Heliyon 10 (2024) e38166

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Livelihood vulnerability to climate change health impacts among Amhara Sayint district community, northeastern Ethiopia: A composite index approach

Genanew Mulugeta Kassaw [a,b,*], Asmamaw Malede [c], Mesfin Gebrehiwot [d]

[a] Department of Public Health, College of Health Sciences, Woldia University, Woldia, Ethiopia
[b] International Ph.D program in Innovative Technology of Biomedical Engineering and Medical Devices, Ming Chi University of Technology, New Taipei, Taiwan
[c] Department of Environmental Health and occupational health & safety, College of Medicine and Health Sciences, University of Gonder, Gonder, Ethiopia
[d] Department of Environmental Health, College of Medicine and Health Sciences, Wollo University, Dessie, Ethiopia

ARTICLE INFO

Keywords:
Climate change
Health impacts
Vulnerability Index
Partial proportional odds model

ABSTRACT

Climate change significantly impacts public health, affecting nearly everyone across the globe and contributing to approximately 10% of global mortality. Ethiopia is particularly vulnerable to the changing climate attributed impacts due to economic, and social determinants. While research on climate change is expanding, it often prioritizes its effects on agriculture. The impacts from public health perspective are frequently overlooked. We address this shortcoming by evaluating the vulnerability of the community in the district of Amhara Sayint, Amhara, northeastern Ethiopia, to the health impacts of climate change, and identifying factors involved. Data was collected using a community-based cross-sectional approach, involving 605 randomly selected households between July Twenty and September Five, 2022. The data collection process utilized a validated and pilot-tested questionnaire, which was administered through face-to-face interview with the aid of Kobo Collect toolbox. The community's vulnerability was assessed using the IPCC's framework of vulnerability. Household's Vulnerability status was then classified into three levels according to their Livelihood Vulnerability Index (LVI) score. A partial proportional odd-sapproach of ordinal logistic regression model was used to identify factors associated with vulnerability to climate change attributed health impacts. Among the 605 respondents, 48% (95% CI: 44.1, 52.1) were identified as vulnerable, and about 4.6 % (95% CI: 3, 6.6) were classified as highly vulnerable. Wealth status ($AOR_1 = 1.8$; 95 % CI: 1.2, 2.8), educational status ($AOR_1 = 2.8$; 95% CI: 1.1, 7.3), marital status ($AOR_2 = 4.7$, 95% CI: 1.6, 13.4), and home crowdedness ($AOR_2 = 2.9$, 95% CI: 1.1, 8.1) significantly associated with vulnerability. Over half of the residents in the district wereeither being vulnerable or highly vulnerable to climate change attributed health impacts. Therefore, prioritizing prevention and preparedness along with conducting spatial analysis to identify high-risk areas for timely intervention, is essential.

* Corresponding author. Department of Public Health, College of Health Sciences, Woldia University, Woldia, Ethiopia.
E-mail address: genemulu8@gmail.com (G.M. Kassaw).

https://doi.org/10.1016/j.heliyon.2024.e38166
Received 8 May 2023; Received in revised form 12 September 2024; Accepted 18 September 2024
Available online 20 September 2024

1. Introduction

Climate change impacts human health through various channels. Direct threats to well-being and survival arise from climate-related hazards, including severe weather events, storms, increasing sea levels, flooding, and droughts [1]. Specific to public health, direct effects include the exacerbation of heat-related illnesses, respiratory problems due to increased air pollution, and the transmission of infectious diseases as climate changes modify the habitats of disease-carrying vectors. Indirectly, climate change affects health through disruptions in food and water supplies, leading to malnutrition and waterborne diseases. Extreme weather events, intensified by climate change, can result in injuries, displacement, and mental health issues [2]. It is reported that, each one-degree Celsius increment in temperature there increase mental illness by 5 % [3]. Certain medications raise the likelihood of mortality by 8 % for each degree Celsius the temperature exceeds 18 °C [4]. Globally, about 5 million people die every year due to heat-related cases [5]. The global report from Intergovernmental Panel on Climate Change (IPCC) indicates over 3 billion people are living in extremely vulnerable conditions [6]. Moreover, climate change is projected to lead to an extra 48,000 deaths annually from diarrhea globally by 2030 [7].

It is evident that, low- and middle-income countries (LMICs) bear a higher burden from both current and future climate events [8]. The impacts attributed by climate change are anticipated to intensify over time, particularly in sub-Saharan countries such as Ethiopia [9]. Drought drives people to migrate, intensify their health needs and deteriorating standard of life, a trend especially pronounced in the Horn of Africa [10]. Beyond its direct effects on public health, climate change leads to impacts access to ground water, incites conflicts over water resources, leading to increment in water prices [11]. In the eastern part of Africa, more than 16 million people lack adequate access to potable water [12].

In 2015, 18.2 million Ethiopians confronted a substantial drought and food insecurity crisis, intensified by failed rains and the influence of the El Niño phenomenon which is superchaged by climate change [13]. The extensive drought affecting the Wollega and Borena regions serves as concrete evidence of the effects of climate change in Ethiopia. Such crisis, including lack of adequate quantity and safe drinking water, is affecting more than ten million people in the country [14]. In response to such crises,Ethiopia strives for climate action to ensure the sustainability of the environment and reduce public exposure [15]. The ongoing strategy such as Climate-Resilient Green Economy (CRGE) is a very good example [16]. This strategy is an initiative developed by the Ethiopian government to address climate change while promoting sustainable economic growth and promoting public health.

However, unless public vulnerability to climate change impacts, including the health impacts, is thoroughly examined and addressed, the public health consequences of climate change will continue to escalate. Nevertheless, existing research has predominantly concentrated on agricultural impacts of climate change and thus farmers were the focus of those studies while largely overlooking the broader public health vulnerability of the general community [17]. Moreover, the prevalence of primarily descriptive research on vulnerability [18,19] has resulted in a significant gap in detailed studies that investigate the factors contributing to public vulnerability to climate change attributed health impacts. Therefore, this study addresses these gaps and aims to assess public vulnerability to climate change attributed health impacts including drought, flooding and the associated factors among Amhara Sayint community, Amhara, Northeastern Ethiopia. The findings from this study help to prioritize intervention measures for minimizing the existing and upcoming climate related disasters. Furthermore, the findings of this study, with other studies, will serve as an informative tool for preparedness, help to ensure healthy lives for all (SDG-3), and urge stakeholders to take decisive actions against climate change and align with global efforts toward sustainable development (SDG-13) [20].

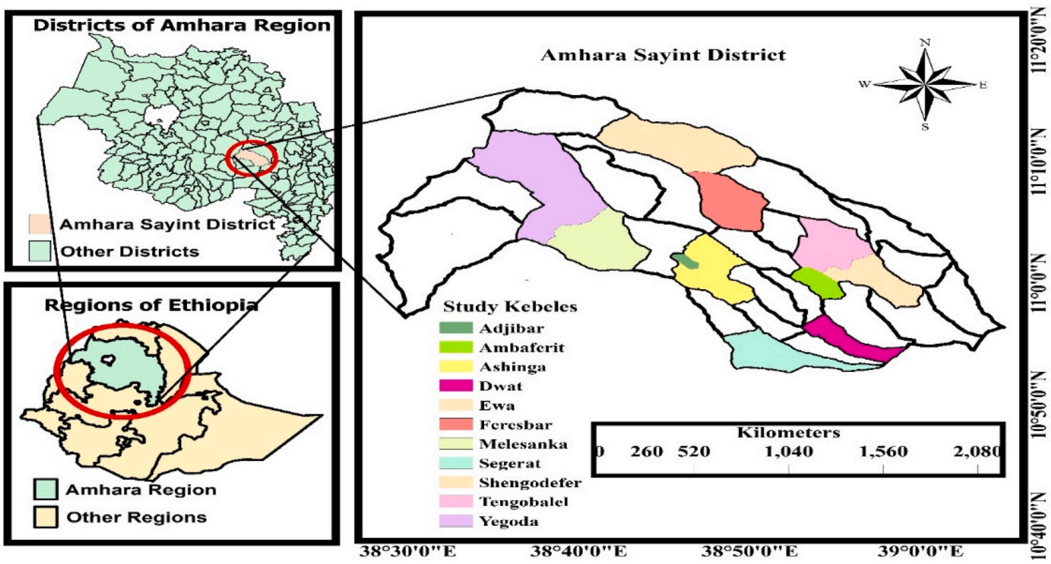

Fig. 1. District of Amhara Sayint, South Wollo Zone, Amhara, Northeastern Ethiopia (Shape file source [21]).

2. Methods and materials

2.1. Study setting and period

This study took place in Amhara Sayint, a district in the South Wollo Zone of the Amhara region in northeastern Ethiopia, from July 21 to September 4, 2022. The district exists approximately 189 km away from the zonal capital, Dessie, and 608 km from the nation's capital, Addis Ababa. Specifically, it is positioned at a latitude of 10° 50′ 0″ N to 11° 10′ 0″ N and a longitude of 38° 30′ 0″ E to 39° 0′ 0″ E (Fig. 1). The district's average yearly maximum temperature for the last 10 years was 28.33 °C, whereas, the average yearly minimum temperature was 4.1 °C. For the last 10 years, the district's daily temperature ranges from 0.2 to 30.4 °C. The total daily rainfall of the district in 2021 was 1825 mm. The study area includes 35 administrative kebeles (*the most basic administrative division*), comprising 34 rural and 1 urban kebele. There is a program called Safety Net which works in the study area on environmental rehabilitation and supporting some households based on their economic status and participation in environmental protection activities.

Due to the district's remote location from the zonal city, research in the area has been limited. Additionally, since most of the district's population lives in outlying areas, they lack the resilient infrastructure needed to manage climate-induced disasters effectively. This could enhance their vulnerability to climate change attributed health impacts. These factors led to the selection of the district for assessing the level of livelihood vulnerability to the health impacts attributed by climate change and the factors involved.

2.2. Study design and population

A cross-sectional study involving Amhara Sayint district community was carried out to evaluate determinants associated with public vulnerability to the health impacts attributed by climate change. The assessment targeted all households in the Amhara Sayint district of the South Wollo zone in Northeastern Ethiopia. Specifically, the research focused on households within selected kebeles of the district. The primary units of analysis and sampling were individual households. Households that were critically ill or had difficulty of communication with the local language were excluded from the study.

2.3. Sample size determination and sampling technique

We used single population proportion formula (eq-1) to determine the sample size. Since there were no existing studies on public vulnerability to the health impacts attributed by climate change, the sample size was based on an assumption that 50 % of households would be vulnerable or highly vulnerable. This can in turn yield a relatively adequate sample size and enhances sample representativeness. Thus, a sample of 640 was considered for this (vulnerability) investigation.

$$\mathrm{n} = \frac{\left(\mathrm{z}a/2\right)^{2} * (P)(1-P)}{(d)^{2}} \tag{Eq(1)}$$

[22], Where.

- ✓ n: size of the sample to be determined.
- ✓ Zα/2: corresponding to a 95% confidence level.
- ✓ a- 5%, at the critical value of 1.96.
- ✓ p: proportion of the sample (50%).
- ✓ d: margin of error (5 %) [23].

In this study, a multistage sampling method was employed, which involved selecting kebeles first and then households. To account for sampling errors, a design effect of 1.5 was applied. Taking into account the 50% proportion, design effect of 1.5, non-response rate of 10%, and missing or incomplete data of 1%, the final sample size was determined to be 640. Among the 35 kebeles of the district, 11 (30%) study kebeles were selected through computer based random sampling method. The total sample was distributed proportionally among the selected kebeles according to the number of households in each (Eq-2).

$$\mathrm{n_j} = \left(\frac{\mathrm{n^*Nj}}{\mathrm{N}}\right) \tag{Eq(2)}$$

Where "n_j" is the sample size allocated for the Kebele$_j$, "N_j" is the total number of households of the Kebele$_j$, & "N" is the number of households in all study kebeles (15,664) and "n" is the total sample size for the study. Sampling was done in consideration of the sample frame consisting of the list of kebeles and households of the kebeles.

To minimize sampling error in the staged sampling process, respondents from each kebele of the district were selected using randomly. The household lists for each selected kebele were sourced from the community health information list (CHI). To ensure representative data, interviews were conducted with the household head or, if unavailable, their spouse. If neither the head nor the spouse was present, attempts were made to revisit the household up to two additional times (a total of three visits). Households that could not be contacted after the third attempt were classified as non-respondents.

2.4. Data collection

The required data was gathered by three public health professionals. In addition, there were two supervisors following up the data collection procedure. Secondary data on climate variables, including daily maximum and minimum temperatures and precipitation for the district from 2012 to 2021, were obtained from the Ethiopia National Meteorology Agency's Eastern Amhara Meteorological Service at the Kombolcha center. The data collection technique and tool used for this study were face-to-face interview and structured questionnaire, respectively. The tool has seven sections, namely, information sheet (Annex-I), consent form (Annex-II), Ethical letter from Wollo University Ethical Review Board (Annex-III), Supportive letter from Zonal Health Department and study area's district Health Office (Annex IV-V) and Letter from Ethiopia Meteorological office Amhara Regional Office (Annex-VI). The principal section of the tool, the questionnaire, found in Annex-VII, can be accessible online at (https://ee.kobotoolbox.org/x/PWaSebia). It was drafted from pertinent literature, with a primary focus on sources [18,24,25] as well as additional references [26–28].

2.5. Variable Measurement

Wealth Index: It is an indicator for the socioeconomic level of a certain community. In this investigation, the wealth index was determined for urban and rural residents separately. The classification was based on nationally standardized wealth indicators. After identifying the principal components using an eigenvalue threshold of 1, the standardized values were divided into five categories: poorest, poorer, middle, richer, and richest.

Vulnerability: It refers to the extent to which a system is vulnerable to and struggles to handle the negative impacts of climate change, including variations in climate and extreme weather events [29].

Livelihood vulnerability to health impacts of climate change: It is the district community's liability to climate change attributed health impacts which was assessed against three indicators of IPCC framework of vulnerability, seven major components, and thirty four sub-components of vulnerability derived from relevant literature [18,24]. It is determined by the composite index approach following livelihood vulnerability index (LVI). It was assessed by critical consideration of indexed subcomponent (eq_3), average of indexed subcomponent (eq_4), adding up of weighted components of each indicator (eq_5), and applying IPCC vulnerability determination equation (eq_6). The framework comprises three major indicators of vulnerability, namely; sensitivity, adaptive capacity and exposure. After all, vulnerability indicators were determined with the application of the vulnerability determination equation.

$$\text{Indexed subcomponent}: = \frac{actual\ (average)\ value - minimum\ value}{Maximum\ Value - Minimum\ Value} \tag{eq3}$$

Then, the major component was determined as

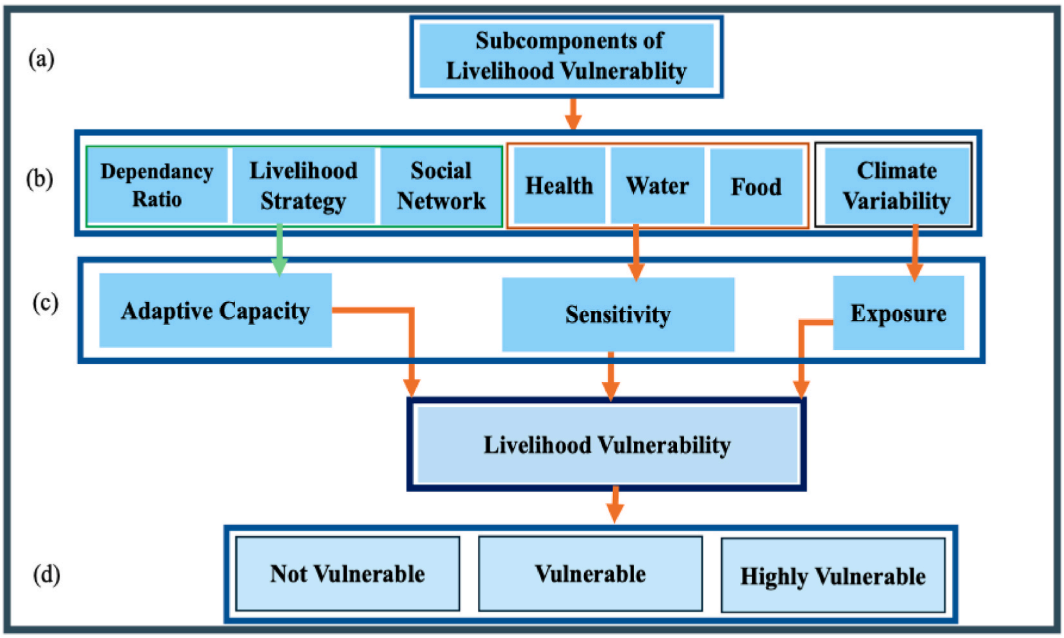

Fig. 2. A diagram detailing the progression from subcomponents (a) to major dimensions (b), and indicators (c) for determining the diverse categories of livelihood vulnerability to health impacts of climate change (d).

$$Major\ \ component = \sum_{sb=1}^{sb=n} \frac{Indexed\ subcomponent}{n}\ where\ n\ is\ the\ number\ of\ subcomponents \quad \text{(eq4)}$$

$$\text{Indicator value} := \sum_{n=1}^{n} \left(\text{wt} \frac{(Weighted\ component\ indexed\ value)}{\sum_{n=1}^{n} (\text{component}'s weight)} \right) \quad \text{(eq5)}$$

$$\text{Livelihood VuInerablity Index (LVI)} := \frac{\text{i}Sensitivity + \text{i}exposure\ indicator + iAdaptive\ Capacity}{wt(Sensitivity) + wt(Exposure) + wt(Adaptive\ capacity)} \quad \text{(eq6)}$$

Composite index approach: It is an approach of combining normalized and/or standardized subcomponents, which are measured in different scales, to a single database. Thus, in this study, each of the measured subcomponents becomes indexed and/or normalized. Those subcomponents with continues scale were indexed using max_min standardization (value-min)/maximum-minimum eq_3. Whereas, those with yes or no response were normalized by considering 1 or 100 % as a pre-determined maximum and 0 as a pre-determined minimum. The indexed subcomponents were averaged to form their respective main components, and then a weighted average of these primary components produced the IPCC's vulnerability indicator (Fig. 2). Example: the subcomponent *"how long (minute) does it take to get to the health facility?*" is the subcomponent of the major component "health" and the indicator "sensitivity". Note that sensitivity is one of the three indicators of vulnerability. This subcomponent is indexed by subtracting the lowest time from a respondent's home to health facility from each individual response.

Then, this value was divided to the range (max-min), and this is how the subcomponents were indexed. This indexed subcomponent was then added to other indexed subcomponents of health, and the summation was divided to the number of subcomponents of health to get the major component ($Eq4$). Likewise, the value of each major component was determined, then each of them multiplied by their respective number of subcomponents and added together. The summation was divided to the total number of subcomponents in that indicator to determine the value of the vulnerability indicator (eq_5). Each of the indicators summed up and averaged to get the LVI. Since numbers of indexed subcomponents were averaged to get to vulnerability index (eq_6), that was how the name composite index approach applied. Since numbers of indexed subcomponents were averaged to get to vulnerability index (eq_6), that was how the name composite index approach applied. Detailed information about the interrelation between subcomponents, major components and indicators of vulnerability to health impacts attributed by climate change found in supplementary material I.

Indicator 1: Adaptive capacity: It is one of the three indicators of vulnerability. It has three major components (dependency ratio, social network, and livelihood strategies). Each of these three major components has three subcomponents. The subcomponents are measurable, and their value is determined directly from the respondents (Annex VII-1st 13 vulnerability questions).

Indicator 2- Sensitivity: This second indicator of vulnerability consists of three major components: health, water, and food. Each of the major components has 3–7 measurable subcomponents (Annex VII-14-25 vulnerability questions).

Indicator 3- Exposure: This represents the third indicator of vulnerability, which includes one primary component with seven subcomponents (refer https://ee.kobotoolbox.org/x/PWaSebia). To assess natural disasters and climate change as significant factors, climate variables such as the standard deviation of average daily maximum temperatures by month from 2012 to 2021, the standard deviation of average daily minimum temperatures by month from 2012 to 2021, and the standard deviation of average monthly precipitation from 2012 to 2021 were utilized. Based on the Livelihood Vulnerability Index (LVI) score, public vulnerability to the health impacts attributed by climate change was categorized as follows: "Not vulnerable" for households with an LVI score from 0 to 0.2; "Vulnerable" for households with an LVI score from 0.21 to 0.4; and "Highly vulnerable" for households with an LVI score exceeding 0.4 [18,24].

2.6. Data quality and analysis

Assurance of data quality was an integral to the study process. Initially, the tool was drafted in English, then translated into Amharic (which is the common language in the area) and it was then back translated to English to ensure accuracy. Experts validated the content and face validity of the questionnaire. Additionally, a pilot test was conducted with 50 samples in the nearby Debre Sina district to assess the clarity of the questions and the reliability of the tool before the main data collection. Data was collected using the server-based KoboCollect tool and subsequently transferred from the Kobo server to STATA version 15.0 using the kobo2stata command for data management, cleaning, and statistical analysis. Prior to analysis, responses to negatively worded questions were reverse coded, categorical data were re-categorized, and continuous data were categorized. Incomplete responses were treated as non-responses and excluded, ensuring that only complete cases were analyzed.

Before determining the outcome of interest and running the model, principal component analysis (PCA) was done, to define a certain data component into a single indicator called wealth index. This is because the wealth index is a latent variable and is considered as a potential predictor for the outcome of interest. All the wealth indicator variables were dichotomized for a feasible analysis. During PCA, certain assumptions (Kaiser Meyer Olkin – KMO and stating the percentage of sampling adequacy (at least 5 observations to a variable)) have been considered. The values of KMO were 72 % for urban and 69 % for rura1, with a p-value of <0.05. Four components were identified, 62.3 % total variance was explained for households, and the complex structure factor (Eigenvalue) was >1. Furthermore, the commonality values were greater than 0.5 and collinearity was above 0.3 [30].

However, before regressing vulnerability, the assumption of multicollinearity was checked. It has been found that the variance inflation factor (VIF) for vulnerability predictors was below 10 (mean VIF = 1.98), notifying no issue of multicollinearity. Furthermore, the tolerance test was considered to minimize the collinearity effect of independent variables on the outcome. In this study, proportional odds (PO) model and its derivative were applied among the three ordinal logistic regression models (namely the adjacent category model, continuous ratio model, and proportional odds model). The model was selected because the outcome of interest (vulnerability) had three orders (not vulnerable, vulnerable, and highly vulnerable) [31].

The parallel line assumption test for vulnerability to the health impacts attributed climate change were checked, and some of the explanatory variables violated the assumption, provided that the slope of these explanatory variables over the cumulative odds of the outcome was not equivalent [32,33]. Thus, partial proportional odds with a relaxed assumption were considered for fitting factors against vulnerability to the health impacts of climate change. Here, the level of vulnerability was coded in an ordered manner, i.e., not vulnerable coded as "0", vulnerable coded as "1", and highly vulnerable was coded as "2". The researcher was interested in determining the odds of being vulnerable and highly vulnerable versus not vulnerable, rather than investigating the odds of being not

Table 1
Socio-demographic and behavioral profiles of respondents concerning vulnerability to climate change attributed health impacts within the community of Amhara Sayint district, Amhara, Northeastern Ethiopia (n = 605).

Explanatory variables	Not vulnerable	vulnerable	Highly vulnerable
	n (%)	n (%)	n (%)
Gender			
Male	195 (32.2 %)	188 (31.1 %)	10 (1.6 %)
Female	91 (15.0 %)	103 (17.0 %)	18 (3.0 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Religion			
Christian	233 (38.5 %)	245 (40.3 %)	27 (3.3 %)
Muslim	53 (8.60 %)	46 (7.6 %)	1 (1.3 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Occupation			
Government employee	24 (4.0 %)	18 (3.0 %)	6 (1 %)
Not government employee	262 (43.3 %)	273 (45.1 %)	22 (3.7 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Educational status			
No formal Education	83 (13.7 %)	113 (18.7 %)	12 (2.0 %)
Primary Education	175 (28.9 %)	164 (27.1)	10 (1.7 %)
Secondary education and above	28 (4.6 %)	14 (2.3 %)	6 (1.0 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Overcrowding status			
Overcrowded	27 (4.5 %)	29 (4.8 %)	7 (1.2 %)
Stable	259 (42.8 %)	262 (43.31 %)	21 (3.5 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Age (Years)			
18–34	68 (11.2 %)	74 (12.2 %)	11 (1.8 %)
35–55	204 (33.7 %)	195 (32.2 %)	15 (25 %)
56–64	14 (2.3 %)	22 (7.2 %)	2 (0.33 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Marital status			
Married	271 (44.8 %)	281 (46.4 %)	22 (3. 62 %)
Divorced	15 (2.5)	10 (1.7 %)	6 (1 %)
Household size			
<5	259 (42.3 %)	262 (43.3 %)	26 (4.3 %)
≥5	27 (4.5 %)	29 (4.8 %)	2 (0.3 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Residence			
Urban	275 (45.5 %)	255 (42.2 %)	7 (1.2 %)
Rural	11 (1.8 %)	36 (6 %)	21 (3.5 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Wealth Index			
Poor	81 (13.4 %)	125 (20.7 %)	9 (1.48 %)
Middle	116 (19.2 %)	91 (15 %)	13 (2.1 %)
Rich	89 (14.7 %)	75 (12.4 %)	6 (1 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
Beneficiary from organization working on Environmental protection			
No	71 (11.7 %)	75 (12.4 %)	10 (16.6 %)
Yes	215 (35.5 %)	216 (35.7 %)	18 (3 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)
CBHI membership			
No	15 (2.5 %)	31 (5.1 %)	11 (1.8 %)
Yes	271 (44.8 %)	260 (43 %)	17 (2.8 %)
Total	286 (47.3 %)	291 (48.1 %)	(28 (4.6)

CBHI: Community Based Health Insurance.

vulnerable. It is because, from a scientific perspective, it is worthy to state about the problem other than the fortune.

First, bivariable analysis of partial proportional odds approach of ordinal logistic regression model was fitted with explanatory variables against vulnerability. Among these, eight (8) predictor variables, variables with p value of <0.25 (Lax-criterion) were selected for the multivariable analysis of partial proportional odds model. The goodness-of-fit test, assessing the similarity between the model and the observed data, was also held with a p-value>0.05. The model output yielded two panels with two different odds ratio (OR) for each explanatory variable. The first panel (AOR_1) was the odds of being in the higher category (i.e., vulnerable or highly vulnerable) of vulnerability versus not vulnerable. The second panel (AOR_2) was the odds of being highly vulnerable against not vulnerable or vulnerable. Those explanatory variables with a p-value of lower than 0.05 were considered as having statistically significant association with the outcome of interest (vulnerability to health impacts attributed climate change). Finally, marginal effects analysis was employed as a post-estimation measure to determine the predicted margins of the outcome of interest in percentage point because of the change in predictor variables while keeping the effects of other variables constant.

3. Results

3.1. Socio-demographic Characteristics of study participants

Out of the 640 households sampled, 605 completed the survey on vulnerability to climate change health impacts, yielding a response rate of 94.5 %. The high non-response rate may be attributed to the survey period coinciding with peak agricultural activity in the area. Approximately 65 % of respondents were male (393 individuals). Participants' ages ranged from 20 to 64 years, with a median age of 40 years. Farming was the primary occupation for most respondents (523, 86.5 %), and nearly all were employed outside the government sector (557, 92.1 %). About one-third (34.38 %) had no formal education. Almost all participants were married (574, 95 %). In terms of wealth categories, 35.5 % were classified as poor, while 28.1 % were categorized as wealthy (Table 1).

Based on the livelihood vulnerability index approach, this study revealed that 286 respondents (47.3 % 95 % CI: 43.2, 51.3) were not vulnerable to health impacts of climate change. Additionally, 291 respondents (48.1 %; 95 % CI: 44.1, 52.2) were vulnerable and 28 respondents (4.6 %, 95 % CI: 3, 7) were highly vulnerable.

3.2. Factors associated with livelihood vulnerability to climate change health impacts

3.2.1. Partial proportional odds model estimation

The result of partial proportional odds model (PPOM) shows that educational status (AOR1 = 2.8; 95 % CI: 1.1, 7.3), wealth index (AOR1 = 1.8; 95 % CI: 1.2, 2.8, marital status (AOR2 = 4.7, 95 % CI: 1.7, 13.5), and overcrowding status (AOR2 = 3, 95 % CI: 1.1, 8.1) were significantly associated with vulnerability to the health impacts attributed by climate change (Table-2). This implies, holding the effects of other variables constant, for respondents who did not attend formal education, the odds of being in a higher category of vulnerability were 2.8 (AOR1 = 2.8; 95 % CI: 1.1, 7.3) times higher relative to these respondents who attended secondary education and above. Similarly, as compared to rich respondents, respondents with poor wealth were 1.8 (AOR1 = 1.8, 95 % CI: 1.2–2.8) times more likely to be in the higher category of vulnerability (vulnerable or highly vulnerable) provided that the effects of other variables kept constant. Furthermore, the odds of being highly vulnerable were 3 (AOR2 = 2.99, 95 % CI: 1.1, 8.1) times greater among respondents living in overcrowded status than these with stable/no overcrowded housing.

Table 2
Partial proportional odds model result for factors of vulnerability to climate change attributed health impacts in Amhara Sayint district, Northeastern Ethiopia.

Factors	Panel-1 (Vulnerable and Highly Vulnerable vs Not vulnerable)			Panel-2 (Highly vulnerable vs Not vulnerable and Vulnerable)		
	Std. Error	AOR_1 (95 % CI)	p-value	Std. error	AOR_2 (95 % CI)	p-value
Educational status (Ref: Secondary Education and above)						
No formal Education	1.4	2.8 (1.1–7.3)	**0.03***	0.4	0.6 (0.1–2.2)	0.429
Primary education	0.9	2 (0.7–5.1)	0.183	0.3	0.4 (0.079–1.6)	0.162
Age	0.18	1.1 (0.8–1.5)	0.586	0.2	0.5 (0.256–1.1)	0.105
Marital status (Ref: Married)						
Divorced	0.381	0.9 (0.4–2.1)	0.961	2.5	4.7 (1.7–13.5)	**0.004***
Occupation (Ref: Government employee)						
Non-government employee	0.335	0.7 (0.3–1.8)	0.438	0.4	0.5 (0.1–2)	0.346
Wealth Index (Ref: Rich)						
Poor	0.4	1.8 (1.2–2.8)	**0.005***	0.6	1.1 (0.4–3.3)	0.826
Medium	0.2	0.9 (0.657–1.501)	0.974	0.8	1.5 (0.5–4.3)	0.77
Household size (Ref: <5)						
≥5	0.3	0.9 (0.5–1.6)	0.771	0.9	1.2 (0.2–5.6)	0.840
Beneficiary from organization working on Environmental protection (Ref: Yes)						
No	0.3	1.1 (0.8–1.6)	0.640	0.7	1.7 (0.7–4)	0.196
Crowdedness (Ref: Stable/not overcrowded)						
Overcrowded	0.4	1.3 (0.8–2.3)	0.306	1.5	**3 (1.1–8.1)**	**0.03***

3.3. Average marginal effects

As part of the post-estimation analysis, the average marginal effect representing the additional percentage point change in the outcome due to a shift in the predictor from one category to another was calculated while holding other predictors at their mean values (Table 3). The analysis revealed that, when other variables were kept constant, only two factors, namely education status and wealth, showed a significant marginal impact on the level of vulnerability.

The result showed that, the predicted probability of being not vulnerable will decrease by 25.2 percentage points for a person with no formal education compared to a person with a secondary education and above (AME = −25.2, 95 % CI: 46.9, −3.5) (Fig. 3). Conversely, the predicted probability of being vulnerable will increase by 28.1 percentage points for a person with no formal education relative to a person with secondary education and above (AME = 28.1, 95 % CI: 0.1, 0.5).

From the result of post-ordinal logistic regression estimation, keeping other variables constant, the predicted probability of being not vulnerable will reduce by 14.9 percentage points for a person identified as poor relative to a person identified as rich (AME = 14.9; 9 % CI; −25.3, −4.6) (Fig. 4).

4. Discussion

Livelihood vulnerability of study participants towards climate change attributed health impacts was investigated based on the IPCC framework of vulnerability. More than half of the respondents were determined as vulnerable and highly vulnerable to climate change attributed health impacts. Our finding is in line with the findings of relevant studies conducted in different parts of Ethiopia ([19,34, 35]).

Our finding is also consistent with the findings from assessment of farmers vulnerability in the Sukoharjo Regency and Klaten Regency, Indonesia [18], investigation on livelihood vulnerability to climate change in Trinidad and Tobago [36], and study on household vulnerability to climate-induced stresses in Kenya [37]. This indicates the universal impacts of climate change as indicated by the IPCC – “climate change is affecting nature and people’s lives everywhere” [38], the Environmental Protection Authority of the US – “everyone is vulnerable” [39], and the World Health Organization (WHO) – “climate change is the biggest health threat facing humanity” [2].

This investigation further revealed that vulnerability to climate change attributed health impacts was associated with having no formal education, divorced marital status, living in overcrowded situations, and poor wealth status. In this study, the significant association of no formal education with being vulnerable to climate change attributed health impacts is in line with the report of IPCC, which indicates that sociodemographic factors including educational status significantly influence public vulnerability [40]. It is also similar to the description of the National Institute of Environmental Health Science, in which people with inadequate education were vulnerable to climate change [41]. This might be due to the fact that people with no education have poor household water management practice and weak health seeking behavior [42,43] which makes them more vulnerable in water and health components of vulnerability to climate change. However, this finding contradicts with a study report in Nigeria that revealed increasing levels of education increase vulnerability to climate change [44]. This contrast might be due to the difference in institutional factors where some organizations in some areas provide aid and training depending on respondents’ level of education [45].

In addition, this investigation revealed that divorced individuals were highly vulnerable to the health impacts attributed by climate change. This is similar to the investigation in Somalia [46]. The possible reason for this might be divorced individuals are financially insecure and live a risky life [47,48] which makes them more vulnerable to the health and food components of vulnerability to climate change.

In our study, public vulnerability was also associated with wealth status, where poorest individuals were highly vulnerable to health impacts of climate change. This is in line with the special report of IPCC, which describes wealth as a significant factor for vulnerability [49]. The possible reason might be that poor individuals are food insecure and have weak livelihood diversity index/-adaptive capacity [50], which reduces their coping capacity and increases their sensitivity to climate change attributed health impacts. Besides, living in overcrowded housing was identified as a significant factor increasing vulnerability. This finding is similar to other relevant investigations in Tuvalu island showing vulnerability to climate change was the combined effects of multiple stressors

Table 3
Mean marginal effects (%) of factors on the probability of vulnerability to climate change attributed health impacts within the community of Amhara Sayint district, Amhara, Northeastern Ethiopia.

Predictors	Not vulnerable	p-value	Vulnerable	p-value	Highly vulnerable	p-value
Educational status (Ref-high school and above)						
No formal Education	**−0.3**	**0.023***	**0.3**	**0.007***	−0.03	0.506
Primary Education	−0.6	0.159	0.2	0.054	−0.04	0.307
Marital status (Ref-Married)						
Divorced	0.004	0.961	−0.1	0.240	0.1	0.086
Overcrowded status (Ref-Stable/not overcrowded)						
Overcrowded	−0.07	0.298	0.015	0.8	0.05	0.125
Wealth (Ref-rich)						
Poor	**−0.149**	**0.004***	**0.1**	**0.005***	0.003	0.824
Medium	0.001	0.974	−0.01	0.771	0.01	0.432

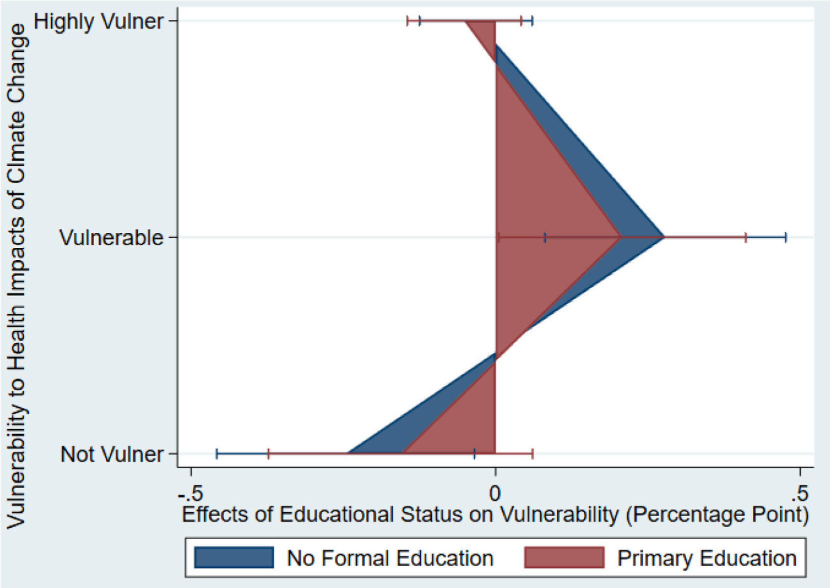

Fig. 3. Average marginal effects of educational status on the predicted probability of vulnerability to the climate change health impacts within the community of Amhara Sayint district, Amhara, Northeastern Ethiopia.

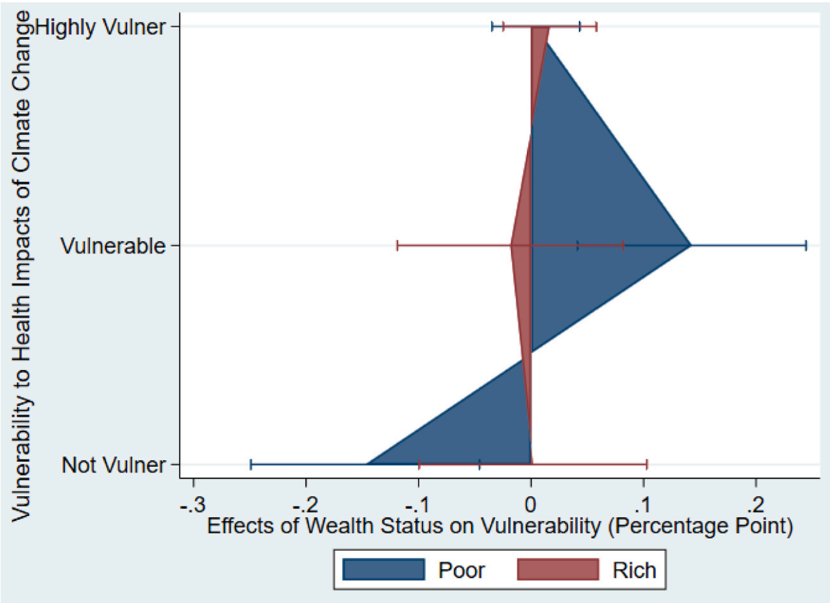

Fig. 4. Average marginal effects of educational status on the predicted probability of vulnerability to the climate change health impacts within the community of Amhara Sayint district, Amhara, Northeastern Ethiopia.

including overcrowding [51,52]. This is because overcrowded housing increases heat related stress and disease [53].

5. Conclusions

Understanding public vulnerability to climate change-attributed health impacts is crucial for timely preparedness and early prevention. This study assessed the extent of public vulnerability to health impacts using a quantitative approach. The findings revealed that approximately 48 % of residents in Amhara Sayint district, Amhara, Northeastern Ethiopia were vulnerable, with 4.6 % categorized as highly vulnerable. Factors such as lack of formal education and poor wealth status were linked to increased vulnerability, while overcrowded housing and a divorced marital status were significant predictors of high vulnerability. The results indicate that a substantial portion of the population is either vulnerable or highly vulnerable to climate change-attributed health impacts. The study emphasizes the need to prioritize preparedness by addressing these associated factors. However, the study's reliance solely on quantitative methods is a limitation. To overcome this, it is recommended to conduct a spatial analysis that incorporates quantitative data and includes a sufficiently large sample size to identify high-risk areas.

Ethical approval

The study adheres to the Declaration of Helsinki, with all procedures conducted according to national standards to ensure respondent anonymity. It received approval from the Institutional Review Board of Wollo University's College of Medicine and Health Sciences (Approval number: CMHS 1536/2014) and also obtained support letter from South Wollo zone health Department (No: ደወጤ/165/2014). Verbal Consent was obtained from the participants involved in the study.

Funding statement

The author(s) received no specific funding for this work.

STROBE-checklist

The STROBE checklist is included as a supplementary material II.

Data availability statement

All the relevant data can be accessed through a formal request directed to the corresponding author, through (genemulu8@gmail.com).

CRediT authorship contribution statement

Genanew Mulugeta Kassaw: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Asmamaw Malede:** Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mesfin Gebrehiwot:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors wish to thank Wollo University, College of Medicine and Health Sciences, Dessie, Ethiopia for their invaluable support. They also appreciate Woldia University, Woldia, Ethiopia for thee technical assistance and extend a special thanks to Ming Chi University of Technology in Taiwan for the help with data analysis. Additionally, the authors acknowledge the commitment of the data collectors, the Amhara Sayint District Health and Environmental Protection Offices, and all participants in the study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e38166.

Abbreviations

AOR	Adjusted odds ratio
CDC	Centre for Disease Control and Prevention
CI	Confidence Interval
COR	Crude Odds Ratio
IPCC	Intergovernmental Panel on Climate Change
Ref	Reference
VIF	Variance inflation factor

References

[1] L.A. Palinkas, M. Wong, Global climate change and mental health, Current Opinion in Psychology 32 (2020) 12–16.
[2] WHO, Climate Change and Health, 2021.
[3] J. Liu, et al., Is there an association between hot weather and poor mental health outcomes? A systematic review and meta-analysis, Environ. Int. 153 (2021) 106533.
[4] A. Lisa, S.H. Page, R. Sari Kovats, Louise M. Howard, Temperature-related Deaths in People with Psychosis, Dementia and Substance Misuse, Cambridge, 2018.
[5] T. Guardian, Extreme temperatures kill 5 million people a year with heat-related deaths rising, study finds, Available from: https://www.theguardian.com/world/2021/jul/08/extreme-temperatures-kill-5-million-people-a-year-with-heat-related-deaths-rising-study-finds, 2021.
[6] IPCC, Climate Change Impacts and Vulnerability, 2022.
[7] WHO, in: Simon Hales, Sari Kovats, Simon Lloyd, Diarmid Campbell-Lendrum (Eds.), Quantitative Risk Assessment of the Effects of Climate Change on Selected Causes of Death, 2030s and 2050s, 2020. Switzerland.
[8] UN, 2022.
[9] WHO, GLOBAL CLIMATE CHANGE AND CHILD HEALTH, 2019.
[10] K. Lindvall, et al., Health status and health care needs of drought-related migrants in the Horn of africa-A qualitative investigation, Int J Environ Res Public Health 17 (16) (2020).
[11] Somalia Climate portal, Climate change overview, country summary, Available from: https://climateknowledgeportal.worldbank.org/country/somalia, 2019.
[12] OCHA, Horn of Africa drought, Regional Humanitarian Overview & Call to Action (Revised 24 August 2022) (2022).
[13] OXFAM EL NIÑO IN ETHIOPIA, And the Southern Oscillation, 2016.
[14] A. De Waal, Evil days : thirty years of war and famine in Ethiopia, in: Evil Days : Thirty Years of War and Famine in Ethiopia, Human Rights Watch, New York, 1991. New York.
[15] E. Fdre, Environmental Policy, 1997.
[16] FDRE, Ethiopia's Climate Resilient Green Economy, 2019.
[17] B. Simane, et al., Review of climate change and health in Ethiopia: status and gap analysis, Ethiop. J. Health Dev. 30 (1 Spec Iss) (2016) 28–41.
[18] S. Suryanto, A. Rahman, Application of livelihood vulnerability index to assess risks for farmers in the Sukoharjo Regency and Klaten Regency, Indonesia, Jàmbá: Journal of Disaster Risk Studies 11 (1) (2019) 1–9.
[19] M.T. Abeje, et al., Communities' livelihood vulnerability to climate variability in Ethiopia, Sustainability 11 (22) (2019) 6302.
[20] United Nations, Climate Action, 2016.
[21] OpenAfrica, Ethiopia shapefiles (2013).
[22] J.L. Kelsey, et al., Methods in Observational Epidemiology, vol. 10, 1996. Monographs in Epidemiology and.
[23] W.W. Daniel, C.L. Cross, Biostatistics: a Foundation for Analysis in the Health Sciences, Wiley, 2018.
[24] M. Hahn, A. Riederer, S. Foster, The Livelihood Vulnerability Index: a pragmatic approach to assessing risks from climate variability and change—a case study in Mozambique, Global Environ. Change 19 (2009) 74–88.
[25] T. Clasen, Household water treatment and safe storage to prevent diarrheal disease in developing countries, Curr Environ Health Rep 2 (1) (2015) 69–74.
[26] Japan- Caribbean Climate Change Project, *Knowledge, Attitude And Practices*, 2016, pp. 46–57.
[27] M. Theresa, Knowledge, Attitude and Practices of NutritionWorkers on Climate Change in Laguna, 2020.
[28] M.S. Rahman, et al., Knowledge, attitudes, and practices on climate change and dengue in Lao People's Democratic Republic and Thailand, Environ. Res. 193 (2021) 110509.
[29] IPCC, IPCC Sixth Assessment Report Impacts, Adaptation and Vulnerability, 2022.
[30] J. Ray-Mukherjee, et al., Using commonality analysis in multiple regressions: a tool to decompose regression effects in the face of multicollinearity, Methods Ecol. Evol. 5 (4) (2014) 320–328.
[31] R.A. Williams, C. Quiroz, Ordinal Regression Models, SAGE Publications Limited, 2020.
[32] R. Williams, Generalized ordered logit/partial proportional odds models for ordinal dependent variables, STATA J. 6 (1) (2006) 58–82.
[33] R. Williams, Understanding and interpreting generalized ordered logit models, J. Math. Sociol. 40 (1) (2016) 7–20.
[34] A.F. Senbeta, J. Olsson, Climate Change Impact on Livelihood, Vulnerability and Coping Mechanisms: A Case Study of West-Arsi Zone, Ethiopia, Lund University, Lund, 2009, p. 54.
[35] Y.B. Azene, M.T. Zeleke, A.B. Chekole, Vulnerability of mountain communities to climate change and natural resources scarcity in Northwest Ethiopia: the case of Debark Woreda, Journal of Degraded and Mining Lands Management 6 (1) (2018) 1467.
[36] K.U. Shah, et al., Understanding livelihood vulnerability to climate change: applying the livelihood vulnerability index in Trinidad and Tobago, Geoforum 47 (2013) 125–137.
[37] F.E.O. Opiyo, O.V. Wasonga, M.M. Nyangito, Measuring household vulnerability to climate-induced stresses in pastoral rangelands of Kenya: implications for resilience programming, Pastoralism 4 (1) (2014) 10.
[38] IPCC. *Sixth Assessment Report* 2021; Available from: https://www.ipcc.ch/report/ar6/wg2/about/frequently-asked-questions/keyfaq1/.
[39] EPA, Climate impacts on human health, Available from: https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-human-health_.html, 2017.
[40] B. Wisner, J. Adams, J. Adams, Environmental Health in Emergencies and Disasters: a Practical Guide, World health organization, 2002.
[41] NIEHS *people who are Vulnerable to climate change,* Available from: https://www.niehs.nih.gov/research/programs/climatechange/health_impacts/vulnerable_people/index.cfm, 2022.
[42] X. Li, et al., Effect of socioeconomic status on the healthcare-seeking behavior of migrant workers in China, PLoS One 15 (8) (2020) e0237867.
[43] D. Tsegaye, et al., Assessment of knowledge and practice of household water treatment and associated factors in rural kebeles of Degadamot woreda, north-West Ethiopia, 2020, J. Bacteriol. Parasitol. 12 (2021) 403.
[44] O.I. Nnadi, J.G. Lyimo, E.T. Liwenga, Socio-economic determinants of vulnerability to climate variability and change across gender in southeast Nigeria, Journal of Agricultural Extension 23 (2) (2019) 122–137.
[45] E.U. Ingwu, S.-M.A. Okey, Entrepreneurial training needs of illiterate women in cross river state, Nigeria, Int. Educ. Stud. 6 (11) (2013) 171–183.
[46] A.A. Mohamed, R.A. Ojwang, Impact of Climate Change and Vulnerability Assessment of Pastoralists Located in South Central Somalia Based on Income and Marital Status, 2020.
[47] B. Kaur, The Effects of Divorce, Attachment, and Perception of Support on Engagement in Risky Behaviors, University of La Verne, 2015.
[48] D.A. Sbarra, M.A. Whisman, Divorce, health, and socioeconomic status: an agenda for psychological science, Current opinion in psychology 43 (2022) 75–78.
[49] O.D. Cardona, et al., Determinants of risk: exposure and vulnerability, in: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 2012, pp. 65–108.
[50] H.C. Winsemius, et al., Disaster risk, climate change, and poverty: assessing the global exposure of poor people to floods and droughts, Environ. Dev. Econ. 23 (3) (2018) 328–348.
[51] J.D. Ford, et al., Adapting to the effects of climate change on Inuit health, American journal of public health 104 (S3) (2014) e9–e17.
[52] S. McCubbin, B. Smit, T. Pearce, Where does climate fit? Vulnerability to climate change in the context of multiple stressors in Funafuti, Tuvalu, Global Environ. Change 30 (2015) 43–55.
[53] N. Scovronick, S.J. Lloyd, R.S. Kovats, Climate and health in informal urban settlements, Environ. Urbanization 27 (2) (2015) 657–678.