

1 Effect of climate variability, crop production, and  
2 household food insecurity on malnutrition among  
3 women: A mediation analysis from a drought-prone  
4 area in Southern Ethiopia

5

6

7

8 Taye Gari<sup>1\*</sup>, Bethlehem Mezgebe<sup>1</sup>, Mehretu Belayneh<sup>1</sup>, Yonas Mersha<sup>2</sup>, Bernt Lindtjørn<sup>1</sup>

9

10

11 <sup>1</sup> School of Public Health, College of Medicine and Health Sciences, Hawassa University,  
12 Hawassa, Ethiopia.

13

14 <sup>2</sup> Computational Data Science Program, Addis Ababa University, Addis Ababa,  
15 Ethiopia

16

17

18

19

20 \* Corresponding author

21 Email: [tayegari@ymail.com](mailto:tayegari@ymail.com) (TG)

22

23

## 24 **Abstract**

25 Malnutrition is viewed as one of climate change's five most considerable adverse health  
26 impacts. As many previous studies have shown correlations between climate, food  
27 production, and social factors on the nutritional status of women, we hypothesized a causal  
28 effect of climate variations on crop production, household food security, and our outcome,  
29 the nutritional status of adult women. Using a cohort design, we ensured a temporal  
30 relationship between the main exposures preceding the mediator and the outcome. Women  
31 living in 904 households from nine randomly selected subsistence farming in rural *Kebeles*,  
32 the lowest administrative unit in the Boricha district, were visited quarterly to collect  
33 nutritional status (outcome variable), household food security status (HHFS), and  
34 sociodemographic information. Climate data was obtained from the Google Earth Engine.  
35 Generalized structural equation modeling (GSEM) was used to measure the association  
36 between rainfall, the normalized difference vegetation index (NDVI), a proxy measure for  
37 crop production, and women's nutritional status (BMI) after adjusting for the mediation  
38 effect of HHFS. The analysis adjusted the clustering effect of *Kebele* and household. The  
39 study showed that the NDVI and HHFS directly affected women's body mass index.  
40 Furthermore, household heads who attended primary education, total energy expenditure of  
41 women, and household wealth were positively associated with women's BMI. On the other  
42 hand, older women and women who were not members of a community-based health  
43 insurance household had a lower BMI. Climate variability, crop production, and household  
44 food security could be causally linked to women's nutritional status, suggesting that rural  
45 people depending on rain-fed subsistence farming for crop production are vulnerable to the  
46 impact of climate variability.

47

- 48 **Keywords** Normalized difference vegetation index (NDVI), Women, BMI, Climate
- 49 variability, Mediation analysis, household food security, famine

## 50 **Introduction**

51 Ethiopia has repeatedly been affected by episodes of drought and famine over the centuries  
52 [1, 2]. Even without drought, acute and chronic forms of malnutrition are prevalent.  
53 However, in recent decades, the prevalence of stunting has been reduced [3]. Malnutrition  
54 among women is also high. As women conduct much of the work in the household,  
55 malnutrition among these individuals affects their daily lives as their work capacity is  
56 reduced [4].

57  
58 The causes of malnutrition among children and adults are complex, but the availability of rain  
59 is crucial as it is closely associated with food productivity in subsistence farming  
60 communities. Hence, some have labeled malnutrition as one of climate change's five most  
61 critical adverse impacts [5]. Poverty remains a leading cause of both malnutrition and famine.  
62 When severe malnutrition occurs during political and social unrest, it is often called a  
63 complex famine [6].

64  
65 Climate variability “includes all the variations in the climate that last longer than individual  
66 weather events.” In contrast, climate change refers to variations that persist for a more  
67 extended period, typically decades or more [7]. Our relatively short research views climate  
68 variability as stress multipliers to factors that indirectly or directly affect nutrition and health.  
69 In areas such as southern Ethiopia, the primary strategy of the population to meet the effects  
70 of global warming would be enhanced adaptation. The countries’ carbon footprint is  
71 negligible but slowly increasing [8]. Adaptation refers to “changes in processes, practices,  
72 and structures to moderate potential damages or benefits from climate change.” Our research  
73 aims to enhance our understanding of these processes and thus improve the livelihoods of  
74 people living in such areas.

75 Nonetheless, systematic evidence quantifying these impacts needs to be improved. Most of  
76 the earlier research on the relationships between nutrition indicators and food insecurity was  
77 correlational and based on cross-sectional studies [5]. Thus, there is limited evidence for a  
78 causal link between climate or weather patterns, food production and availability, and  
79 malnutrition. What need to be improved are interdisciplinary studies linking the possible  
80 chain of events from weather variability to food production and malnutrition, particularly for  
81 rural subsistence farmers. Long-term survey data, such as cohort studies and interventional  
82 research, can capture the dynamic nature of food poverty and show causal relationships [5].  
83 We hypothesize that causal pathways link climate variability, food production, and  
84 malnutrition. Thus, by studying one smaller community over time, our study aimed to  
85 investigate associations between climate variability on crop production and malnutrition  
86 among women in subsisting farming and drought-prone communities in southern Ethiopia.  
87 Furthermore, we aimed to see how community interventions could influence the  
88 abovementioned association.

89

## 90 **Methods**

### 91 **Climate in Ethiopia**

92 The study area in Boricha in Sidama in Southern Ethiopia receives rain twice yearly, from  
93 March to May and June to September. Rain-fed agriculture owned by smallholder farmers  
94 dominates the primary land use. Reliance on rain-fed farming for subsistence and rainfall  
95 variability exposes people to high risks of harvest loss, quickly resulting in food insecurity.  
96  
97 Precipitation trends in Ethiopia indicate that southern Ethiopia's rainfall has decreased since  
98 1971 [9]. From February to May, the main rain period in Boricha, precipitation declined by

99 2.6 mm/year in the spring region from 1971–2010. Thus, since 1971, rainfall may have been  
100 reduced by as much as 30 % [9]. On resource-poor farms in southern Ethiopia, the spring  
101 crop may determine whether the annual productivity reaches the critical margin [10].  
102

102

103

## 104 **Study setting**

105 This study was conducted in a former Boricha *woreda* (recently split into Boricha, Darara,  
106 and Bilate *woredas*), located in the western part of the Sidama Region. The study *Kebeles*  
107 were selected from Boricha *woreda* before it was divided into three, and thus, the study  
108 *Kebeles* were categorized under two of the new *woredas* called Boricha and Bilate Zuria  
109 *woredas*. The area covers about 600 km<sup>2</sup> (Fig 1).  
110

110

111

112 **Figure 1:** Map of the study area in the Sidama Region and Ethiopia

113

114 Boricha is a relatively flat area, with a decline in altitude from east to west. The altitude  
115 varies from 1320 m in the west to 2080 m in the east. In between, there are some scattered  
116 mountain ridges. As recently as a few generations ago, the acacia forest covered the area, but  
117 it has become increasingly bare. Very few rivers cross this area. The areas to the lower  
118 altitude are severely degraded. Another dominant land use land cover is the scattered trees.  
119 They are found to be mixed with farmland and those planted by the dwellers.

120

121 Generally, Boricha can be regarded as a water-starved area. Because of this, people in  
122 most *Kebeles* (the lowest administrative unit in Ethiopia and contains a health post staffed by

123 two health extension workers) largely depend on artificial ponds that usually dry after the  
124 rains. Livestock are essential, and cattle, goats, and donkeys are the primary livestock. The  
125 principal crops are maize, haricot bean, coffee, and horticultural crops. The higher altitude  
126 areas are green, with eucalyptus, fruit, coffee trees, and an ensete (*Ensete ventricosum*)  
127 growing around every house. However, no natural forest exists, and communal grazing land  
128 is limited [11].

129

130

### 131 **Study population**

132 The details of the study population were presented elsewhere [12]. In 2021, the districts of  
133 Boricha and Bilate Zuria *Woredas* (the third level of the administrative divisions of Ethiopia  
134 – after zones and the regional states) were chosen as the study areas. The *woreda* is further  
135 subdivided into *Kebeles* (the lowest administrative unit. With a population estimated at  
136 130,000, Boricha had one district hospital, three health facilities, and thirteen health posts. On  
137 the other hand, Bilate Zuria served an estimated 147,000 people with five health centers and  
138 17 health posts [13].

139

140

### 141 **Study design**

142 This study is an open and dynamic cohort conducted from June 2021 to June 2022. We  
143 selected the same homes as in a previous cohort study [11] to ensure we acquired  
144 comprehensive nutrition and food intake data over more extended periods. We focused on  
145 women in rural communities because the households are both farmers and dependent on  
146 weather changes for their livelihoods.

147

## 148 **Sampling and sample size**

149 A multiphase sampling method was employed in the selection of research subjects. Nine of  
150 the 30 rural *Kebeles* in the districts were chosen randomly. The cluster sampling method was  
151 then used to select households. The study included all eligible females aged 15 to 49 who  
152 lived in the chosen households.

153

154 OpenEpi 3.03 (Open-Source Epidemiologic Statistics for Public Health; [www.OpenEpi.com](http://www.OpenEpi.com))  
155 was used to calculate the sample size. The sample size chosen for the study was based on the  
156 outcome of maternal body mass index (BMI). A sample size of 904 women was determined  
157 using assumptions from a previous cohort study: the percentage of mothers with a BMI less  
158 than 18.5 kg/m<sup>2</sup> during the pre-harvest season was 54.7%, and the rate during the post-  
159 harvest period was 41.7% [14]. A confidence level of 95% and a power of 80% were  
160 considered, with a ratio of unexposed to exposed individuals set at 1:1. Considering a design  
161 effect of 1.5 and assuming a 20% non-response rate, the final sample size was estimated to be  
162 904 women.

163

## 164 **Measurements**

165 Quarterly visits were made to each household. Enumerators gathered information on all  
166 births, deaths, and migrations at each house they visited. We conducted a baseline census in  
167 June 2021 and then gathered quarterly data on household food insecurity, nutrition status, and  
168 sociodemographic characteristics. Weight in kilograms divided by height in square meters  
169 was used to create the outcome variable, body mass index (BMI). This study used data  
170 collected between June 2021 and June 2022.

171



## 172 **Climate Data**

173 There is only one meteorology station per district, but there is no station at the *Kebele* level.  
174 Moreover, the data collection at these weather stations was not regular; thus, the data needed  
175 to be completed for several months. Weather data for the *Kebeles* was not available.  
176 Therefore, the precipitation, temperature, and Normalized Difference Vegetation Index  
177 (NDVI) data were downloaded from Google Earth Engine (accessed via  
178 <https://earthengine.google.com/signup> after signing up). The temperature data was  
179 downloaded from ERA5-Land monthly averaged data using GRIB format via the following  
180 link: [https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=form)  
181 [means?tab=form](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=form). The monthly rainfall was obtained using the Climate Hazards Group  
182 InfraRed Precipitation (CHIRPS) [15] with a spatial resolution of 0.05 degrees. This study  
183 uses each *Kebele's* average precipitation, temperature, and NDVI.

184  
185 The remote sensing method, NDVI, tracks vegetation dynamics. It may be computed using  
186 canopy reflectance in the near-infrared and infrared bands and is less reliant on soil  
187 characteristics [16]. The NDVI measures how green and dense the vegetation is captured in a  
188 satellite image and is widely employed in crop health and production monitoring. It also  
189 serves as a surrogate for measuring the impact of rainfall variability on vegetation conditions.  
190 The NDVI has been used as a stand-in measure for crops in Ethiopia [17].

191  
192 We used the United States Geological Survey (USGS) [18] data server to obtain a  
193 retrospective time series of the NDVI, utilizing three distinct datasets with a monthly  
194 temporal resolution. Calculated from satellite imagery, it captures visible and near-infrared  
195 light wavelengths reflected by vegetation; NDVI measures the difference between these  
196 wavelengths. Where: NIR represents the reflectance values of the near-infrared wavelengths,

197 and RED represents the reflectance values of the red wavelengths. This computation  
198 generates a value ranging from -1 to +1, with higher values indicating denser, healthier  
199 vegetation (closer to +1) and lower values signifying less vegetation or areas with non-  
200 vegetative cover (approaching -1) [19]. The average NDVI was obtained from the satellite  
201 using Sentinel-2 MSI (Multispectral Instrument, Level-2A), sensor: SENTINEL-2, and with a  
202 spatial resolution of 10 meters [15]. JavaScript code calculated the monthly average NDVI  
203 for the nine study *Kebeles*.

204

## 205 **Statistical methods**

206 The data were collected using a cohort design to ensure that the main exposures preceded the  
207 mediator and the mediator preceded the outcome. Thus, the mediation enabled us to assess  
208 causality and reduce confounding [20]. The socio-demographic data were collected at the  
209 start of the study, and we assume that it remained constant over the study period. A Structural  
210 Equation Model (SEM) is a multivariate statistical method considered a causal model that  
211 includes the linear regression model and Path Analysis [21]. The Path Analysis model  
212 includes observed variables and allows a variable to be dependent and independent  
213 simultaneously. In addition, several dependent variables can be included, and the indirect and  
214 direct effects can be measured.

215 Data were entered and cleaned using SPSS Version 26 (IBM Corp, Armonk, NY), and  
216 STATA Version 17 (Stata Corp, Texas, USA) software was used to analyze the data.

217 Descriptive statistics, such as numerical summary measures and diagrams, were used to  
218 summarize the data. The wealth index was constructed using principal component analysis  
219 using household assets such as possession of farmland, animals, a mobile phone, an animal  
220 cart, a motorcycle, etc., and housing, such as the type of roof, wall, and floor. Household food

221 security level was measured using questionnaires validated in different populations in  
222 Southern Ethiopia [22, 23].

223 BMI, the outcome variable, was a continuous variable with a normal distribution, and  
224 therefore, a linear regression model was used to measure the predictors of BMI. The data  
225 were collected from three levels: *Kebele*, households, and individuals. Thus, BMI value could  
226 be dependent among women in the same *Kebele*. Still, differences between houses and  
227 *Kebeles* would invalidate the assumption of standard regression models. In addition, there  
228 could be a dependency among the repeated measurements made on the same women over the  
229 study period. Thus, we employed a multilevel multiple linear regression model to account for  
230 the dependency for mediation analysis. The ICC was computed to check for clustering and  
231 dependency, and we observed that the ICC was 0.08 for *Kebele* and 0.12 for households.  
232 Therefore, the effect of *Kebele* and household levels was accounted for in the final model.  
233 The model's goodness-of-fit was checked using Akaike's information criteria (AIC) and  
234 standardized root mean squared residual (SRMR) [24]. The AIC was small, 64328, in the  
235 final or complete model compared to a model without government intervention variables such  
236 as safety net and Community-Based Health Insurance (CBHI) (AIC = 84816). The  
237 standardized root mean squared residual (SRMR) was also in an acceptable range (0.034). A  
238 P-value <0.05 was considered statistically significant.

239 The path diagram was developed using the average change in women's BMI as the outcome  
240 variable, measured four times over one year, and exposure variables such as one month lag in  
241 NDVI from the measured household food insecurity (HHFI) and two months lag in total  
242 rainfall from NDVI. This allowed us to measure the natural sequence of events and  
243 correspond to the conceptual framework.

244 Mediation analysis is a statistical technique used to examine how one variable (the predictor  
245 variables) affects another (the outcome variable) through one or more intervening factors  
246 [25]. A mediation or path analysis was done to measure the relationship between rainfall,  
247 crop production using NDVI as a proxy crop measure, and women's nutritional status (BMI)  
248 after adjusting for the mediation effect of household food security. This study considered the  
249 HHFS a mediator variable in measuring the relationship between NDVI and BMI. This was  
250 checked, and the observed regression coefficient of the exposure variable (NDVI) in the first  
251 model (without a mediator) increased from 0.42 to 0.66 in the second model (with a mediator  
252 variable). The generalized structural equation modeling (GSEM) was used to measure the  
253 sequential mediation effect of household food security status on women's BMI after  
254 accounting for clustering at *kebele* (level 3) and household (level 2). The final model was  
255 selected using the following steps: first, the unadjusted path model was fitted with NDVI  
256 (exposure), household food security score (mediator), and BMI (outcome) variable. Then, the  
257 entire mediation analysis model was fitted after adjusting for potential confounding variables.  
258 We measured the effects of sociodemographic variables to assess the potential impact of  
259 factors that indirectly or directly affect the pathway from precipitation/rainfall to nutritional  
260 status/BMI. These include household use of the government's safety net program, use of  
261 health insurance, and wealth status, measured in June 2021, and we assumed it to be constant  
262 throughout the study period. A theoretical conceptual framework developed by Phalkey et al.  
263 (2015) was used in the path analysis (Fig 2) [5].

264

265

266

267 **Figure 2** Conceptual framework adapted from the initially developed by Phalkey et al. [5]

268

## 269 **Ethical consideration**

270 The research was approved by the Institutional Review Board at Hawassa University College  
271 of Medicine and Health Sciences (Ref.No. IRB/181/13 and dated 20/05/2021) and revised in  
272 IRB/275/13. Permission to undertake our study was also obtained from the Sidama Region  
273 and relevant local authorities. Local leaders in the *Kebele*, village leaders, and community  
274 elders were informed about the study objectives, procedures, and benefits. Informed written  
275 consent was obtained from each participant. Participation by household members was  
276 voluntary, and measures were taken to ensure their respect, dignity, and freedom.

277

## 278 **Results**

### 279 **Sociodemographic Characteristics**

280 Overall, all women (1057) from 904 households living in nine *Kebeles* were followed and  
281 evaluated quarterly. The number of women assessed was 910 in September 2021, 903 in  
282 December 2021, 866 in March 2022, and 803 in June 2022. The number of women per  
283 *Kebeles* ranged from 99 women in Gonowa Bulano *Kebele* to 136 women in Sadamo Dikicha  
284 *Kebele*. About two-thirds (61.3 %) of the women were living in households whose heads had  
285 attended formal education; 15.8 % of the heads of the households were employed or traders;  
286 only 10.9% of households were members of community-based health insurance; 23.1 % of  
287 households were beneficiaries of the safety net program; and 33.7 % of the households were  
288 poor (Table 1).

289

290

291 **Table 1: Sociodemographic and other characteristics of the study participants**

<b>Description</b>	<b>Frequency</b>	<b>Percent</b>
<b>Name of Kebele</b>		
Sadamo Dikicha	136	12.9
Alawo Siiso	107	10.1
Furara Aldaada	128	12.1
Aldaada Deelee	104	9.8
Kitawo Dambie	113	10.7
Gonowa Bulano	99	9.4
Sadamo cala	120	11.4
Qonsore Haranja	131	12.4
Hanja Goro	119	11.2
<b>Household head education</b>		
No formal education	648	61.3
Grade 1-6	184	17.4
Grade 7-9	130	12.3
Grade >=10	95	9
<b>Occupation of HH head</b>		
Employed and trader	167	15.8
Others	890	84.2
<b>Community Based Health Insurance</b>		
Yes	115	10.9
No	942	89.1
<b>Safety-Net Beneficiary</b>		
Yes	244	23.1
No	813	76.9
<b>Wealth Status</b>		
Poor	356	33.7
Middle	392	37.1
Rich	309	29.2

292

293

## 294 **Household food insecurity and women's nutritional status**

295 The lowest household food insecurity score (4.0) in December coincides with the highest  
296 women's mean BMI (20.6) for the same month. The mean (standard deviation, SD) BMI of  
297 the women was 20.2 (2.2) kg/m<sup>2</sup> in September 2021, 20.6 (2.2) kg/m<sup>2</sup> in December 2021,  
298 20.57 (2.3) kg/m<sup>2</sup> in March 2022, and 20.3 (2.3) kg/m<sup>2</sup> in June 2022. A statistically  
299 significant difference in BMI was observed between September and December 2021 (t-test -  
300 4.4; P <0.001). On the other hand, the median (interquartile range) of household food  
301 insecurity was 10.0 (6.0-16.0) in September 2021, 4.0 (0.0-9.0) in December 2021, 8.0 (4.0-  
302 13.0) in March 2022, and 11.0 (7.0-16.0) in June 2022.

303

## 304 **Monthly Rainfall, Temperature, and NDVI**

305 As shown in Fig 3, the total monthly rainfall varied over the months. The monthly total  
306 rainfall peaked biannually between July and October 2021 and between mid-February and  
307 April 2022. Similarly, the average monthly NDVI was high between August and November  
308 2021. There was a positive correlation between NDVI and one-month lag rainfall, with a  
309 correlation coefficient of 0.53 (P <0.001). The average monthly temperature was between 16  
310 and 22 degrees Celsius (Fig 3).

311

312 **Figure 3** Monthly NDVI, rainfall and temperature in the study area

313

## 314 **Predictors of body mass index in multilevel multivariable model**

315 In the multilevel multiple regression analysis, after controlling for potential confounders, the  
316 NDVI and household wealth index were positively associated with women's BMI. An  
317 increase in the household food security score (HHFS) score was positively associated with

318 BMI, but the age of the women was negatively associated with BMI. The change in BMI was  
 319 higher among household heads who attended primary education compared. Moreover, a  
 320 higher body mass index was observed among those not members of CBHI and non-  
 321 beneficiaries of the safety net program (Table 2).  
 322 **Table 2** Multilevel regression model to measure association between BMI, outcome variable,  
 323 and different covariates

<b>Variables</b>	<b>β coefficient (95% CI)</b>	<b>P-value</b>
Age in years	-0.01 (-0.02 - -0.005)	0.008
NDVI <sup>§</sup>	0.72 (0.27 - 1.17)	<0.001
HHFS <sup>#</sup>	0.52 (0.37 – 0.68)	<0.001
Household safety net beneficiary		
Yes	1:00	
No	0.18 (0.01 - 0.36)	0.043
Total energy expenditure in a day	0.17 (0.06 – 0.27)	0.002
Community based health insurance member		
Yes	1:00	
No	0.43 (0.19 - 0.67)	<0.001
Household wealth status	0.18 (0.10 - 0.26)	<0.001
Household head education attended 1-6 grade		
No	1:00	
Yes	0.48 (0.27 - 0.68)	<0.001
Household head occupation		
Employed/trader	0.22 (0.01 - 0.44)	0.041
Others	1:00	-

324 <sup>§</sup>: Average Normalized Difference Vegetation Index (lag two months); <sup>#</sup>: Average household Food security score



## 325 **Mediation analysis**

326 We continued with the mediation analysis using the multilevel linear regression model  
327 results. As shown in Table 3 and Fig 4, on average, a unit increase in NDVI was associated  
328 with a direct effect of an increase in women's body mass index by about a coefficient of 0.67,  
329 95% CI (0.23 to 1.11). The indirect impact of NDVI on BMI via household food insecurity  
330 was -0.21, 95% CI (-0.28 to -0.13). The proportion of total effect mediated was 43%.  
331 Similarly, an increase in household food security score (0.06 m/kg<sup>2</sup> (95% CI 0.04 to 0.07)),  
332 total energy expenditure (0.17, 95% CI (0.06 to 0.27)), and household wealth index  
333 (Coefficient 0.18, 95% CI 0.11 to 0.26) were positively associated with women's BMI. The  
334 BMI of the women was higher among household heads who had attended primary education.  
335 Furthermore, women's BMI was lower among CBHI. An increase in women's age was  
336 negatively associated with their BMI. No significant association was observed between the  
337 safety net beneficiary and the household head's occupation.

338

339

340 *NB: Categorical variables coded as CBHI (0=no, 1=yes), Safety net (0=no, 1=yes) TEE: Total energy*  
341 *expenditure in kilo calories a day.*

342

343 **Figure 4:** Path diagram showing the relationship between changes in women's BMI  
344 measured quarterly between June 2021 and June 2022) and lag in rainfall, NDVI, and HHFS.

345

346

347

348

349

350

351

352

353

354

355

356

357 **Table 3:** Mediation analysis of the direct, indirect, total, and proportion of total effect mediated on women's BMI (outcome variable)  
 358

Effect of	Outcome	Direct effect (95% CI)	Indirect effect (95% CI)	Total effect (95% CI)	Proportion of total effect mediated
NDVI <sup>§</sup>	BMI via HHFS	0.66 (0.22 to 1.10)**	-0.20 (-0.28 to -0.13)***	0.46 (0.01 to 0.90)*	0.43
HHFS <sup>#</sup>	BMI	0.06 (0.04 to 0.07)***		0.06 (0.02 to 0.09)***	
CBHI <sup>&amp;</sup>	BMI via HHFS	-0.50 (-0.74 to -0.27)***	-0.99 (-1.54 to -0.44)***	-0.36 (-0.60 to -0.13)**	2.75
HH <sup>@</sup> head education 1 to 6	BMI via HHFS	0.67 (0.47 to 0.87)***	1.10 (0.66 to 1.55)***	0.76 (0.56 to 0.96)***	1.45
Safety net	BMI	-0.15 (-0.33 to 0.02)		-0.15 (-0.33 to 0.02)	
Wealth status	BMI via HHFS	0.18 (0.10 to 0.26)***	0.02 (-0.01 to 0.06)	0.18 (0.11 to 0.27)***	0.11
Occupation	BMI via HHFS	-0.19 (-0.41 to 0.01)	0.15 (-0.04 to 0.34)	-0.24 (-0.46 to -0.03)*	0.63
Age	BMI	-0.01 (-0.02 to 0.003)*		-0.01 (-0.02 to 0.003)*	
RF <sup>##</sup>	NDVI	0.0036(0.0034 to 0.0038)***			
TEE	BMI	0.17 (0.06 – 0.27)		0.17 (0.06 – 0.27)	

359 *§: Normalized Difference Vegetation Index; #: Household food security score; &: Community Based Health Insurance; @: Household; ##: Rainfall.* The final model was  
 360 selected using AIC

## 361 **Discussion**

362 As we hypothesized, our study shows a direct effect of rainfall on the NDVI and an indirect  
363 effect of the NDVI via HHFS on women's BMI. Using a cohort design, we ensured a  
364 temporal relationship between the main exposures preceding the mediator and the outcome.

365 Thus, the mediation analysis enabled us to assess causality and reduce confounding.

366 Furthermore, our relatively short research shows that climate variability is a stress multiplier  
367 to factors that indirectly or directly affect nutrition and health, such as wealth, health  
368 insurance, education, and workload.

369

370 Our analytical model accounted for data clustering at the *Kebele* and household levels to  
371 obtain a precise measure of the coefficients' standard error. We adjusted for potential  
372 confounding effects of important sociodemographic variables. The time sequence of the  
373 occurrence of exposure, mediator, and outcome variables was used to build a mediation  
374 analysis model, adding evidence to claim for cause links between climate variability and crop  
375 production, household food security, and malnutrition.

376

377 The advantage of studying in smaller areas is that it enables us to address details obtained  
378 through household studies. Even if this may limit the generalization of the findings, the study  
379 area is representative of drought-prone and subsistence farming rural communities in  
380 Ethiopia, a country with repeated episodes of climate variability and change, crop failures,  
381 and famines.

382

383 A limitation of our study is that we didn't directly measure the food production in the  
384 affected household but used remote sensing information. Although NDVI data correlates well  
385 with food production, future studies should evaluate the use of remote sensing with the

386 variety of foods produced on local farm plots. Furthermore, our study used self-reports while  
387 measuring HHFS, which might introduce measurement bias. This might be because  
388 participants might have reported a household's food insecurity with the expectation of getting  
389 food aid. However, earlier and repeated validation studies from similar areas in Ethiopia  
390 assessed the food insecurity measuring tool as reliable [22, 23].

391  
392 Our study confirms earlier results from Ethiopia and Africa that rainfall was associated with  
393 NDVI, a proxy for crop production, and that crop production, household food security, and  
394 wealth were correlated to an increase in women's BMI [26-30]. Unlike previous studies in  
395 southern Ethiopia, we did not find an association between using the safety net program (SNP)  
396 and women's BMI [31]. Similarly, we did not demonstrate any effect of the Safety Net  
397 program. However, the number of persons using health insurance and the safety net program  
398 was small, and an inadequate sample size could explain the lack of associations in our study.  
399 On the other hand, our mediation model improved when including these variables.

400  
401 The lack of longitudinal data is a serious constraint for researchers in countries such as  
402 Ethiopia. Our study demonstrates that it is possible to retrospectively access valid climate  
403 data from publicly available sources and combine them with relatively short-duration studies.

404  
405 Climate variability, crop production, and household food security could be causally linked to  
406 women's nutritional status, suggesting that rural people depending on rain-fed subsistence  
407 farming for crop production are vulnerable to the impact of climate variability. Government  
408 interventions such as education, CBHI, and SNP could help mitigate the effect of climate  
409 variability. In the current study area, mitigating climate variability through improving

410 household food security, wealth status, and educational status could reduce the climate  
411 variability stress in the affected populations.

412

413

## 414 Acknowledgments

415 We thank the COGENT project for funding this study, the Sidama National Regional State  
416 Health Bureau, and the Boricha and Bilate Zuria district health offices for their support. We  
417 would also like to thank the study participants and data collectors for their contributions.

418

419

420

421

## 422 References

423

- 424 1. Pankhurst, R., *The history of famine and epidemics in Ethiopia prior to the twentieth*  
425 *century*. (No Title). 1985, Addis Ababa: Relief and Rehabilitation Commission.
- 426 2. Kloos, H. and B. Lindtjorn, *Malnutrition and mortality during recent famines in*  
427 *Ethiopia: implications for food aid and rehabilitation*. Disasters, 1994. **18**(2): p. 130-  
428 9.
- 429 3. Golan, J, D Heacdey, K Hirvonen, and Hoddinot. "Changes in Child Undernutrition  
430 in Ethiopia, 2000 - 2016." Chap. 23 In *The Oxford Handbook of Ethiopian Economy*,  
431 *edited by F Cheru, C Cramer and A Oqubay, 399-411*. New York: Oxford University  
432 Press, 2019.
- 433 4. Alemu, T. and B. Lindtjorn, *Physical activity, illness and nutritional status among*  
434 *adults in rural Ethiopian community*. International Journal of Epidemiology, 1995.  
435 **24**(5): p. 977.
- 436 5. Phalkey, R.K., et al., *Systematic review of current efforts to quantify the impacts of*  
437 *climate change on undernutrition*. Proc Natl Acad Sci U S A, 2015. **112**(33): p.  
438 E4522-9.
- 439 6. Burkholder, B. and M. Toole, *Evolution of complex disasters*. Lancet, 1995. **346**: p.  
440 1012-5.
- 441 7. Field, C.B., et al., *IPCC, 2012: summary for policymakers: managing the risks of*  
442 *extreme events and disasters to advance climate change adaptation*, in *Planning for*  
443 *Climate Change*. 2018, Routledge. p. 111-128.

- 444 8. Climate Watch. *Climate Watch Historical GHG Emissions*. 2023 [cited 2024 8.6.24];  
445 Available from: [https://www.climate-](https://www.climate-watchdata.org/ghg-emissions?source=Climate%20Watch)  
446 [watchdata.org/ghg-](https://www.climate-watchdata.org/ghg-emissions?source=Climate%20Watch)  
447 emissions?source=Climate%20Watch.  
448 9. Viste, E., D. Korecha, and A. Sorteberg, *Recent drought and precipitation tendencies*  
449 *in Ethiopia*. Theoretical and Applied Climatology, 2012. **112**(3-4): p. 535-551.  
450 10. McCann, J.C., *A great agrarian cycle? Productivity in highland Ethiopia, 1900 to*  
451 *1987*. The Journal of Interdisciplinary History, 1990. **20**(3): p. 389-416.  
452 11. Belayneh, M., E. Loha, and B. Lindtjörn, *Seasonal Variation of Household Food*  
453 *Insecurity and Household Dietary Diversity on Wasting and Stunting among Young*  
454 *Children in A Drought Prone Area in South Ethiopia: A Cohort Study*. 2021. **60**(1): p.  
455 44-69.  
456 12. Mezgebe, B., et al., *Seasonal variations in household food security and consumption*  
457 *affect women's nutritional status in rural South Ethiopia*. 2024.  
458 13. Sidama Regional Health Bureau, *Health Sector Transformation Plan-II*. 2021, Sidama  
459 Regional Health Bureau: Hawassa.  
460 14. Roba, K.T., et al., *Seasonal variation in nutritional status and anemia among*  
461 *lactating mothers in two agro-ecological zones of rural Ethiopia: A longitudinal*  
462 *study*. Nutrition, 2015. **31**(10): p. 1213-8.  
463 15. *UCSB CHIRPS v2p0 daily-improved (2016)*.  
464 <https://iridl.ldeo.columbia.edu/SOURCES/UCSB/CHIRPS/v2p0/daily-improved>  
465 16. Rouse, J.W., et al., *Monitoring vegetation systems in the Great Plains with ERTS*.  
466 NASA Spec. Publ, 1974. **351**(1): p. 309.  
467 17. Moussa Kourouma, J., et al., *Assessing the spatio-temporal variability of NDVI and*  
468 *VCI as indices of crops productivity in Ethiopia: a remote sensing approach*.  
469 Geomatics, Natural Hazards and Risk, 2021. **12**(1): p. 2880-2903.  
470 18. *United States Geological Survey (USGS) (May 2024)*. <https://www.usgs.gov/>.  
471 19. Landsat Missions, *Landsat normalized difference vegetation index*. US Geological  
472 Survey, 2020.  
473 20. VanderWeele, T.J., *Mediation analysis*, in *Modern epidemiology*, T.L. Lash, et al.,  
474 Editors. 2021, Wolters Kluwer: Philadelphia. p. 655-675.  
475 21. Hayes, A.F., *Introduction to Mediation, Moderation, and Conditional Process*  
476 *Analysis. A Regression-Based Approach*. Third Edition ed. 2017: Guilford  
477 publications.  
478 22. Hagos, S.G., et al., *Is the adapted Household Food Insecurity Access Scale (HFIAS)*  
479 *developed internationally to measure food insecurity valid in urban and rural*  
480 *households of Ethiopia?* BMC Nutrition, 2015. **1**(1): p. 2.  
481 23. Kabalo, B.Y., et al., *Performance of an adapted household food insecurity access*  
482 *scale in measuring seasonality in household food insecurity in rural Ethiopia: a*  
483 *cohort analysis*. BMC Nutrition, 2019. **5**(1): p. 54.  
484 24. Marcoulides, K.M., N. Foldnes, and S. Grønneberg, *Assessing Model Fit in Structural*  
485 *Equation Modeling Using Appropriate Test Statistics*. Structural Equation Modeling:  
486 A Multidisciplinary Journal, 2020. **27**(3): p. 369-379.  
487 25. Hayes, A.F., *Introduction to mediation, moderation, and conditional process*  
488 *analysis: A regression-based approach*. 2017: Guilford publications.  
489 26. Feng, S., et al., *Time lag effect of vegetation response to seasonal precipitation in the*  
490 *Mara River Basin*. Ecological Processes, 2023. **12**(1): p. 49.  
491 27. Hagos, S., et al., *Climate change, crop production and child under nutrition in*  
*Ethiopia; a longitudinal panel study*. BMC Public Health, 2014. **14**(1): p. 884.

- 492 28. Ahmed, R. and S. Ejeta Chibsa, *Undernutrition among exclusive breastfeeding*  
493 *mothers and its associated factors in Southwest Ethiopia: A community-based study.*  
494 2024. **20**: p. 17455057241231478.
- 495 29. Rajabzadeh-Dehkordi, M. and F. Mohammadi-Nasrabadi, *Food insecurity, body mass*  
496 *index, socio-economic status, and food intake in lactating and non-lactating mothers*  
497 *with children under two years.* 2023. **9**(1): p. 62.
- 498 30. Mtumwa, A.H., E. Paul, and S.A.H. Vuai, *Determinants of undernutrition among*  
499 *women of reproductive age in Tanzania mainland : original research.* South African  
500 Journal of Clinical Nutrition, 2016. **29**(2): p. 75-81.
- 501 31. Kabalo, B.Y. and B. Lindtjørn, *Seasonality and predictors of childhood stunting and*  
502 *wasting in drought-prone areas in Ethiopia: a cohort study.* 2022. **12**(11): p.  
503 e060692.  
504



# Household locations within nine rural Kebeles in the western Sidama, Ethiopia

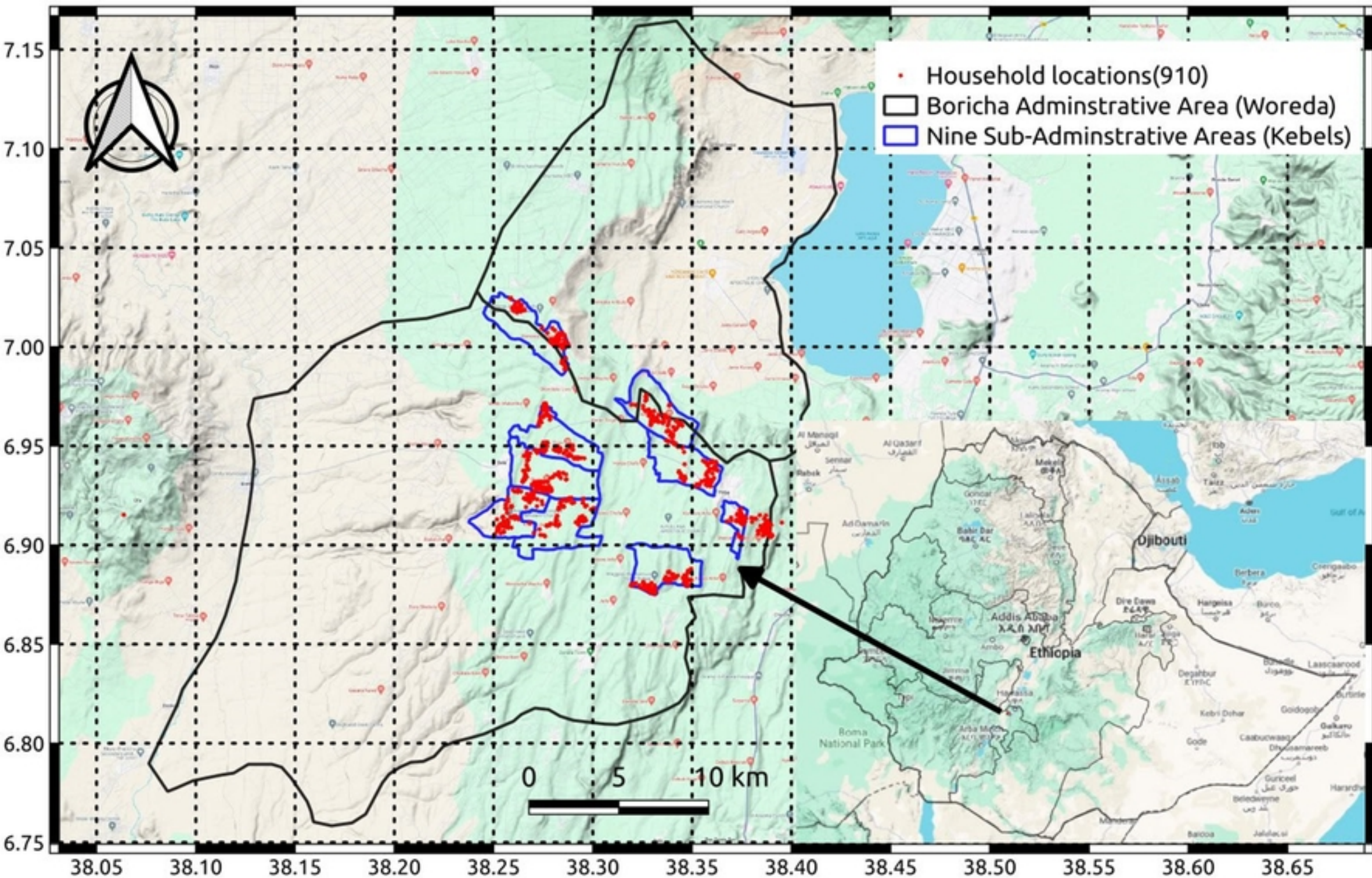


Figure 1



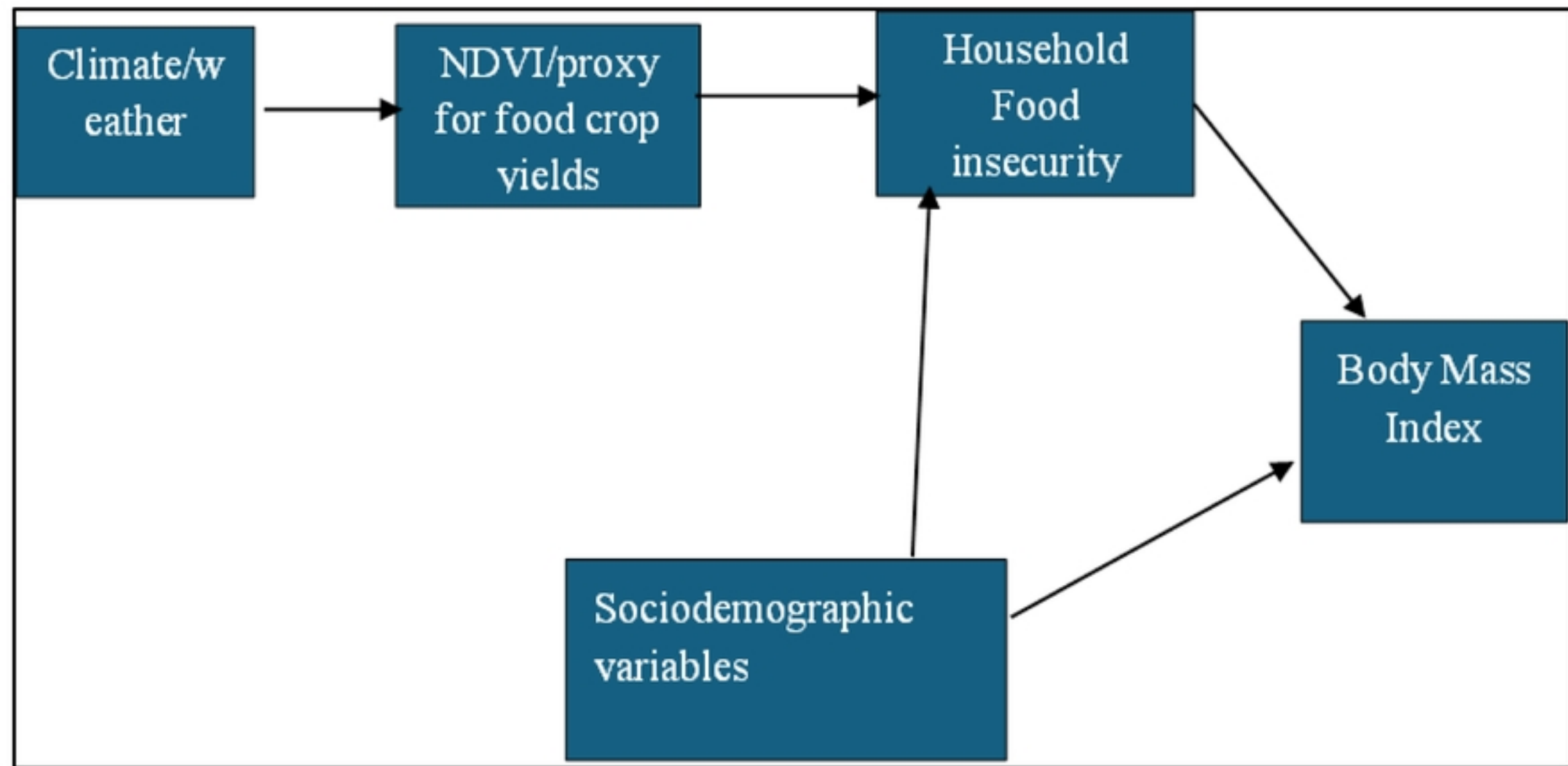


Figure 2

This manuscript is a preprint and has not been peer reviewed. The copyright holder has made the manuscript available under a Creative Commons Attribution 4.0 International (CC BY) [license](https://creativecommons.org/licenses/by/4.0/) and consented to have it forwarded to [EarthArXiv](https://eartharxiv.org/) for public posting.

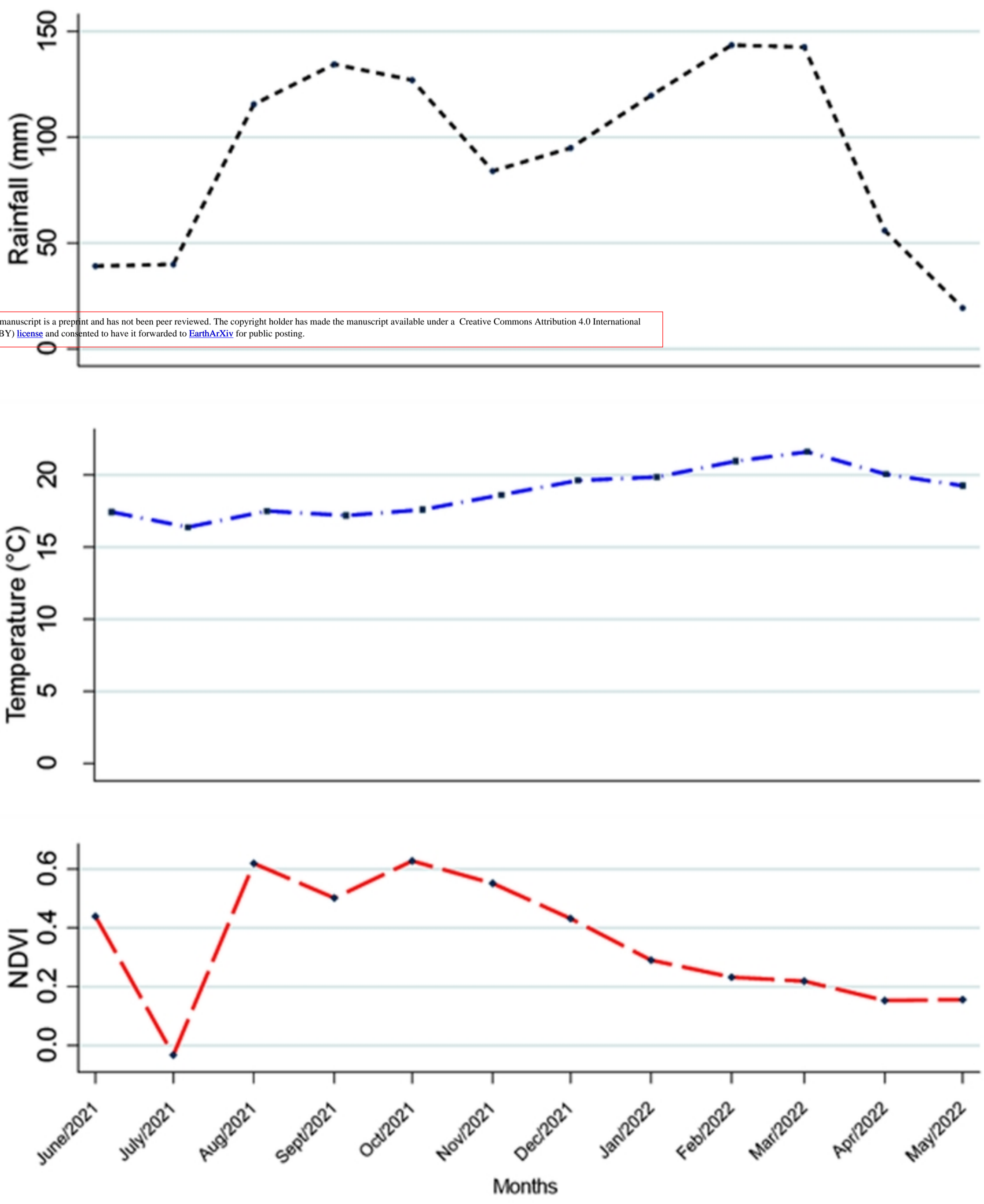


Figure 3

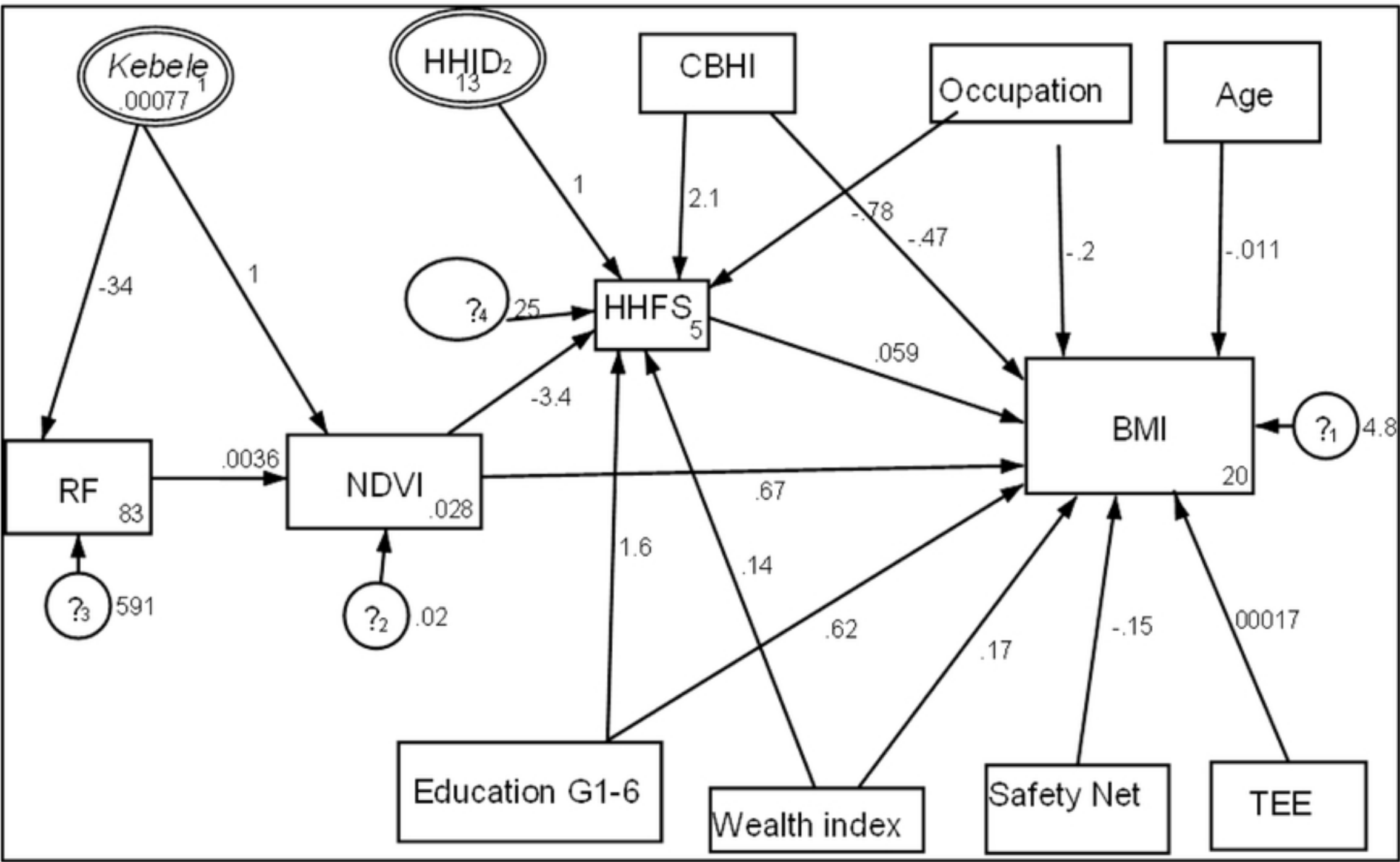


Figure 4