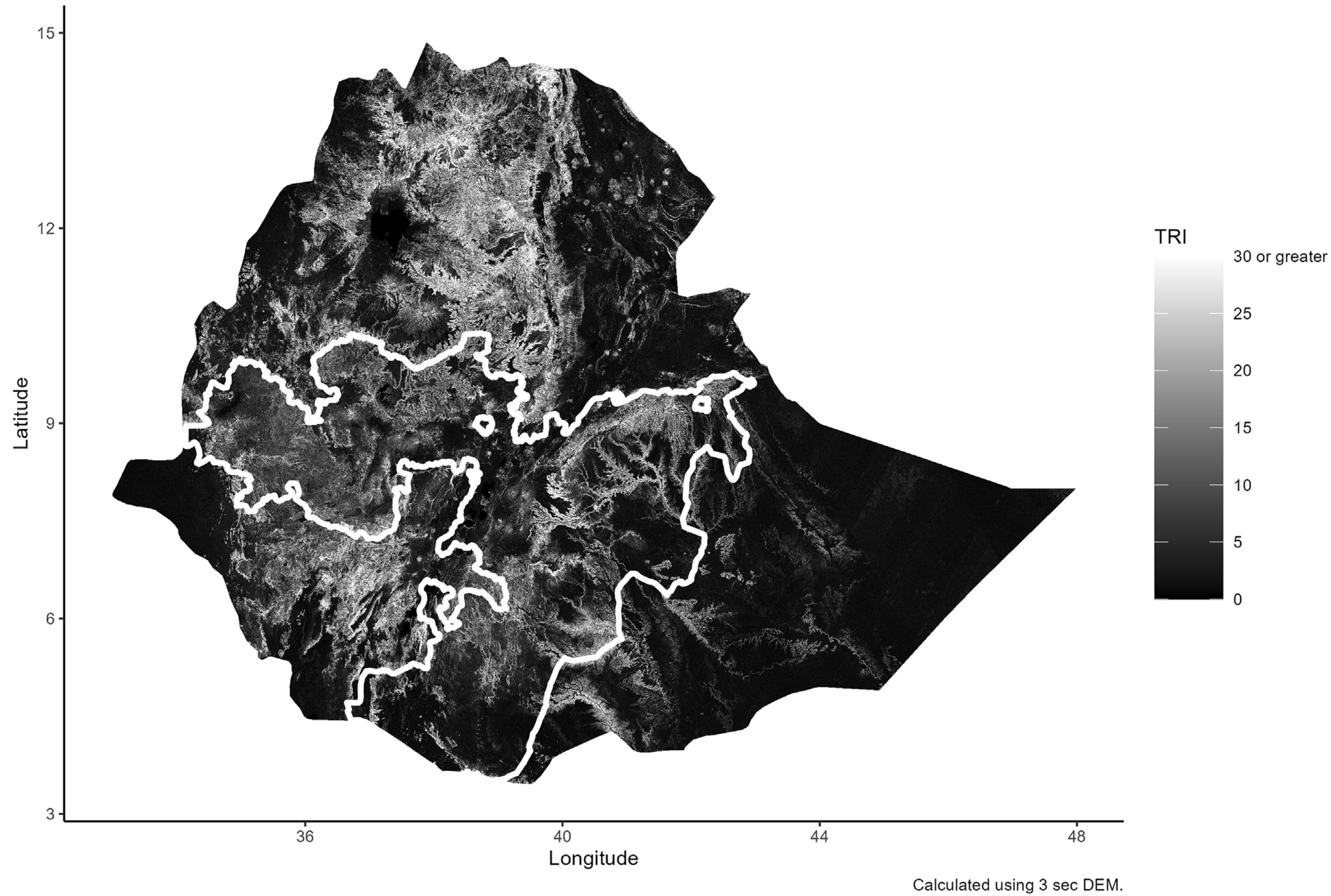

FIGURE 6 Map of Ethiopia Terrain—Oromia Region. This graph highlights the Oromia region's terrain (with outline) measured by TRI. The lighter shades indicate places where the terrain is more rugged or sloped, whereas the darker shades indicate moderate to low terrain ruggedness.

To understand these dynamics in Ethiopia's geography, we compare the Oromia region to the rest of Ethiopia. We observe that the mean of the DHS kilometres of roads within a 5-km buffer for household clusters is relatively higher within Oromia than the other regions combined (see Table A1). We superimpose the DHS regions over a road density map for Ethiopia in Figure 5 and find that the infrastructure for primary roads is concentrated mainly within and around the surrounding areas of the Oromia region, particularly near Addis Ababa. In addition, we superimpose the Oromia region on the TRI ruggedness map in Figure 6 where we note that Oromia is also characterised by moderate terrain ruggedness especially around Addis Ababa, in relation to the other regions.

These findings suggest that the better quality of infrastructure within the Oromia region contributes to improved child health outcomes. Moreover, the presence of the capital city in the Oromia regional state could also indicate easier access to healthcare facilities, in terms of transport and better road networks, which corroborates the findings from the mediation analysis, whereas people located in remote areas may find it difficult to access the capital city.[15] Indeed, children stunting reduction was the highest in Addis Ababa (the capital city located in the Oromia region) and Oromia region over the last two decades between 2000 and 2019. Children stunting declined by 54% and 34% in Addis Ababa and Oromia region, respectively.[16] The region is also the largest in Ethiopia, which may explain why the ruggedness results for Ethiopia were attenuated by including Oromia in the region effects.

The implications of our findings are twofold. First, we observe that terrain ruggedness can increase transaction costs of movement from one area to another which can affect the provision of public goods, such as access to health services and trading markets (Darrouzet-Nardi & Masters, 2017; Hirvonen & Hoddinott, 2016; Ouma et al., 2021). Second, even countries with relatively flat plains, such as Cameroon and Nigeria, are associated with increased stunting in children. According to Jimenez-Ayora and Ulubaşoğlu (2015), extracting rents and dominating citizens in ways that undermine economic development is a lot easier on flat terrain. Moreover, other external factors can reinforce the geographical disadvantages. In Nigeria, military control during the 1990s and insurgency issues from militia groups (mostly the Boko Haram since 2002) create a security risk (Acemoglu & Robinson, 2019, pp. 4–5). For example, the provision of health services may be restricted or people may be afraid to travel to clinics, which can affect child health outcomes (Sami et al., 2020). Movement and co-ordination in relatively flat terrains are also easier when targeting civilians or delivery trucks. On the other hand, countries with relatively more rugged terrain, such as Ethiopia, and also susceptible to poor child health outcomes, may end up with dense populations in centralised locations, as indicated by the Oromia region, which can make provision of public goods less challenging because of better infrastructure and access to healthcare facilities, compared with those areas in the mountainous regions of Ethiopia.

6 | CONCLUSION

The study examines the effects of terrain ruggedness on child health outcomes (stunting) in Burundi, Cameroon, Ethiopia and Nigeria. Using the latest two geo-located DHS surveys from each country and calculated land elevation measures, we find that Burundi, Cameroon and Nigeria's terrain ruggedness is associated with increased stunting in children, whereas Ethiopia has mostly negative outcomes. Our findings in Ethiopia are contrary to our expectations. We expected that ruggedness, such as that found in Ethiopia, would be mostly associated with poor child health outcomes because of the inaccessibility of public goods and health services. Further investigation, however, shows that the Oromia region, with ample fertile land supporting crop and livestock production in the country, which also has the Addis Ababa market (the capital city) and the logistical hubs, is driving the insignificant child health outcomes.

[15]A robustness check with night light intensity also confirms that the greatest light intensity is found in the capital city, Addis Ababa, an indication of better quality of infrastructure. See Figure A1.

[16]Ethiopian Public Health Institute (EPHI) [Ethiopia] and ICF. 2021. Ethiopia Mini Demographic and Health Survey 2019: Final Report. Rockville, Maryland, USA: EPHI and ICF.

Once we control for the Oromia region, our results in Ethiopia align with the other three countries and our expectations.

Although our study may be limited by the survey data that we use, we maintain that the findings document substantial socio-economic inequality in child stunting in the sample, which is not only determined by immediate factors but also by underlying and contextual factors, suggesting the need for coherent actions. Overall, the findings suggest that expansion in public investment through embarking on the development of infrastructures, especially in areas where people have to cover large distances to access healthcare services, is vital for improving children's health outcomes and human capital accumulation.

ACKNOWLEDGEMENTS

We acknowledge the comments received at the Virtual Western Economic Association International Conference. We also acknowledge comments from the Economic Development and Well-being Research Group (EDWRG) seminars, University of Johannesburg.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interest.

ORCID

Carolyn Chisadza https://orcid.org/0000-0002-9340-210X

REFERENCES

Abd salam El Vilaly, M., Jones, M.A., Stankey, M.C., Seyi-Olajide, J., Onajin-Obembe, B., Dasogot, A., et al. (2021) Access to paediatric surgery: the geography of inequality in Nigeria. *BMJ Global Health*, 6(10), 1–11. Available from: https://doi.org/10.1136/bmjgh-2021-006025

Acemoglu, D., Johnson, S. & Robinson, J.A. (2001) The colonial origins of comparative development: an empirical investigation. *American Economic Review*, 91(5), 1369–1401. Available from: https://doi.org/10.1257/aer.91.5.1369

Acemoglu, D. & Robinson, J.A. (2019) *The narrow corridor: states, societies, and the fate of liberty*. New York: Penguin Press.

Agha, S. (2000) The determinants of infant mortality in Pakistan. *Social Science & Medicine*, 51(2), 199–208. Available from: https://doi.org/10.1016/S0277-9536(99)00460-8

Agler, R. & De Boeck, P. (2017) On the interpretation and use of mediation: multiple perspectives on mediation analysis. *Frontiers in Psychology*, 8(1984), 1–11.

Akombi, B.J., Agho, K.E., Renzaho, A.M., Hall, J.J. & Merom, D.R. (2019) Trends in socioeconomic inequalities in child undernutrition: evidence from Nigeria Demographic and Health Survey (2003–2013). *PLoS ONE*, 14(2), e0211883. Available from: https://doi.org/10.1371/journal.pone.0211883

Allen, B., Bourke, R. & Gibson, J. (2005) Poor rural places in Papua New Guinea. *Asia-Pacific Viewpoint*, 46(2), 201–217. Available from: https://doi.org/10.1111/j.1467-8373.2005.00274.x

Angdembe, M.R., Dulal, B.P., Bhattarai, K. & Karn, S. (2019) Trends and predictors of inequality in childhood stunting in Nepal from 1996 to 2016. *International Journal for Equity in Health*, 18(42), 1–17. Available from: https://doi.org/10.1186/s12939-019-0944-z

Arendt, J.N., Christensen, M.L. & Hjorth-Trolle, A. (2021) Maternal education and child health: causal evidence from Denmark. *Journal of Health Economics*, 80(C), 102552. Available from: https://doi.org/10.1016/j.jhealeco.2021.102552

Asefa, M., Cao, M., He, Y., Mekonnen, E., Song, X. & Yang, J. (2020) Ethiopian vegetation types, climate and topography. *Plant Diversity*, 42(4), 302–311. Available from: https://doi.org/10.1016/j.pld.2020.04.004

Balk, D., Pullum, T., Storeygard, A., Greenwell, F. & Neuman, M. (2004) A spatial analysis of childhood mortality in West Africa. *Population, Space and Place*, 10(3), 175–216. Available from: https://doi.org/10.1002/psp.328

Baron, R. & Kenny, D. (1986) The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. Available from: https://doi.org/10.1037/0022-3514.51.6.1173

Beegle, K. & Christiaensen, L. (2019) *Accelerating poverty reduction in Africa*. World Bank Publications: The World Bank. Washington, D.C. Available from: https://doi.org/10.1596/978-1-4648-1232-3

Berhane, H.Y., Jirström, M., Abdelmenan, S., Berhane, Y., Alsanius, B., Trenholm, J., et al. (2020) Social stratification, diet diversity and malnutrition among preschoolers: a survey of Addis Ababa. *Ethiopia. Nutrients*, 12(3), 712. Available from: https://doi.org/10.3390/nu12030712

Conley, T.G. (1999) GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1), 1–45. Available from: https://doi.org/10.1016/S0304-4076(98)00084-0

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., et al. (2015) System for automated geoscientific analyses (SAGA) v. 2.1.4. *Geoscientific Model Development*, 8(7), 1991–2007. Available from: https://doi.org/10.5194/gmd-8-1991-2015

Conti, G., Heckman, J. & Urzua, S. (2010) The education-health gradient. *American Economic Review*, 100(2), 234–238. Available from: https://doi.org/10.1257/aer.100.2.234

Cornwell, K. & Inder, B. (2015) Child health and rainfall in early life. *The Journal of Development Studies*, 51(7), 865–880.

Darrouzet-Nardi, A.F. & Masters, W.A. (2017) Nutrition smoothing: can proximity to towns and cities protect rural children against seasonal variation in agroclimatic conditions at birth? *PLoS ONE*, 12(1), e0168759. Available from: https://doi.org/10.1371/journal.pone.0168759

De Onis, M. & Blössner, M. (2003) The World Health Organization global database on child growth and malnutrition: methodology and applications. *International Journal of Epidemiology*, 32(4), 518–526. Available from: https://doi.org/10.1093/ije/dyg099

Dell, M., Jones, B.F. & Olken, B.A. (2012) Temperature shocks and economic growth: evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3), 66–95. Available from: https://doi.org/10.1257/mac.4.3.66

Dewey, K.G. & Begum, K. (2011) Long-term consequences of stunting in early life. *Maternal & Child Nutrition*, 7(Suppl 3), 5–18. Available from: https://doi.org/10.1111/j.1740-8709.2011.00349.x

Ekholuenetale, M., Tudeme, G., Onikan, A. & Ekholuenetale, C.E. (2020) Socioeconomic inequalities in hidden hunger, undernutrition, and overweight among under-five children in 35 sub-Saharan Africa countries. *Journal of the Egyptian Public Health Association*, 95(9), 1–15.

ElHaj, K., Alshamsi, D. & Aldahan, A. (2023) GeoZ: a region-based visualization of clustering algorithms. *Journal of Geovisualization and Spatial Analysis*, 7(15), 1–14. Available from: https://doi.org/10.1007/s41651-023-00146-0

Engerman, S.L., Sokoloff, K.L., Urquiola, M. & Acemoglu, D. (2002) Factor endowments, inequality, and paths of development among new world economies [with comments]. *Economia*, 3(1), c41–c109.

Fang, Y.P. & Ying, B. (2016) Spatial distribution of mountainous regions and classifications of economic development in China. *Journal of Mountain Science*, 13(6), 1120–1138. Available from: https://doi.org/10.1007/s11629-015-3714-4

Feinstein, L. (2003) Inequality in the early cognitive development of British children in the 1970 cohort. *Economica*, 70(277), 73–97. Available from: https://doi.org/10.1111/1468-0335.t01-1-00272

Forsido, S.F., Tsegay, N.K., Tamiru, D., Belachew, T. & Hensel, O. (2021) Undernutrition and associated factors among children under 2 years of age in Jimma Zone, Southwest Ethiopia. *Journal of Public Health*, 1-9(12), 2911–2919. Available from: https://doi.org/10.1007/s10389-021-01515-z

Galasso, E. & Wagstaff, A. (2019) The aggregate income losses from childhood stunting and the returns to a nutrition intervention aimed at reducing stunting. *Economics & Human Biology*, 34, 225–238. Available from: https://doi.org/10.1016/j.ehb.2019.01.010

Gallardo-Albarrán, D. (2018) Health and economic development since 1900. *Economics & Human Biology*, 31(C), 228–237. Available from: https://doi.org/10.1016/j.ehb.2018.08.009

Gayawan, E., Adarabioyo, M.I., Okewole, D.M., Fashoto, S.G. & Ukaegbu, J.C. (2016) Geographical variations in infant and child mortality in West Africa: a geo-additive discrete-time survival modelling. *Genus*, 72(5), 1–20. Available from: https://doi.org/10.1186/s41118-016-0009-8

Harper, C., Marcus, R. & Moore, K. (2003) Enduring poverty and the conditions of childhood: lifecourse and intergenerational poverty transmissions. *World Development*, 31(3), 535–554. Available from: https://doi.org/10.1016/S0305-750X(03)00010-X

Headey, D., Stifel, D.C., You, L. & Zhe, G. (2017) Remoteness, urbanization and child nutrition in Sub-Saharan Africa. In: *IFPRI discussion paper 1694*. Washington, D.C.: International Food Policy Research Institute. https://ssrn.com/abstract=3098490

Heckman, J.J. (2006) Skill formation and the economics of investing in disadvantaged children. *Science*, 312(5782), 1900–1902. Available from: https://doi.org/10.1126/science.1128898

Hirvonen, K. & Hoddinott, J. (2016) Agricultural production and children's diets: evidence from rural Ethiopia. *Agricultural Economics*, 48(4), 469–480. Available from: https://doi.org/10.1111/agec.12348

Hoddinott, J., Alderman, H., Behrman, J.R., Haddad, L. & Horton, S. (2013) The economic rationale for investing in stunting reduction. *Maternal & Child Nutrition*, 9(Suppl 2), 69–82. Available from: https://doi.org/10.1111/mcn.12080

Hussain, A., Ali, S.M.K. & Kvåle, G. (1999) Determinants of mortality among children in the urban slums of Dhaka City, Bangladesh. *Tropical Medicine & International Health*, 4(11), 758–764. Available from: https://doi.org/10.1046/j.1365-3156.1999.00485.x

Iacobucci, D., Saldanha, N. & Deng, X. (2007) A mediation on mediation: evidence that structural equation models perform better than regressions. *Journal of Consumer Psychology*, 17(2), 140–154. Available from: https://doi.org/10.1016/S1057-7408(07)70020-7

Jimenez-Ayora, P. & Ulubaşoğlu, M.A. (2015) What underlies weak states? The role of terrain ruggedness. *European Journal of Political Economy*, 39(2015), 167–183. Available from: https://doi.org/10.1016/j.ejpoleco.2015.04.014

Kismul, H., Acharya, P., Mapatano, M.A. & Hatloy, A. (2018) Determinants of childhood stunting in the Democratic Republic of Congo: further analysis of demographic and health survey 2013–14. *BMC Public Health*, 18(1), 74. Available from: https://doi.org/10.1186/s12889-017-4621-0

Le, K. & Nguyen, M. (2020) Shedding light on maternal education and child health in developing countries. *World Development*, 133(C), 105005. Available from: https://doi.org/10.1016/j.worlddev.2020.105005

Li, J., Mattes, E., McMurray, A., Hertzman, C. & Stanley, F. (2009) Social determinants of child health and wellbeing. *Health Sociology Review*, 18(1), 3–11. Available from: https://doi.org/10.5172/hesr.18.1.3

Lufumpa, C.L., Louis, K.K., Jmal, Y., Lakpa, D. & Adidi, I. (2020) *The Africa infrastructure development index (AIDI) 2020*. Abidjan, Cote d'Ivoire: African Development Bank Group.

Makanga, P.T., Schuurman, N., Sacoor, C., Boene, H.E., Vilanculo, F., Vidler, M., et al. (2017) Seasonal variation in geographical access to maternal health services in regions of southern Mozambique. *International Journal of Health Geographics*, 16(1), 1. Available from: https://doi.org/10.1186/s12942-016-0074-4

Mendiratta, V. (2015) Impact of rainfall shocks on child health: Evidence from India. PSE Working Papers halshs-01211575, HAL. Available from: https://ideas.repec.org/p/hal/psewpa/halshs-01211575.html

Mulatya, D.M. & Mutuku, F.W. (2020) Assessing comorbidity of diarrhea and acute respiratory infections in children under 5 years: evidence from Kenya's Demographic Health Survey 2014. *Journal of Primary Care & Community Health*, 11, 2150132720925190. Available from: https://doi.org/10.1177/2150132720925190

Nsabimana, A. & Mensah, J.T. (2020) *Weather shocks and child nutrition: Evidence from Tanzania*. WIDER Working Paper 2020/57. Helsinki: UNU-WIDER. Available from: https://doi.org/10.35188/UNU-WIDER/2020/814-6

Nshimyiryo, A., Hedt-Gauthier, B., Mutaganzwa, C., Kirk, C.M., Beck, K., Ndayisaba, A., et al. (2015) Risk factors for stunting among children under five years: a cross-sectional population-based study in Rwanda using the 2015 Demographic and Health Survey. *BMC Public Health*, 19(1), 175. Available from: https://doi.org/10.1186/s12889-019-6504-z

Nunn, N. & Puga, D. (2012) Ruggedness: the blessing of bad geography in Africa. *Review of Economics and Statistics*, 94(1), 20–36. Available from: https://doi.org/10.1162/REST_a_00161

Okwaraji, Y.B., Cousens, S., Berhane, Y., Mulholland, K. & Edmond, K. (2012) Effect of geographical access to health facilities on child mortality in rural Ethiopia: a community based cross sectional study. *PLoS ONE*, 7(3), e33564. Available from: https://doi.org/10.1371/journal.pone.0033564

Ouma, P., Macharia, P.M., Okiro, E. & Alegana, V. (2021) Methods of measuring spatial accessibility to health care in Uganda. In: Makanga, P.T. (Ed.) *Practicing health geography. Global perspectives on health geography*. Cham: Springer, pp. 77–90 https://doi.org/10.1007/978-3-030-63471-1_6

Pappachan, B. & Choonara, I. (2017) Inequalities in child health in India. *BMJ Paediatrics Open*, 1(1), e000054. Available from: https://doi.org/10.1136/bmjpo-2017-000054

Pezzulo, C., Bird, T., Utazi, E.C., Sorichetta, A., Tatem, A.J., Yourkavitch, J., et al. (2016) *Geospatial modeling of child mortality across 27 countries in Sub-Saharan Africa. DHS spatial analysis reports No. 13*. Rockville, Maryland, USA: ICF International.

Pfeffer, D., Lucas, T., May, D., Harris, J., Rozier, J., Twohig, K.A., et al. (2018) malariaAtlas: an R interface to global malariometric data hosted by the Malaria Atlas Project. *Malaria Journal*, 17(1), 352. Available from: https://doi.org/10.1186/s12936-018-2500-5

Pickett, K.E., Vafai, Y., Mathai, M. & Small, N. (2022) The social determinants of child health and inequalities in child health. *Paediatrics and Child Health*, 32(3), 88–94. Available from: https://doi.org/10.1016/j.paed.2021.12.003

Porter, G. (2002) Living in a walking world: rural mobility and social equity issues in Sub-Saharan Africa. *World Development*, 30(2), 285–300. Available from: https://doi.org/10.1016/S0305-750X(01)00106-1

Porwal, A., Agarwal, P.K., Ashraf, S., Acharya, R., Ramesh, S., Khan, N., et al. (2021) Association of maternal height and body mass index with nutrition of children under 5 years of age in India: evidence from comprehensive national nutrition survey 2016-18. *Asia Pacific Journal of Clinical Nutrition*, 30(4), 675–686. Available from: https://doi.org/10.6133/apjcn.202112_30(4).0014

Quamme, S.H. & Iversen, P.O. (2022) Prevalence of child stunting in Sub-Saharan Africa and its risk factors. *Clinical Nutrition Open Science*, 42, 49–61. Available from: https://doi.org/10.1016/j.nutos.2022.01.009

Quansah, E., Ohene, L.A., Norman, L., Mireku, M.O. & Karikari, T.K. (2016) Social factors influencing child health in Ghana. *PLoS ONE*, 11(1), e0145401. Available from: https://doi.org/10.1371/journal.pone.0145401

Rice, A., Sacco, L., Hyder, A. & Robert Black, R. (2000) Malnutrition as an underlying cause of childhood deaths associated with infectious diseases in developing countries. *Bulletin of the World Health Organization*, 78(10), 1207–1221.

Sachs, J., Mellinger, A. & Gallup, J. (2001) The geography of poverty and wealth. *Scientific American*, 284(3), 70–75. Available from: https://doi.org/10.1038/scientificamerican0301-70

Sami, S., Mayai, A., Sheehy, G., Lightman, N., Ties, B., Wild, H., et al. (2020) Maternal and child health service delivery in conflict-affected settings: a case study example from Upper Nile and Unity States, South Sudan. *Conflict and Health*, 14(1), 34. Available from: https://doi.org/10.1186/s13031-020-00272-2

Sappington, J.M., Longshore, K.M. & Thompson, D.B. (2007) Quantifying landscape ruggedness for animal habitat analysis: a case study using bighorn sheep in the Mojave Desert. *Journal of Wildlife Management*, 71(5), 1419–1426. Available from: https://doi.org/10.2193/2005-723

Shiru, M., Shahid, S., Chung, E. & Alias, N. (2019) Changing characteristics of meteorological droughts in Nigeria during 1901–2010. *Atmospheric Research*, 223(July), 60–73. Available from: https://doi.org/10.1016/j.atmosres.2019.03.010

Skoufias, E., Vinha, K. & Sato, R. (2019) *All hands on deck: reducing stunting through multisectoral efforts in Sub-Saharan Africa*. World Bank Publications: The World Bank. Washington, D.C. Available from: https://doi.org/10.1596/978-1-4648-1396-2

Spencer, N. (2003) Social, economic and political determinants of child health. *Pediatrics*, 112(3), 704–706. Available from: https://doi.org/10.1542/peds.112.S3.704

Spencer, N. (2018) The social determinants of child health. *Paediatrics and Child Health*, 28(3), 138–143. Available from: https://doi.org/10.1016/j.paed.2018.01.001

Subramanian, S.V., Ackerson, L.K., Smith, G.D. & John, N.A. (2009) Association of maternal height with child mortality, anthropometric failure, and anemia in India. *JAMA*, 301(16), 1691–1701. Available from: https://doi.org/10.1001/jama.2009.548

Tounkara, M., Sangho, O., Beebe, M., Whiting-Collins, L.J., Goins, R.R., Marker, H.C., et al. (2022) Geographic access and maternal health services utilization in Sélingué Health District, Mali. *Maternal and Child Health Journal*, 26(3), 649–657. Available from: https://doi.org/10.1007/s10995-021-03364-4

van der Merwe, E., Clance, M. & Yitbarek, E. (2022) Climate change and child malnutrition: a Nigerian perspective. *Food Policy*, 113, 102281. Available from: https://doi.org/10.1016/j.foodpol.2022.102281

Wamani, H., Astrom, A.N., Peterson, S., Tumwine, J.K. & Tylleskär, T. (2007) Boys are more stunted than girls in Sub-Saharan Africa: a meta-analysis of 16 demographic and health surveys. *BMC Pediatrics*, 7(1), 17. Available from: https://doi.org/10.1186/1471-2431-7-17

Weiss, D.J., Nelson, A., Vargas-Ruiz, C.A., Gligorić, K., Bavadekar, S., Gabrilovich, E., et al. (2020) Global maps of travel time to healthcare facilities. *Nature Medicine*, 26(12), 1835–1838. Available from: https://doi.org/10.1038/s41591-020-1059-1

Wigley, A.S., Tejedor-Garavito, N., Alegana, V., Carioli, A., Ruktanonchai, C.W., Pezzulo, C., et al. (2020) Measuring the availability and geographical accessibility of maternal health services across sub-Saharan Africa. *BMC Medicine*, 18(1), 1, 237–10. Available from: https://doi.org/10.1186/s12916-020-01707-6

World Health Organization. (1995) *Physical status: the use of and interpretation of anthropometry*, Report of a WHO Expert Committee. Geneva: World Health Organization.

World Health Organization. Geneva, Switzerland. World Health Organization(2010) *Nutrition landscape information system (NLIS) country profile indicators: interpretation guide*. Geneva, Switzerland: World Health Organization, p. 134.

World Health Organization. (2019) *Levels and trends in child malnutrition: key findings of the 2019 edition of the joint child malnutrition estimates*. Geneva: World Health Organization.

Xu, J., Yang, M., Hou, C., Lu, Z. & Liu, D. (2021) Distribution of rural tourism development in geographical space: a case study of 323 traditional villages in Shaanxi, China. *European Journal of Remote Sensing*, 54(sup2), 318–333. Available from: https://doi.org/10.1080/22797254.2020.1788993

Yourkavitch, J., Burgert-Brucker, C., Assaf, S. & Delgado, S. (2018) Using geographical analysis to identify child health inequality in sub-Saharan Africa. *PLoS ONE*, 13(8), e0201870. Available from: https://doi.org/10.1371/journal.pone.0201870

Zhao, X., Lynch, J.G., Jr. & Chen, Q. (2010) Reconsidering Baron and Kenny: myths and truths about mediation analysis. *Journal of Consumer Research*, 37(August), 197–206. Available from: https://doi.org/10.1086/651257

How to cite this article: Chisadza, C., Clance, M., van der Merwe, F. & Yitbarek, E. (2023) Ruggedness and child health outcomes: Evidence from Burundi, Cameroon, Ethiopia and Nigeria. *South African Journal of Economics*, 91(4), 498–527. Available from: https://doi.org/10.1111/saje.12354

APPENDIX A

TABLE A1 Ethiopian regional comparison.

Columns by: Regions	All excluding Oromia	Oromia	Total
n (%)	16,987 (84.7)	3065 (15.3)	20,052 (100.0)
Primary variables			
Stunting, *n* (%)			
No, *n* (%)	9235 (61.0)	1774 (62.4)	11,009 (61.2)
Yes, *n* (%)	5903 (39.0)	1071 (37.6)	6974 (38.8)
Vector ruggedness measure, mean (sd)	0.279 (0.021)	0.286 (0.014)	0.280 (0.020)
Terrain ruggedness measure, mean (sd)	6.030 (3.837)	6.210 (3.323)	6.057 (3.764)
km of roads, mean (sd)	15.805 (48.646)	3.775 (8.852)	13.966 (45.116)
Area province, mean (sd)	9.6e+07 (9.0e+07)	3.2e+08 (0.000)	1.3e+08 (1.2e+08)
km roads province, mean (sd)	1779.128 (1324.984)	7887.818 (0.000)	2712.857 (2513.857)
m roads per sq. km province, mean (sd)	0.103 (0.299)	0.024 (0.000)	0.091 (0.277)
Demographic variables			
Medical distance problem, *n* (%)			
Yes, *n* (%)	10,522 (62.0)	2440 (79.7)	12,962 (64.7)
No, *n* (%)	6458 (38.0)	623 (20.3)	7081 (35.3)
Time to water, mean (sd)	55.246 (83.335)	46.164 (62.899)	53.852 (80.602)
Maternal height in centimetres, mean (sd)	157.744 (6.794)	157.192 (6.078)	157.659 (6.692)
Child's age in months, mean (sd)	28.919 (17.382)	28.642 (17.786)	28.877 (17.445)
Gender of child, *n* (%)			
Male, *n* (%)	8627 (50.8)	1581 (51.6)	10,208 (50.9)
Female, *n* (%)	8360 (49.2)	1484 (48.4)	9844 (49.1)
Diarrhoea in last 2 weeks, *n* (%)			
No, *n* (%)	14,556 (86.6)	2684 (88.3)	17,240 (86.8)
Yes, *n* (%)	2259 (13.4)	355 (11.7)	2614 (13.2)
Fever in last 2 weeks, *n* (%)			
No, *n* (%)	13,920 (82.9)	2585 (85.1)	16,505 (83.2)
Yes, *n* (%)	2879 (17.1)	454 (14.9)	3333 (16.8)
Primary education, *n* (%)			
No, *n* (%)	12,796 (75.3)	2183 (71.2)	14,979 (74.7)
Yes, *n* (%)	4191 (24.7)	882 (28.8)	5073 (25.3)
Secondary education, *n* (%)			
No, *n* (%)	16,029 (94.4)	2993 (97.7)	19,022 (94.9)
Yes, *n* (%)	958 (5.6)	72 (2.3)	1030 (5.1)
More than secondary education, *n* (%)			
No, *n* (%)	16,465 (96.9)	3033 (99.0)	19,498 (97.2)
Yes, *n* (%)	522 (3.1)	32 (1.0)	554 (2.8)
Iron supplements, *n* (%)			
No, *n* (%)	15,352 (91.8)	2791 (93.2)	18,143 (92.0)
Yes, *n* (%)	1367 (8.2)	205 (6.8)	1572 (8.0)

TABLE A1 (Continued)

Columns by: Regions	All excluding Oromia	Oromia	Total
Breastfeeding, *n* (%)			
No, *n* (%)	2689 (15.8)	460 (15.0)	3149 (15.7)
Yes, *n* (%)	14,291 (84.2)	2602 (85.0)	16,893 (84.3)
Middle income, *n* (%)			
No, *n* (%)	14,597 (85.9)	2382 (77.7)	16,979 (84.7)
Yes, *n* (%)	2390 (14.1)	683 (22.3)	3073 (15.3)
High income, *n* (%)			
No, *n* (%)	11,271 (66.4)	2028 (66.2)	13,299 (66.3)
Yes, *n* (%)	5716 (33.6)	1037 (33.8)	6753 (33.7)
Urban, *n* (%)			
Rural, *n* (%)	13,698 (80.6)	2879 (93.9)	16,577 (82.7)
Urban, *n* (%)	3289 (19.4)	186 (6.1)	3475 (17.3)
Average precipitation, mean (sd)	79.814 (34.889)	99.130 (26.101)	82.766 (34.403)
Malaria prevalence, mean (sd)	0.005 (0.005)	0.003 (0.001)	0.005 (0.005)
Soil suitability, mean (sd)	3.549 (1.734)	3.312 (1.488)	3.513 (1.701)
Exposure to UV radiation, mean (sd)	2.0e+04 (1313.618)	1.9e+04 (745.619)	2.0e+04 (1264.018)

Table A2 reports the results when we change the buffers to 2-km buffers for urban households and 5-km buffers for rural households.

TABLE A2 Ruggedness variation and stunting using the vector ruggedness measure: Different household buffers.

	(1) Burundi	(2) Cameroon	(3) Ethiopia	(4) Nigeria
Log ruggedness	0.018	0.465**	−0.040	0.117**
	(0.127) [0.117]	(0.192) [0.194]	(0.087) [0.086]	(0.050) [0.051]
Demographic controls	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Number of observations	8377	4219	16,527	43,793
R-squared	0.175	0.096	0.114	0.106

Note: Coefficients reported. We report two standard errors below each coefficient The first in parentheses are standard errors adjusted for two-way clustering by location. The second in square brackets are the Conley (1999) standard errors adjusted for spatial correlation.
*p < 0.10, **p < 0.05, and ***p < 0.01.

Table A3 shows the results for when we ran a simulation (with 1000 iterations) that excluded 5% of the sample. The results are consistent with our initial findings that ruggedness increases stunting for Burundi, Cameroon and Nigeria but is negative and statistically insignificant for Ethiopia.

TABLE A3 Ruggedness variation and stunting using the vector ruggedness measure: bootstrap simulations.

	(1) Burundi	**(2) Cameroon**	**(3) Ethiopia**	**(4) Nigeria**
Log ruggedness	0.147	0.579***	−0.043	0.126**
	(0.169)	(0.199)	(0.089)	(0.052)
Demographic controls	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Number of observations	8377	4219	16,527	43,793
R-squared	0.175	0.097	0.114	0.106

Note: Coefficients reported. Standard errors adjusted for two-way clustering by location in parentheses.
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Table A4 reports results for a sample of 16 countries.[17] On average, ruggedness is positively associated with stunting in sub-Saharan Africa.

TABLE A4 Ruggedness variation and stunting using the vector ruggedness measure.

Log ruggedness	**0.016*** (0.006)**	**0.007 (0.006)**	**0.019*** (0.006)**
Survey FE	No	Yes	Yes
Region FE	No	No	Yes
Number of observations	115,339	115,339	115,339
R-squared	0.062	0.083	0.099

Note: Coefficients reported. Conley (1999) standard errors adjusted for spatial correlation.
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

[17]Burundi, Benin, Cameroon, Ethiopia, Guinea, Kenya, Lesotho, Liberia, Madagascar, Mali, Nigeria, Rwanda, Sierra Leone, Uganda, Zambia, Zimbabwe.

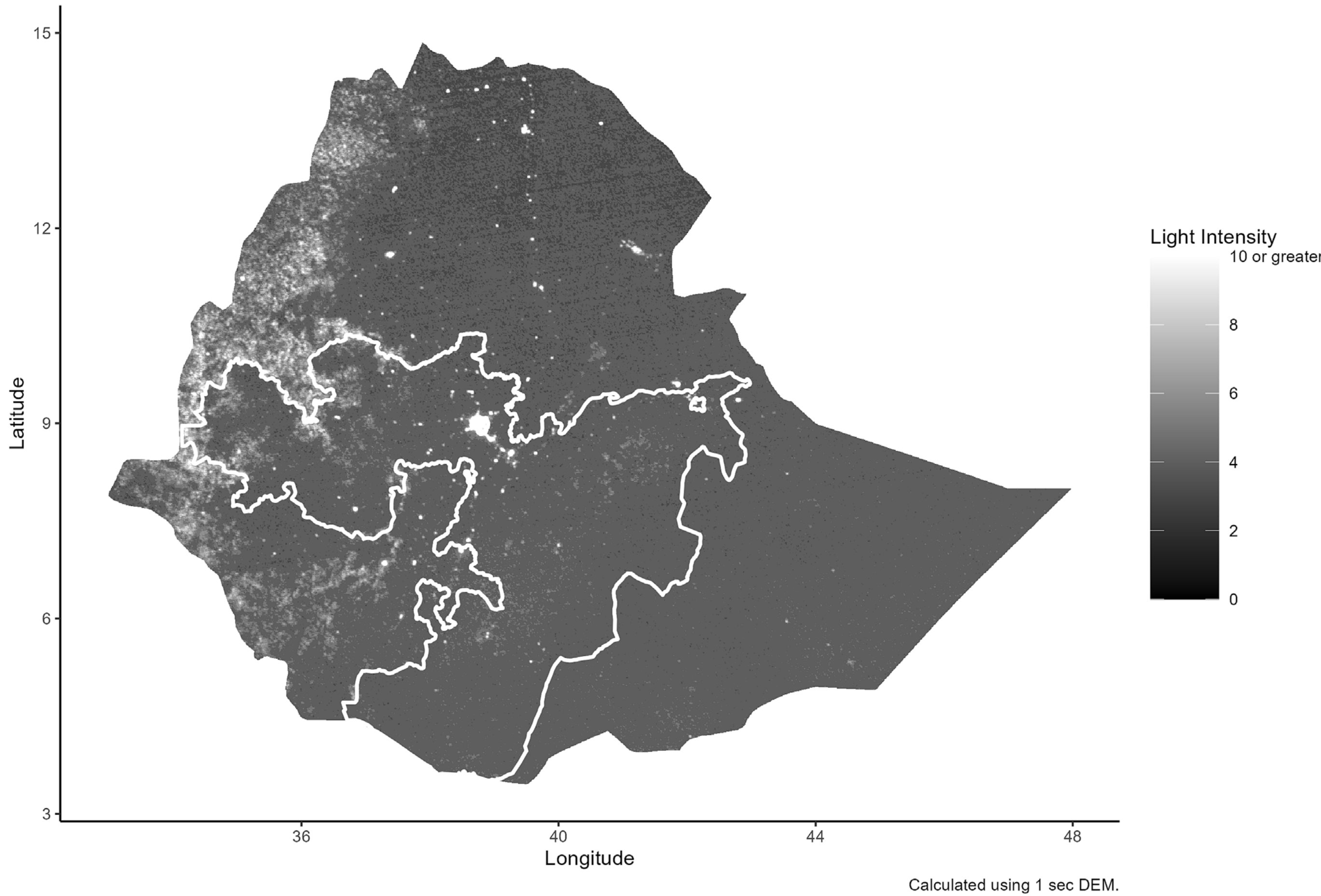

FIGURE A1 Average Night Lights in Ethiopia in 2013—Oromia Region. This graph shows the average night light intensity in Ethiopia. Oromia region is highlighted with Addis Ababa (capital city) recording the highest average night light intensity.