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Research article

Is stunting in children under five associated with the state of vegetation in the Democratic Republic of the Congo? Secondary analysis of Demographic Health Survey data and the satellite-derived leaf area index

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ABSTRACT

Background: The prevalence of stunting in the Democratic Republic of the Congo (DRC) is one of the highest globally. However, only a few studies have attempted to measure the association between stunting and vegetation, which is an important food source. The leaf area index (LAI) is an excellent measure for the vegetation state.
Objective: This paper intended to measure the association between the LAI and stunting among children under five years of age in the DRC. Its aim was to better understand the boundary conditions of stunting and explore potential links to climate and environmental change.
Methods: This paper adopts a secondary data analysis approach. We used data on 5241 children from the DRC Demographic Health Survey (DHS) 2013–2014, which was collected from a nationally representative cross-sectional survey. We used the satellite-derived LAI as a measure for the state of vegetation and created a 10-km buffer to extract each DHS cluster centroid's corresponding mean leaf-area value. We used a generalised mixed-effect logistic regression to measure the association between LAI and stunting, adjusting the model for mother's education, occupation and birth interval, as well as child's age and national wealth quintile. A height-for-age Z-score (HAZ) was calculated and classified according to WHO guidelines.
Results: Children in communities surrounded by high LAI values have lower odds of being stunted (OR [odds ratio] = 0.63; 95% CI [confidence interval] = 0.47–0.86) than those exposed to low LAI values. The association still holds when the exposure is analysed as a continuous variable (OR = 0.84; 95% CI = 0.74–0.95).

Abbreviations: LAI, Leaf Area Index; DHA, Demographic and Health Survey; DRC, the Democratic Republic of the Congo; HAZ, Height-for-Age Z-score; CI, Confidence Interval; OR, Odds Ration.

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When stratified in rural and urban areas, a significant association was only observed in rural areas (OR = 0.6; 95% CI = 0.39–0.81), but not in urban areas (OR = 0.9; 95% CI = 0.5–0.5). Furthermore, the study showed that these associations were robust to LAI buffer variations under 25 km.

Conclusions: Good vegetation conditions have a protective effect against stunting in children under five years of age. Further advanced study designs are needed to confirm these findings.

1. Introduction

Childhood undernutrition is a significant cause of mortality globally: 3.1 million children under five years die of undernutrition annually, accounting for 45% of total child deaths. Southern Asia and sub-Saharan Africa (SSA) are the most affected regions [1]. Among undernutrition-related problems, stunting is the most prevalent; globally, almost 149 million children were affected by stunting in 2020 [2]. Galway et al. [3] estimated that stunting affects 56 million pre-school children in SSA. The Democratic Republic of the Congo (DRC) has one of the highest prevalences of stunting in Africa (estimated at 43%), with some provinces exceeding 50%, according to the last Demographic Health Survey (DHS; 2013–2014) [4]. Recently, the DRC's National Institute of Statistics updated this figure to 42% [5]. These numbers are alarming, considering the direct consequences of stunting: weak cognitive development, poor academic achievement, and low economic productivity in adulthood [6]. According to Currie and Almond [7], these consequences are the most difficult to reverse through post facto remediation.

The most important determinants of stunting are socio-economic factors such as social inequality, poor economic growth and the need for better sanitation for women [8]. M'Kaibi et al. [9] reported that, in Kenya, households with stunted children were significantly more food insecure and had worse dietary diversity scores than households with no stunted children. In the case of the DRC, Kismul et al. [10] identified mother's education and age, wealth quintile and early initiation of breastfeeding as the main determinants of childhood stunting.

Only a few studies have examined the potential environmental determinants of stunting: safe drinking water, hygiene and sanitation [11]. Ecological/environmental factors are rarely linked to stunting because they are too complex to be measured. However, with the development of remote-sensing satellite technologies, environmental and ecological variables can be quantified and linked to stunting and other health outcomes.

Remote-sensing satellites identify objects – or environmental variables – by measuring their electromagnetic radiation [12]. The state of vegetation is one of the essential variables of stunting; this is because the vegetation is a source of food, fuel and 80 medicinal plants, as well as a provider of various ecosystem services [12]. Vegetation supports people's livelihoods and maintains human health, especially in developing countries [13,14]. Some empirical studies have demonstrated the association between stunting and vegetation state, as shown by satellite observation of forest cover [15,16]. Johnson and Brown [17] studied the association between the normalised difference vegetation index (NDVI) and stunting in West Africa. Kinyoki et al. [15] found a strong association between an enhanced vegetation index and stunting in Somalia.

The limitation of the above studies is that only a set of satellite-derived vegetation proxies are investigated (mainly the NDVI and the enhanced vegetation index), and mostly in semi-arid countries. To our knowledge, an investigation of the leaf area index (LAI) as an important measure for vegetation structure, has not yet been conducted. The LAI is a biophysical variable that measures the total green leaf area per unit of horizontal ground surface area [18,19]. It has been widely used to assess plant canopy structure and growth [20,21] and can capture the magnitude of biosphere-climate interactions [22]. According to Weiss et al. [23], the LAI controls for many of the vegetation's physiological processes, such as evapotranspiration, photosynthesis, transpiration and rainfall interception. In the context of a changing climate, population growth, persisting levels of undernutrition and a high rate of deforestation in SSA, it is crucial to address these knowledge gaps [24].

This study aimed to measure the association between stunting and the LAI in the DRC using DHS 2013–14 data. Furthermore, we also hoped to assess the extent to which rural and urban areas are related to this association.

2. Methods

2.1. Study sites

The data for this study comes from the DRC, a large country located in tropical Central Africa. With a surface area of 2,345,000 km^2, the DRC stretches from 5°23′N to 13°26′S, and from 12°12′E to 31°17′E. The climate is warm and humid (annual mean temperature: 25 °C), except for in the south-eastern highlands [25], where the climate is relatively moderate (annual mean temperature: ±21 °C). The country has two wet seasons and two dry seasons. July is the coldest month, and March is the warmest. The average annual precipitation is 1800 mm, and the average number of rainy days is 115. The tropical evergreen forest dominates the vegetation, with seasonal variation in the Cuvette Centrale [26]. A semi-deciduous forest borders this central basin, and the savanna ecosystem covers 33% of the country [27]. More than 70% of the population lives in rural areas, depending directly on goods and services provided by the forest ecosystems. Agriculture is the primary source of income in the DRC. We conducted this research in the DRC because of the high prevalence of stunting, the availability of DHS survey data, the presence of the second-largest tropical forest in the world, and the population's dependence on the forest.

2.2. DHS data acquisition and study period

The data on stunting was retrieved from a national representative survey, the DHS, which was conducted between August 2013 and February 2014. The survey was conducted under the authority of the United States Agency for International Development (USAID) and is accessible upon authorisation (https://dhsprogram.com/data/available-datasets.cfm).

2.3. Ethical consideration

Ethics approval was not applied in this study because the data is secondary and is available in the public domain. A written request was sent to the DHS Program, and permission was granted to download data from http://www.dhsprogram.com (letter number 1251772). More details regarding DHS data and ethical standards are available at: http://goo.gl/ny8T6X.

2.4. Population

Based on the most recent census conducted in 1984, the population of DRC was estimated at 30.7 million. It was around 78 million in 2012, according to the projection of INS [5]. Almost 70% of the population lives in rural areas. However, the overall density of the population is relatively low, with 24 habitants per km^2. The population of DRC is very young – 61% of the population is aged below 20 years.

2.5. Study design

The DHS is based on a cross-sectional study design and uses a probabilistic-stratified two-stage cluster design to collect data. First, areas are drawn from the most recent census data based on each stratum's probability in proportion to its size. Second, based on equal probability systematic sampling, a sample of 25–35 households is drawn from the list of households within each enumerated area. Details related to sample sizes and participants' characteristics are described by Rutstein and Rojas [28] and fully explained in the DHS *Sampling and Household Listing Manual* of the United States Agency for International Aid (USAID) [29].

In the DRC, each province (of 26 in total) constituted a study domain from which two strata were drawn: urban and rural. In the urban strata, a first-stage proportional random sample was drawn to select quarters (smallest administration boundary) from the exhaustive list of the county. Then, a second-stage equal random sample was drawn to select 34 households from each selected quarter. In rural strata, a first random sample was drawn from the list of sectors of the country. A second random sample was drawn to select villages derived from selected sectors. Finally, 34 households were selected from a third random sample, drawn from selected villages. In total, 18,360 households (5474 in urban areas and 12,886 in rural areas) were surveyed, and villages (379) and quarters (161) constitute cluster units.

Participants in the DHS survey were household women (18,360) aged between 15 and 49 years and who were present the night before the survey. Men aged between 15 and 59 were selected from half of the selected households. In this study, we included all non-pregnant women of child-bearing age from 15 to 49 years old and their children under the age of five years.

DHS data also contains geographical coordinates, which are related to cluster units. The coordinates are randomly displaced to comply with ethical considerations, for up to 5 km in rural areas and up to 2 km in urban areas.

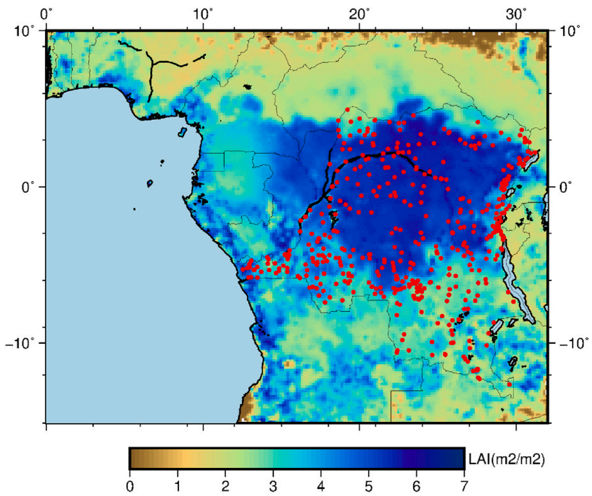

Fig. 1. Spatial distribution of the leaf area index (LAI; mean values from 2009 to 2014) and Demographic Health Survey (DHS) survey data used in this study (in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

2.6. LAI data

The second type of dataset is the LAI, defined as the total green leaf area per unit of horizontal ground surface area [18,19] – this includes leaves, stems, branches and fruits [30]. The index can be measured in the field [31] or estimated using satellite images [32]. The LAI used in this study is derived from satellite images obtained from the European Centre for Medium-Range Weather Forecasts. Price [33] provided more details on how to derive a satellite LAI. The satellite-derived LAI represents the surface area of one side of all the leaves found over an area of land for high vegetation: evergreen trees, deciduous trees, mixed forest/woodland, and interrupted forest [34]. Its values indicate the state of the vegetation (greening, mature, senescent or dormant) and vary between 0 and 7 m^2/m^2 (Fig. 1).

2.7. Outcome variable

The only outcome variable of this study is the height-for-age Z-score (HAZ), which represents stunting. This is calculated based on the WHO Child Growth Standards and obtained from the DHS 2013–14 dataset. Children are considered stunted if their HAZ falls below -2.0 standard deviations (SD) [35]. Stunting captures the impact of long-term environmental characteristics on childhood malnutrition.

2.8. Exposure definition

LAI data was pre-processed before being used in the regression model. Monthly LAI spatial data (from 2009 to 2014) obtained from the satellite were averaged to get spatial year data, which were related to DHS data using DHS global positioning system (GPS) coordinates. Including LAI data for the years preceding the DHS surveys (2009, 2010, 2011) is important because stunting is the result of long-term environmental conditions [17].

LAI extracted from DHS GPS coordinates were dichotomised using a median value of 4.21 m^2/m^2. The LAI values superior to the median values were denoted as 'high LAI', while the LAI inferior or equal to the median were denoted as 'low LAI'. We also analyse LAI as a continuous variable, because there is no previous study supporting the dichotomisation.

2.9. Covariates

Covariates could weaken or strengthen the association between stunting and the LAI if they are not controlled in the regression model. These variables are: the child's age, wealth quintile, previous birth interval, mother's working status, and education level [1,10]. These have been obtained from the 2013–2014 DHS dataset; details on how to measure them are clearly explained by the DHS [4].

2.10. Linking DHS data to the LAI

We used a 10-km buffer around each DHS cluster and averaged the LAI values within the buffer. Therefore, households within the same cluster share the same LAI value. The R statistical software (version 3.5.0) [36] made these manipulations possible.

2.11. Statistical analysis

We implemented all statistical analyses in R software [36] and assessed the differences between groups using Pearson's chi-squared test. All tests were two-sided, and we set the level of significance to $p < 0.05$. Multicollinearity between the independent variables was assessed using the variance inflation factor (VIF). We used the generally accepted VIF cut-off value of 2.5. We evaluated the association between LAI and childhood stunting using mixed-effects logit models. A mixed-effects logit model is a type of logistic regression in which random effects are added to linear predictors [37]. The model accommodates correlation via random effects, while retaining the ability to model non-normal distributions and allowing models of a specific form [37]. The mixed-effect logistic regression is estimated as follows:

$$logit(Y_{ijk}) = \alpha + \beta_1 LAI + \delta X_{ijk} + \theta \tag{1}$$

where Y_{ijk} is the state of the national status (stunting or not stunting) in child i in household j living in DHS cluster k, and α is a constant representing the baseline log odds for LAI, the independent variable, varied by the DHS cluster. X represents the child- (child age), household- (wealth quantile) and mother-level controlling variables mentioned above, which can potentially influence stunting when the model is adjusted. In a crude regression, δ is set to zero. The fixed parameter β_1 quantifies the effect of the exposure variable LAI and measures the association between LAI and the dependent variable. Finally, θ represents the random cluster effect. We reported the crude regression and adjusted the odds ratio (OR) of the model.

2.12. Sensitivity analysis

We fitted an additional model with LAI analysed as a continuous outcome. Two more adjusted models measured the association between stunting and LAI in rural and urban areas separately. To test the robustness of the association, we repeated the main analysis, using different buffer distances for the exposure variable: 1 km; 5 km; 15 km; 25 km; and 30 km.

3. Results

3.1. Population characteristics

Of the 18,716 households in the DHS data, 5348 contained non-pregnant women of child-bearing age (from 15 to 49 years) and children under the age of five years. Among these households, we excluded 107 households/children because the child had an extreme HAZ value (i.e. a HAZ above six standard deviations [SD] or below 6 SD), probably due to measurement errors. We analysed 5241 children, of whom 2371 lived in areas of low LAI and 2870 in areas of high LAI. The characteristics of the women and children involved in this study are presented in Table 1. According to the wealth quintile, the communities living in high LAI areas are dominated by the poorer and poorest classes, while the middle class dominates those who live in low LAI clusters. Of the women in the DHS data, only 39% had completed secondary school, and more than half do not work. The majority of the children were between 30 and 39 months.

3.2. Main analysis

Table 2 shows the results of the generalised mixed-effect logistic model for the whole dataset when the LAI is a dichotomous variable. Children living in an area with a higher LAI are compared with those living in an area with a lower LAI (the reference group). Children living in an area with a higher LAI are 34% less likely to be stunted than those exposed to a lower LAI, with the link being statistically significant (OR: 0.66; 95% Cl = 0.48–0.90). The association's direction and magnitude still hold when we adjust the model for the child's age, wealth quintile, previous birth interval, mother's work status, and mother's education level (OR = 0.68; 95% Cl = 0.50–0.93). The values of the VIF indicate the absence of multicollinearity in the model. Among the control variables, the child's age and the mother's previous birth interval and work status are not associated with the odds of being stunted. The wealth quantile is associated with the odds of being stunted; that is, the wealthier the household, the less likely it is that the child will be stunted, by a factor of 0.22 (95% CI: 0.14–0.34), 0.57 (95% CI: 0.42–0.78), and 0.76 (95% CI: 0.59–0.98) for wealthiest, wealthy, and middle-class households, respectively. The mother's secondary education is also associated with the odds of a child being stunted, by a factor of 0.66 (95% CI: 0.54–0.80), relative to the mother having received a primary education.

3.3. Sensitivity analysis

The association between the LAI and stunting is robust, because the association still holds when the LAI is considered as a continuous variable (as indicated in Table 3). For every LAI unit increase, there is a 14% decrease in stunting (OR = 0.86; 95% CI = 0.75–0.98). This decreases by 16% when the model is adjusted for the child's age, wealth quintile, previous birth interval, mother's

Table 1
Descriptive characteristics of the analytical sample.

Individual-level variables	Low LAI*	High LAI*	*p*-values
Child's age in months	**n (%)**	**n (%)**	0.025
0–5 months	37 (1.5)	29 (1)	
6–11 months	262 (11.1)	275 (9.6)	
12–17 months	217 (9.2)	319 (11.1)	
18–23 months	240 (10.1)	259 (9)	
24–29 months	221 (9.3)	263 (9.2)	
30–35 months	1394 (58.8)	1725 (60)	
Wealth quintile	**n (%)**	**n (%)**	<0.001
Poorest	415 (17.5)	792 (27.6)	
Poorer	488 (20.6)	669 (23.3)	
Middle	580 (24.5)	527 (18.4)	
Wealthier	539 (22.7)	446 (15.5)	
Wealthiest	349 (14.7)	436 (15.2)	
Previous birth interval	**n (%)**	**n (%)**	0.687
No previous birth	581 (24.5)	725 (25.3)	
Interval <24 months	898 (37.9)	1075 (37.5)	
Interval 24–35 months	516 (21.8)	594 (20.7)	
Interval >36 months	376 (15.9)	476 (16.6)	
Mother's education	**n (%)**	**n (%)**	0.010
Primary	1392 (58.7)	1801 (62.8)	
Secondary	963 (40.6)	1048 (36.5)	
Higher	16 (0.7)	21 (0.7)	
Mother's work status	**n (%)**	**n (%)**	<0.001
Agriculture	377 (15.9)	548 (19.1)	
Non-agricultural	608 (25.6)	862 (30.0)	
Not working	1386 (58.5)	1460 (50.9)	

* LAI = leaf area index.

Table 2
Odds ratios (ORs) of a generalised mixed-effect logistic model measuring stunting, in which the leaf area index (LAI) is analysed as a dichotomous variable.

Individual-level variables	OR (crude)	OR (adjusted)	VIF
Child's age in months (ref: 0–5 months)			1.01
6–11 months		0.9 (0.43–1.91)	
12–17 months		0.89 (0.42–1.88)	
18–23 months		0.76 (0.36–1.62)	
24–29 months		1.23 (0.58–2.60)	
30–35 months		0.95 (0.47–1.95)	
Wealth quintile (ref: Poorest)			1.15
Poorer		0.95 (0.75–1.22)	
Middle		**0.76 (0.59–0.98)***	
Wealthier		**0.57 (0.42–0.78)***	
Wealthiest		**0.22 (0.14–0.34)***	
Previous birth interval (ref: No prev. birth)			1.02
Interval <24 months		0.87 (0.71–1.07)	
Interval 24–35 months		0.87 (0.69–1.10)	
Interval >36		0.84 (0.65–1.09)	
Mother's education (ref: Primary)			1.08
Secondary		**0.66 (0.54–0.80)***	
Higher		0.33 (0.07–1.62)	
Mother's work status (ref: Agric. work)			1.12
Not working		0.88 (0.67–1.15)	
Non-agricultural		0.86 (0.65–1.15)	
LAI (ref: Low LAI)			1.01
High LAI	**0.66 (0.48–0.90)***	**0.68 (0.50–0.93)***	

The model (crude) is implemented in the second column without controlling variables, while the model (adjusted) is implemented in the third column with controlling variables.
VIF = variance inflation factor.
* denotes $p < 0.05$.

work status, and mother's education level (OR = 0.84; 95% CI = 0.74–0.95). Similarly to when the LAI is analysed as a dichotomous variable, the child's age and the mother's previous birth interval and work status are not associated with the odds of being stunted.

Table 4 shows the association between LAI and childhood stunting in urban versus rural areas. The association between LAI and childhood stunting is statistically significant and negative in rural areas (OR = 0.6; 95% CI = 0.39–0.81), after controlling for the

Table 3
Odds ratios (ORs) of a generalised mixed-effect logistic model measuring stunting when the leaf area index (LAI) is analysed as a continuous variable.

Individual-level variables	OR (crude)	OR (adjusted)
Child's age in months (ref: 0–5 months)		
6–11 months		0.91 (0.43–1.92)
12–17 months		0.89 (0.42–1.88)
18–23 months		0.76 (0.36–1.62)
24–29 months		1.23 (0.58–2.60)
30–35 months		0.95 (0.47–1.95)
Wealth quintile (ref: Poorest)		
Poorer		0.95 (0.75–1.22)
Middle		**0.76 (0.59–0.98)***
Wealthier		**0.57 (0.42–0.78)***
Wealthiest		**0.22 (0.14–0.34)***tbl3fnlowast
Previous birth interval (ref: No prev. birth)		
Interval <24 months		0.87 (0.65–1.17)
Interval 24–35 months		0.87 (0.69–1.10)
Interval >36		0.84 (0.65–1.09)
Mother's education (ref: Primary)		
Secondary		**0.66 (0.55–0.81)***tbl3fnlowast
Higher		0.33 (0.07–1.65)
Mother's work status (ref: Agriculture)		
Not working		0.88 (0.65–1.17)
Non-agricultural		0.87 (0.65–1.17)
LAI		
LAI (continuous)	0.86 (0.75–0.98)*	**0.84 (0.74–0.95)***

The model (crude) is implemented in the second column without controlling variables, while the model (adjusted) is implemented in the third column with controlling variables.
* denotes $p < 0.05$.

child's age, wealth quintile, previous birth interval, mother's work status, and mother's education level. However, this association does not hold in urban areas (OR = 0.9; 95% CI = 0.5–1.5), where the mother's work status and previous birth interval are not associated with stunting. In urban areas, the mother's secondary education level is associated with lower odds of being stunted relative to the mother's primary education level. Previous birth intervals of 24–35 months and >35 months are associated with lower odds of being stunted in a rural area, with factors of 0.7 (95% CI: 0.52–0.96) and 0.7 (95% CI = 0.56–0.97), respectively. In a rural area, being from the wealthiest and wealthier households is likely to reduce the odds of being stunted by a factor of 0.2 (95% CI: 0.06–0.82) and 0.5 (95% CI: 0.36–0.78), respectively, while in an urban area, only the wealthiest households are associated with lower stunting (OR = 0.3; 95% CI = 0.2–0.6).

4. Discussion

The objective of this study has been to measure the association between childhood stunting in the DRC and the LAI, which serves as a measure for vegetation state. Using the same DHS dataset, this association is differentiated between urban and rural areas. We found that living in an area with a high LAI significantly reduced the likelihood that children would be stunted. We also found a significant negative association between childhood stunting and the LAI that was observed only in rural areas. In contrast, there was no significant association between childhood stunting and the LAI in an urban area.

The association between forest cover/vegetation and childhood stunting has previously been observed in a few other studies that use different vegetation proxies (most often, the NDVI). Using data from 25 low- and middle-income countries, Rasolofoson et al. [38] have demonstrated that exposure to forests significantly reduces child stunting (by around 7%). Sununtnasuk [39] also showed the NDVI statistically reducing the probability of stunting in Nepal. However, Acharya et al. [40] have found only a marginal association between forest cover and childhood stunting in SSA. Johnson and Brown [17] found an inconsistent association between the NDVI (using a forest-cover proxy) and childhood stunting; they determined a positive association in Benin, negative in Mali, and no association in Burkina Faso and Guinea. Some other studies, using variables considered to be direct causes of stunting, have indirectly shown the benefit of forest cover in terms of its association with reduced stunting [3,16]. For example, Gol et al. [41] quantified the benefit of forest cover in terms of its positive effect on other nutritional outcomes directly related to childhood stunting, for example, finding that greater forest cover is associated with a reduced risk of diarrhoeal disease. Net forest-cover loss is associated with reduced dietary diversity and the reduced consumption of vitamin A-rich food among children in Malawi. Rasolofoson et al. [16] estimated that exposure to forests leads to at least 25% greater dietary diversity in children compared to that of children in non-forested areas. The novel point of our study pertains to the use of the LAI as an indicator of the vegetation state. For the DRC, the LAI exhibits a more robust link to stunting than the other vegetation-related indices cited above.

The association between forest cover (here, LAI) and childhood stunting can be explained by the fact that forest ecosystems are the main source of local and affordable foods, especially in rural areas in which most communities live close to forests [42]. Most forest

Table 4
Odds ratios (ORs) of a generalised mixed-effect logistic model measuring stunting in urban and rural areas.

	Urban		Rural	
	OR (crude)	OR (adjusted)	OR (crude)	OR (adjusted)
Child's age in months (ref: 0–5 months)				
6–11 months		1.1 (0.2–4.7)		0.9 (0.36–2.05)
12–17 months		1.1 (0.3–4.9)		0.8 (0.35–2.00)
18–23 months		0.7 (0.2–3.1)		0.8 (0.32–1.87)
24–29 months		0.7 (0.3–6.0)		1.2 (0.51–2.91)
30–35 months		0.7 (0.2–4.1)		1.0 (0.41–2.17)
Wealth quintile (ref: Poorest)				
Poorer		0.6 (0.3–1.2)		1.0 (0.76–1.27)
Middle		0.6 (0.3–1.1)		0.8 (0.61–1.05)
Wealthier		0.7 (0.4–1.3)		**0.5 (0.36–0.78)***
Wealthiest		**0.3 (0.2–0.6)***		**0.2 (0.06–0.82)***
Previous birth interval (ref: No prev. birth)				
Interval <24 months		1.0 (0.7–1.6)		0.8 (0.65–1.04)
Interval 24–35 months		1.5 (0.9–2.4)		**0.7 (0.56–0.97)***
Interval >36		1.4 (0.8–2.2)		**0.7 (0.52–0.96)***
Mother's work status (ref: Agric. work)				
Not working		1.0 (0.6–1.6)		0.9 (0.65–1.3)
Non–agricultural work		0.7 (0.4–1.0)		1.1 (0.73–1.66)
Mother's education (ref: Primary)				
Secondary		**0.4 (0.3–0.6)***		0.8 (0.65–1.05)
Higher		00 (00–00)		4.1 (0.23–73.1)
LAI (ref: Low LAI)				
High LAI	0.78 (0.43–1.38)	0.9 (0.5–1.5)	**0.61 (0.43–0.87)***	**0.6 (0.39–0.81)***

The LAI is analysed as a dichotomic variable. The crude models are implemented without controlling variables, while the adjusted models are controlled for the child's age, wealth quintile, previous birth interval, mother's work status and mother's education level.

* denotes $p < 0.05$.

foods, such as bushmeat, insects, fruits and nuts, contain high nutritional values [43], which are also the primary diet of children in Africa. Forest areas are therefore associated with high dietary diversity, which is directly related to children's nutritional status [44,45]. Recently, Gol et al. [41] reviewed 81 articles linking dietary diversity and growth outcomes in children aged under five years; they found that 79% of the articles highlighted the association between low dietary diversity and stunting. The loss of forest cover may lead to the depletion of micronutrient intake [46,47]. According to Rowland et al. [47], forest areas provide approximately 15% of the recommended vegetables and fruit and nearly 96% of meat in developing countries. Fungo et al. [48] showed that the forest provides the daily vitamin A intake for women in Cameroon, while Makoudjou et al. [49] demonstrated that forests provide food security and proteins for the population of Cameroon. Golden et al. [50] found a significant association between wildlife meat and higher haemoglobin concentrations in Madagascar.

Forest cover can also indirectly reduce the probability of stunting by acting on factors like diarrhoea, time allocated for firewood collection, and income. According to various studies, the risk of diarrhoea is much reduced in forested areas [17,51]. A plausible explanation for this last factor is that water that is surrounded by forests is less infected by pathogenic bacteria. Another factor, the time women spend gathering sufficient firewood for cooking, is much reduced in forest areas compared to non-vegetated areas. Therefore, women living in forested areas can save more than 80% of their energy, compared to what they would expend in non-forested areas [52]. They can then allocate more time to taking care of the children and improving their nutritional status.

According to some other studies and as mentioned above, communities living in forests generate more income than those living in non-forested areas. This is possible through the commercialisation of non-timber forest products (NTFPs). Vedeld et al. [53] investigated 57 study cases and concluded that forest products comprise 22% of a forest household's total income. According to Angelsen et al. [54], natural forest products represent 77% of total household income in 24 developing countries. In the DRC, NTFPs are an important source of household consumption and income; the Food and Agriculture Organization of the United Nations has indicated that around five million women in West Africa earn 80% of their income from forest products [55].

The lack of association between childhood stunting and the LAI in urban areas is probably due to the low prevalence of stunting there compared to rural areas: a 15% difference, according to a recent study on the DRC [10]. Another cause could be the high deforestation rate in urban areas, resulting in LAI values under the median value and low variation in the LAI across urban clusters.

Among the controlled variables, studies have shown that children living in the poorest households – as indicated by their wealth quintile – are associated with higher odds of being stunted. This finding aligns with that of Kismul et al. [10] and can be explained by the fact that better living conditions contribute to better childcare and improved access to food. However, this relationship is stronger in rural areas than urban, probably because the wealth quintile within the DHS survey data has been constructed differently in the two regions; in addition, social inequality could be much more robust in rural areas [56]. Another variable is the mother's secondary education level, which is associated with the odds of being stunted. However, we found no association between stunting and a mother's secondary education level. The small sub-sample we have taken could explain the lack of significance of secondary education among mothers. In the sub-analysis, mothers having higher education represent only 0.7% of the sample (Table 1).

Although we controlled for many possible confounders (control variables), the major limitation is the nature of this study, which does not inform the temporality of the cause and effect nor its susceptibility to retaining a residual confounding. There may be other possible confounders that are not considered in this study; therefore, the control of the current confounders may not be enough. For example, the regression model assumes there are no differences between mothers arising from factors like differences in intra-household food allocation behaviours, genetic predispositions, preferences regarding child health, and family preferences. Moreover, because the study area is quite big, the study does not consider exogenous variables such as local nutritional interventions by the government or by non-governmental organisations. Such uncontrolled heterogeneities could bias the results; only an experimental study design could control these heterogeneities. Another aspect that can add to the residual confounding is the stratification of the variable, for example, matching subjects who are within five months of age. It is also difficult to assess whether the exposure came before the outcome, and whether the children were born and had stayed in the same area. Additionally, this study found that increased LAI was generally associated with lower socio-economic status. This might have masked a true effect of LAI on stunting.

The random displacement of geographical coordinates is another potential source of bias. To address this type of bias, a sensitivity analysis was conducted that varied the LAI buffer distance; the results indicate that the association between the LAI and childhood stunting holds with a buffer distance below 20 m (Fig. 2). Removing individuals with missing data could also lead to bias, resulting in a wider confidence interval, as observed in the result, even if the association remains statistically significant.

5. Conclusion

This study proves that the state of vegetation (as expressed by the LAI) is one of the drivers of childhood stunting all over the DRC in general and in rural areas in particular. However, we find no association between the LAI and childhood stunting in urban areas. This research's findings apply only to children under five years of age living in the DRC. This study can help policymakers to integrate forest conservation as an intervention aimed at bettering the population's nutritional status and combating the stunting seen in children in rural areas.

Author contribution statement

Freddy Bangelesa: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Anne Hatløy, Paulin Mutombo, Branly Mbunga, Mwanack Kakule Matina, Pierre Akilimali, Heiko Paeth, Mala Ali Mapatano:

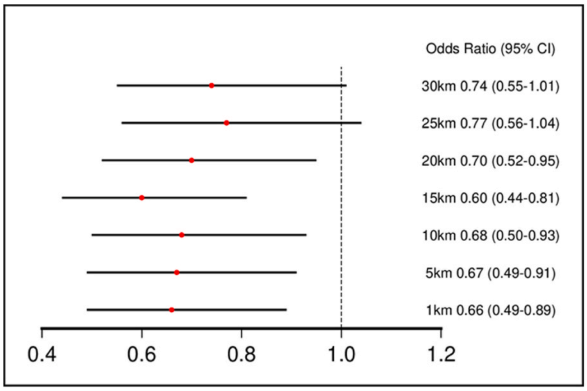

Fig. 2. Sensitivity analysis with a variation in the buffer distance.

Analysed and interpreted the data; Wrote the paper.

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Data availability statement

Data associated with this study has been deposited at the DRC Demographic Health Survey under the accession number 2013–2014 DHS.

Declaration of interest's statement

The authors declare no competing interests.

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