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Case Report

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Drought Exposure and Health Expenditure Patterns Among Farming Households in Northwestern Bangladesh

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Abstract

Farming households in Bangladesh are increasingly exposed to intensifying drought, with social, economic, environmental, and health consequences. Healthcare is also among the most expensive services in Bangladesh, which leaves farmers more susceptible to drought-related diseases. This study aimed to examine the current drought scenario and the association between drought conditions and farming households' health expenditures and healthcare in the northwestern region of Bangladesh using both primary data from the 2022–2023 production year (collected in October 2023) and secondary rainfall and temperature data from 1972 to 2022. The analysis unfolds in two segments. The Standardized Precipitation Evapotranspiration Index (SPEI) was employed to examine the current drought scenario, interpolated from two weather stations onto a 0.05° (~5 km) grid and created upazila-level summarization. Household outcomes were then estimated using a censored least absolute deviation (CLAD) model, which addresses data censoring and non-normality behavior, and a multinomial logistic regression model (MNL) in which drought exposure is measured by households' self-reported severity rather than SPEI value was used to examine the association between self-reported drought severity and households' health expenditure and choice of health services. The results reveal that household education, spouse's age, off-farm activities, credit access, use of savings, and drought severity were significantly associated with household health expenditures. Due to high out-of-pocket health expenses, health expenditure is inelastic to income, with an elasticity of 0.019 for off-farm income, stating that health expenditure rises less proportionately with household earnings. Households reporting moderate drought impact spend about 4.6% more per capita on healthcare than those reporting severe impact, and 3.22% more than those reporting weak drought. Household education, the dependency ratio, both farm and off-farm income, and drought severity were determined the choice of healthcare services. The findings of the study, while based on northwestern Bangladesh, are pertinent to other drought-affected agricultural areas in low- and middle-income nations, where climate stress, income volatility, substantial out-of-pocket health costs, and restricted access to formal healthcare similarly influence household welfare. The findings of this study suggest that health policies such as health insurance for farmers can play a necessary role in coping with drought-related diseases and high out-of-pocket expenses.

Keywords: Drought, Farming Households, Health Expenditures, Health care services, CLAD, MNL, Bangladesh.

1 Introduction

Human activities, including economic expansion, urbanization, and the rapid expansion of the Fourth Industrial Revolution, have intensified greenhouse gas emissions and have significant implications for climate change adaptation and mitigation. Global temperature (GT) has already risen by 1.2°C , and there is a 66% likelihood of breaching the threshold of 1.5°C by 2027 (BBC, 2023; The Guardian,

2023). Sea-level rise, category four and five storms, extreme rainfall, persistent droughts, and flooding now occur with greater frequency, posing severe threats to livelihoods and nutritional and physical health, while increasing morbidity and mortality rates (Anabaraonye et al., 2023; Mullins et al., 2019; Zhang et al., 2018; White, 2017). The World Health Organization estimated that approximately 12.6 million deaths each year are attributable to an unhealthy environment (WHO, 2016), and globally, approximately 58% of contaminated diseases, including malaria, dengue, diarrhea, influenza, pneumonia, and cholera, have become more frequent as a result of climate change (Varghese et al., 2023; Bosello et al., 2006). Non-communicable diseases follow a similar trajectory, with approximately 80% of related deaths occurring in developing countries (Grosskurth, 2019; WHO, 2018; Islam et al., 2014).

Bangladesh experiences a complex and interconnected set of health risks, placing it near the top of the risk index for climate-affected countries (Udmale et al. 2015; IPCC 2007). Under the nation's tropical climate pattern, the average temperature has risen by 0.5°C up to 2019, with projections indicating an additional 1.5°C rise by 2050, exposing the population to heat stress, floods, and most notably pervasive drought (WHO, 2021; Eyasmin et al., 2021; Alauddin et al., 2014). A rise of 1°C in temperature increases both communicable and non-communicable diseases by 5.7%, and a 1% increase in humidity increases them by 1.6% (Ngaruiya et al., 2022; World Bank 2021; Pattanayak et al., 2009). According to WARPO (2001), 51% of the population is highly vulnerable to drought, a vulnerability that constrains household consumption and expenditure decisions, including those relating to healthcare services.

Unlike floods, droughts have cumulative and multifaceted repercussions, with far-reaching social, economic, and health consequences transmitted through production, income stability, food security, water availability, sanitation, and healthcare (Kakoly, 2022; De Alwis and Noy 2017; Yusa et al. 2015; Lohmann and Lechtenfeld 2015). Rural livelihoods in Bangladesh depend largely on agriculture, which is reduced by drought-induced losses in production and income (De et al., 2017). These losses extend to labor productivity, so that farming households face three simultaneous pressures on overall household expenditure. Drought-induced illness worsens household health conditions and raises health expenditure precisely when income is falling, while higher out-of-pocket (OOP) expenditure, inadequate healthcare, and insufficient health professionals magnify the burden (Kabir et al., 2016; Hayashi et al., 2007; Ahmed et al., 2006; WHO, 2013). Comparable evidence shows that farmers experience substantial income loss with knock-on effects on food costs and health expenditure (Productivity Commission, 2020; Gebrehiwot & Fekadu, 2025; Birthal et al., 2021). Additionally, drought exposure is associated with a 46% higher risk of child wasting and underweight and a 0.5% increase in households health spending as a share of total expenditure (Stanke et al., 2020; EconRSA, 2022). Constrained income, together with drought-induced stressors such as poor sanitation and water scarcity, further restrict investment in preventive healthcare and nutritious food, raising the risk of illness and malnutrition. Even when health costs become inevitable, households prioritize short-term needs over long-term healthcare, reducing doctor visits or delaying medical care.

The existing literature has explored the effects of drought on health and healthcare expenditure in countries such as Vietnam, Sri Lanka, and Iran (De Alwis & Noy, 2017; Khalili et al., 2020; Lohmann & Lechtenfeld, 2015). In Bangladesh, numerous studies (Alamgir et al., 2015; Dey et al., 2011; Eyasmin et al., 2021) have examined drought patterns, agricultural vulnerability, and climate-related health risks, while Kibria et al. (2022) explored the impact of drought on agriculture and human health in the southern part of Bangladesh. Notwithstanding these contributions, the literature remains limited. OOP health expenditure among farming households has received insufficient attention as an outcome of drought exposure; Khalili et al. (2020) and Lohmann & Lechtenfeld (2015) have explained the impact of drought on health expenditure and healthcare services individually; however, two decisions are made under a single income constraint and are better analyzed jointly, and the northwestern region, which owing to its geographic location is prone to moderate to severe chronic drought (Das et al., 2023; Eyasmin, et al., 2021; Eyasmin et al., 2017; Alauddin et al., 2014), remains empirically unexamined.

The current study addresses this gap in understanding the causal relationship between rural healthcare costs and drought in northwest Bangladesh. Additionally, unlike earlier studies that examined drought, health, or expenditure separately, this study highlights how severe meteorological drought has been across the upazilas of the northwestern region and whether self-reported drought severity is associated with rural farming households' per capita OOP medical expenditures and their choice of healthcare services. The novelty of this study lies in its contribution to the exploration of regional drought assessment alongside households' health expenditure and healthcare access in northwestern Bangladesh. In treating expenditure and provider choice as parallel outcomes of a single constrained decision, the study explains why households delay or forgo care even as unavoidable costs rise and identifies where drought relief, health financing, and rural healthcare provision require coordination. This study has broader international relevance because it examines a challenge that is increasingly prevalent in numerous climate-vulnerable rural regions worldwide, beyond its local study. The evidence from northwestern Bangladesh provides valuable insights for comprehending similar drought–health–expenditure linkages in comparable scenarios throughout Asia, Africa, and other vulnerable regions.

2 Literature Review

Climate change, driven by rising temperatures and more frequent heat waves, is progressively increasing the severity and long-term effects of drought worldwide (IPCC, 2022). Among the several climate change challenges, drought stands out as one of the most complex to assess, in part because its effects accumulate slowly and are transmitted through agricultural production, rural household income, and human health rather than through immediate physical destruction. A substantial literature identifies drought as a major threat to global health, posing risks to both physical and mental well-being (Costello et al., 2009; Berry et al., 2018; Grigorieva et al., 2022; Salvador et al., 2020; Jalazadeh et al., 2022). The impacts that extend beyond immediate consequences to shape food and livelihood insecurity and to amplify existing health burden (Haines et al., 2019). Evidence from India and China further shows that drought exacerbates conflicts over water, groundwater depletion, resource scarcity, and weakens farmer's resilience (Udmale et al., 2014; Zhang et al., 2022; Khetwani et al., 2020; Quandt, 2021; Bahta & Myeki, 2022). The resilience of rural farming households is therefore directly threatened by drought, which is a severe socioeconomic and public health stressor, rather than just an environmental hazard.

Studies tracing how drought affects health outcomes describe a consistent chain running from production loss through consumption reallocation to morbidity. Drought exerts limited and ambiguous effects on household income and expenditure, forcing households to reallocate spending away from education and health to secure food (Khalili et al., 2021; Arceo-Gomez et al., 2020) and El Niño-induced droughts alter household consumption through production losses and food price rises (Kasie et al., 2020; Swain, et al., 2006; Rachunok, et al., 2023). These shifts in food consumption reduce farmers' labor productivity and weaken immunity, raising their exposure to health risks (IPCC 2022; Le et al. 2022; Salvador et al. 2022; UNDDR 2021; Sena et al. 2018; WHO 2014). Drought additionally exacerbates waterborne, mosquito-borne, food-poisoning, and other infectious diseases in developing nations (UNICEF 2019; Algur et al. 2021; Asmall et al. 2021; CDC, 2018; Gronlund et al. 2018). Where illness is left untreated for some time, it can lead to non-communicable respiratory and cardiovascular conditions that carry a risk of death (Patz et al., 2005; Lafferty et al., 2009; Rohr et al., 2011; Gage et al., 2008). The chain is thus well established up to the point of morbidity, but what happens to household spending and treatment behavior thereafter is far less well documented.

Health risk becomes a financial burden where OOP expenditure is high, since a larger share of healthcare costs is paid directly for prescriptions, drugs, and doctor visits, and such costs worsen households' health conditions while causing long-term and permanent damage (Huq et al., 2015). Confronted with unavoidable illness and limited income, households choose between paying for care and economizing on it – through a cheaper provider, postponed visit, or forgo treatment altogether.

These responses substitute for one another, yet the literature has examined them in isolation, with expenditure studies and provider-choice studies developing along separate lines. An observed increase in medical spending consequently cannot be interpreted without knowing whether the household simultaneously downgraded the type of care it sought, and a shift toward informal providers cannot be read as coping without knowing the accompanying expenditure.

In Bangladesh, drought severely affects the agricultural economy, leading to a significant decrease in agricultural production and income generation, with subsequent impacts on human health (IPCC, 2007; Udmale et al., 2015; Khalili et al., 2020). Farming households also work under direct exposure to weather, which makes them more susceptible to health risks and income and productivity loss. Existing research (Adnan et al., 2018; Lechtenfeld et al., 2014; Mukherjee et al., 2018) has revealed the detrimental effects of drought on physical health and the resulting increase in healthcare costs, particularly among households that are heavily reliant on agriculture and lack adequate coping mechanisms. Rural households that depend heavily on agriculture for their livelihoods are especially vulnerable to the adverse effects of drought. A parallel body of work has examined catastrophic health expenditure and its determinants, including climate shocks (Alam et al., 2024; Alam et al., 2022; Datta et al., 2018; Begum et al., 2021; Huq et al., 2015). These two strands have nonetheless remained largely unconnected, and neither has focused on the drought-prone northwestern region, where rural households depend most heavily on agriculture for their livelihoods.

What emerges from this literature is a set of resolved gaps. The literature traces drought to morbidity in considerable detail, but short of OOP health expenditure among farming households as an outcome of drought exposure. Expenditure and healthcare access have been analyzed separately, although both are responses to a single income constraint and are interpretable only in relation to each other. Index-based studies use the Standardized Precipitation Index (SPI) to map the spatial distribution of meteorological drought and its associated health risks (Alamgir et al., 2015; Dey et al., 2011). What they capture is the climatological environment surrounding the household, not the exposure the households themselves report. Survey-based studies, on the other hand, capture the latter, recording perceived severity at the level at which spending and treatment decisions are actually made. Few studies employ both, leaving regional drought assessment and household outcome analysis to proceed on different tracks. These divisions are reinforced by a methodological literature in which distributed lag models establish a direct relationship between temperature and mortality (Yang et al., 2012; Almeida et al., 2010), fixed effects models capture climate shocks as confounding factors (Berhane, 2015; Lohman et al., 2015), generalized structural equation models, quantile regression, and standard consumption regression identify the drivers of catastrophic health impacts (Gari et al., 2024; Lechtenfeld et al., 2014; Khalili et al., 2021), and Bangladeshi studies rely predominantly on binary logistic regression. Health expenditure is nevertheless censored at zero and heavily skewed, and provider choice is genuinely multi-category rather than binary. Since, estimators that ignore censoring or collapse provider alternatives discard the variation of interest. The present study addresses these gaps by pairing a regional drought assessment with a household-level analysis of both medical expenditure and healthcare service choice in northwestern Bangladesh.

3 Research Design

3.1 Data Sources

Droughts are more likely to affect the northwestern region of Bangladesh owing to its geographical characteristics. According to the BMD report (2022), the northwestern region experienced 89% less precipitation than in previous years. Nature-based livelihoods, health, and overall human life are stressed by heatwaves and droughts.

Both primary and secondary data were used to conduct the study. Secondary data for rainfall and temperature were obtained from the Bangladesh Bureau of Statistics (BBS). Face-to-face interviews and a well-structured and pre-tested questionnaire, including farmers' perceptions of drought, health expenditure, and decisions on accessing health care services, were used to conduct the survey during the production year 2022–23. The data collection process was conducted in October 2023. Because health expenditure is not incurred regularly, households reported their annual health expenditure during the production year 2022–23, which was subsequently converted to a monthly per capita basis.

Because of time and budget constraints, two districts, Pabna and Natore, from the Northwestern region, and two Upazilas (sub-districts), namely Ishwardi from Pabna and Lalpur from Natore, were selected purposively based on the following characteristics: (a) agriculture is the primary source of income, (b) it is a drought-prone area, and (c) it has a subsistence population. Furthermore, both Natore and Pabna belong to the Barind tract and are characterized by low rainfall, high evapotranspiration, and persistent groundwater depletion. Several studies (Sadiq, et al., 2023; Zhu, et al., 2025) have found that 30% of the land in Rajshahi, Natore, Pabna, and Naogaon experienced moderate-to-severe drought during the last few decades. Because the number of farming households differed significantly between upazilas, an equal number of households were chosen randomly within each upazila. The desired sample size was calculated using an equation that aligned with previous studies (Kanyenji et al., 2021a; Kanyenji et al., 2020):

$$n_0 = \frac{z_{tab}^2 d(1-d)}{me^2} = \frac{(1.96)^2 \times 0.5 \times 0.5}{(0.06)^2} = 267 \approx 300$$

where, n= sample size

z = tabulated z-value at the 95% level of significance.

d = estimate degree of variability

me = margin of error

The constraints of time, cost, accessibility, and respondent variability required errors of margins that balance statistical reliability against feasibility. A household survey commonly adopts errors of margin between 5% and 10% (Cochran, 1977; Israel, 1992). The current study used 6% of precision level to reduce statistical discrepancy (Kanyenji et al., 2020). The formula returns 267 and sets a target of 350 and 300 retained after fixing missing and incomplete information which is evenly distributed throughout the selected Upazilas. Therefore, 175 farming households were randomly selected using the lists provided by the agriculture extension officer. As it is difficult to collect expenditure data from households, to reduce the risk of missing or incomplete information, recording errors, and no response, a 13% sample reserve was used. A final sample of 300 households was therefore used to explain the study.

Ethical Consent: This study was reviewed and approved by the Research and Ethical Committee, Department of Economics, PUST, Reference PUST, ECO/23/11(8), approved 22 November 2023, chaired by Professor Dr. Mir Khaled Iqbal Chowdhury. The study was conducted in accordance with the ethical principles set out in the Declaration of Helsinki for Social Science and with the data protection requirements of the Government of Bangladesh. All participant knew and approved verbally for using their information anonymously. No identifying information has available in the study or supplementary documents.

3.2 Methodology

3.2.1 Meteorological Drought Index

There are four types of droughts: meteorological (low rainfall), hydrological (water level deficiency in streams), agricultural (low soil moisture), and socioeconomic (high water demand) (Wilhite, 1985).

Agricultural drought is pertinent here, as it directly indicates soil moisture deficit and crop stress, and the study sample consists of farming households. Additionally, agricultural drought requires long-term data on soil moisture, crop-water ratio, evapotranspiration, and crop stress, which are no longer available for the study area. Since the study area has experienced low precipitation and high temperatures (Eyasmin et al., 2017), meteorological drought is the appropriate index. Unlike other droughts, including agricultural drought, which is attributed to soil moisture depletion, meteorological drought reflects the combined influence of low rainfall and high temperatures. The impact on households' health has already emerged immediately with the onset of meteorological drought, rather than subsequent to the depletion of soil moisture. Because the study focuses on households' health expenditure, SPEI is an appropriate index for characterizing drought conditions relevant to households' health. To examine meteorological drought, several methods, such as the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Reconnaissance Drought Index (RDI), are used. Due to limited regional data on soil moisture, complex water balance calculations, PDSI, and RDI cannot be used. Additionally, these advanced methods are used to calculate global warming (Vicente-Serrano, et al., 2010). SPEI has its advantages in flexibility, simplicity, and data availability. Furthermore, Bangladesh is characterized by seasonal drought lasting for 3–5 months. SPEI can capture this seasonal drought. This advantage of SPEI helps in calculating metrological drought over SPI.

The SPEI was proposed by Vicente-Serrano et al. (2010), building on the potential evapotranspiration method of Thornthwaite (1948). This method is widely used for its simplicity and applicability as a multiscale drought assessment that incorporates rainfall and temperature together.

The method was calculated using a multiscale assessment. First, climatic water balance is evaluated by $WB_i = Prcp_i - Pe_i$

Where, $WB_i = \text{Climatic Water Balance at time } i$.

$Prcp_i = \text{Rainfall at time } t$

$Pe_i = \text{Potential Evapotranspiration}$

And, Pe_i is calculated by $Pe_i = 16 \left(\frac{10MT}{HI} \right)^\beta$

Where, $MT = \text{Mean temperature}$,

$HI = \text{Heat Index}$

And then SPEI calculated by,

Equationally, $SPEI = \frac{WB_i - \mu_i}{S_i}$

Where, $WB_i = \text{Climatic Water Balance}$

$\mu_i = \text{Mean Water Balance}$.

$S_i = \text{Standard deviation of Water Balance}$.

Table 1: The classification of Metrological Drought based on SPEI (Vicente-Serrano, et al., 2010)

Range	Drought Definition
$+2 \leq SPEI$	Acutely wet
$1.5 \leq SPEI < 2$	Severely wet
$1 \leq SPEI < 1.5$	Moderately wet
$-1 \leq SPEI < +1$	Normal
$-1.5 \leq SPEI \leq -1$	Mild Drought

$$-2 \leq SPEI < -1.5$$

$$SPEI < -2$$

Moderate Drought
Extreme Drought

The SPEI ranges between +2 and – 2. If the SPEI is higher than +2, the area is acutely wet, and if the SPEI is lower than -2, the area is critically drought prone (Vicente-Serrano, et al., 2010). Rstudio was used to extract SPEI values and generate a map of SPEI in the study area. The 3-month SPEI was used to conclude drought conditions. After extracting the SPEI, 12 values were generated for each year and only the minimum SPEI was used to capture drought perfectly. Therefore, the spatial resolution of the drought index is the upazila rather than the 5 km grid cell. The grid serves as an intermediate surface for cartographic display and zonal aggregation, and because it is derived from only two observation stations (Ishwardi and Natore), differences between adjacent cells within an upazila reflect distance weighting rather than independent measurement. The upazila-summarised gridded data is employed to delineate the drought characteristics, however, excluded from the estimation and used to confirm the households' self-reported drought severity for the 2022-23 production year in Northwestern Bangladesh.

3.2.2 Standard Consumption Regression

A reduced form of the standard consumption regression was used to analyze the association between self-reported drought and farmers' health expenditure. This approach is widely used in relevant studies (Lohmann et al. 2015; Arouri et al. 2015; Bui et al. 2014) for its inclusion of a dummy variable for drought occurrences. If $\ln(Z_i)$ is the per capita health expenditure for i th household, which includes hospitalization costs, doctor fees, test fees in some hospital admissions, and operation costs.

Then,

$$\ln(Z_i) = \beta + \sum_{n=1}^k \alpha_n D_{nj} + \delta_1 Y_{hj} + \gamma_2 K_j + \mu_h$$

Where, Z_i = Per capita health expenditures (out-of-pocket expenditure) of household h in village j

Y_{hj} = household's characteristics

K_j = healthcare characteristics

D_{nj} = the degree of affected by drought.

n = the severity of drought occurring in last 12 months.

Some households implemented adaptation strategies against drought, such as irrigation, pest control, and insect-tolerant varieties, thereby reducing their vulnerability to drought. Some households reported no health expenditures during 2022–23, which were assigned to the value zero rather than missing data. This makes the response heteroscedastic and non-normally distributed. If the error term is homoscedastic and normally distributed, the Tobit regression is appropriate. Thus, the Breush-Pagan (345.43) (BPG) test for homoscedasticity and the conditional moment (148.2) (CM) for normality test and both are statistically significant at 1% level of significance, i.e. the error term is heteroscedastic and non-normally distributed. Therefore, heteroscedastic and non-normally distributed error term suggested that Tobit model is not appropriate here to explain the farming household's health expenditure. On the other hand, according to the assumptions of Heckman selection model (HSM), dependent includes some regressors which are not included in independent and dependent variables never be censored for selection. Sometimes, it is too hard to find such an excluded variable and may induce high level of multicollinearity which induce to choose another model rather than HSM (Kelifa, 2023). Therefore, data is continuous, and the observed values are integers, the double-hurdle model capture true distribution (Mullahy, 1998). Since, the data is small and below the threshold i.e. left censored and the error term needs to be robust to heteroscedasticity and normally distributed, the Censored Least Absolute Deviation (CLAD) Method was used to estimate farming households' health expenditure, which was proposed by Powell (1986). Additionally, several studies (Khalili et al. 2020; and Lohmann

322 & Lechtenfeld, 2015) used the CLAD model in same left-censored data. Moreover, the CLAD
 323 coefficients explain how it impacts the median of the left-censored, which is restricted to zero, and the
 324 restrictions need to be robust to outliers and skewed error terms, which makes the model more preferable
 325 for the study. In the meanwhile, the mean VIF is 1.34 which indicates that there is no multicollinearity
 326 in the variables.

327

Table 2: Variables used in the study

Dependent Variables	Measurement Unit	Type	Statistics/ Frequency	Priori Expectation
Per capita health expenditure	Taka annually (in thousands)	Continuous	Mean = 10.67 (SD = 3.87)	
Healthcare services options	1=Public healthcare services 2=Private healthcare Services 3=Pharmaceutical Stores 4= Homeo Services 5= Traditional (Herbal) Service 6= Self-medication (take non-prescribed medicine by their own experience)	Categorical	1: n=78 2: n=94 3: n=35 4: n=43 5: n=21 6: n=29	
Explanatory Variables				
Gender	1 for male, 0 for female	Dummy	1: n=205 0: n=95	+
Household Head's Age	Years	Continuous	Mean = 45.31 (SD = 10.66)	+
Household Head's Education	Years of Schooling	Continuous	Mean = 4.47 (SD = 4.16)	-
Spouse Age	Years	Continuous	Mean = 35.98 (SD = 19.61)	+
Spouse Education	Years of Schooling	Continuous	Mean = 1.77 (SD = 3.01)	-
Dependency Ratio	Percentage	Continuous	Mean = 69.53 (SD = 40.91)	+
Off-farm income	Annual Taka (in thousands)	Continuous	Mean = 9.47 (SD = 7.25)	-
Farm Income	Annual Taka (in thousands)	Continuous	Mean = 1.9902 (SD = 1.4209)	-
Distance to healthcare canter	Kilometres (Km)	Continuous	Mean = 6.66 (SD = 5.31)	+
Credit Access	1 for have access credit, 0 otherwise	Dummy	1: n=98 0: n=202	+
Use Savings	1 for use saving, 0 otherwise	Dummy	1: n=171 0: n=129	-
Severe Drought (1/0)	1 for experiencing severe drought, 0 otherwise	Dummy	1: n=45 0: n=255	+
Moderate Drought (1/0)	1 for experiencing moderate drought, 0 otherwise	Dummy	1: n=193 0: n=105	+
Weak Drought (1/0)	1 for experiencing weak drought, 0 otherwise	Dummy	1: n=62 0: n=238	+
Precipitation – Natore	mm	Continuous	Mean = 119.50 (SD = 136.45)	
Temperature – Natore	°C	Continuous	Mean = 25.90 (SD = 4.44)	
Precipitation – Ishwardi	mm	Continuous	Mean = 129.21 (SD = 147.04)	
Temperature – Ishwardi	°C	Continuous	Mean = 25.74 (SD = 4.69)	

328

329 3.2.3 Multinomial Logit Model

330 The health care services defined as the different methods of healthcare as like private and public
 331 hospital, medicine store, homeo treatment and self-medication. Since, the choice of utilization is

categorized into more than two variables, Multinomial Logit (MNL) was employed to explain the utilization of health care choice (Maddala, 1983).

If Y_i is the choice of health care services, then, $P(Y = m/X)$, $m = 1, 2, 3, \dots, m$. If X be a $1 \times K$ vector, The MNL model has express as

$$P(Y = m/X) = \exp(X\beta_m) / \left[1 + \sum_{h=1}^m \exp(X\beta_h) \right], m = 1, 2, 3, \dots, m$$

Where, $\beta_m = K \times 1, m = 1, 2, 3, \dots, m$

The assumption of MNL holds only then, when the parameters were unbiased and consistent. In this regard, respondent responses one opinion which they often use or otherwise. However, to explain actual change in respect to the independent variables which express the marginal effects, stated that,

$$\frac{\delta P_m}{\delta P_n} = P_m \left(\beta_{mn} - \sum_{m=1}^{m-1} P_m \beta_{mn} \right)$$

The marginal effects explain the change of choice made in response to explanatory variables. (Fatuae et al., 2014; Deressa et al., 2009; Green 2000).

4 Results and Discussion

4.1 Meteorological Drought in the Study Area

Figures 1 and 2 explain SPEI in the Natore and Pabna districts, respectively. We extracted the metrological drought for the monthly rainfall and temperature data from BBS (2023) between 1972 and 2022 from two stations and mapped the drought intensity for 2022 by R for Pabna and Natore Districts. The inverse distance weighting (IDW) method was used to create an observation-based gridded dataset that was interpolated to a regular grid of 0.05° (~ 5 km) owing to the inadequate station density to account for exposure at any single point in the study area. To compare across the region, the 3-month SPEI was calculated and created from the observed-based gridded data for spatial visualization and interpolation and summarized at the upazilas of the Pabna and Natore districts. Monthly rainfall data for the years 1972–2022 were used to map a 3-month SPEI for 2022. Here, after extracting, 3-months SPEI, 12 values were generated for each year. For 2022, the study used only the lowest value of 3-month SPEI to capture the severe drought significantly.

The upazilas (sub-districts) were categorized into seven categories of extremely dry, moderately dry, mild dry, mild wet, moderately wet, very wet, and extremely wet. According to Fig. 1, drought severity in Natore district was moderately high. However, a few wetlands, such as Chalan beel and local rivers, kept some areas wet, where Singra Upazila was recognized as extremely dry. Several studies (Ghosh et al., 2015; Alauddin, 2014) found an upward trend in drought intensity.

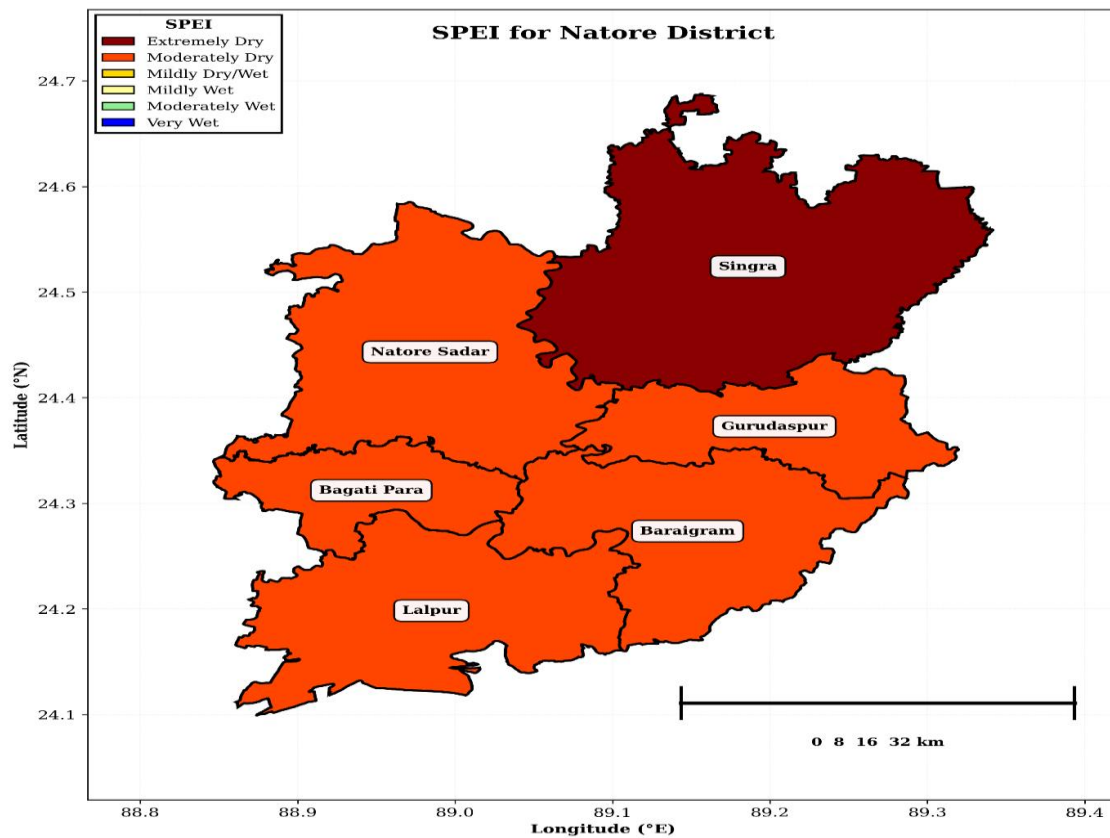


Figure 1: Drought Scenario 2022 for Natore District, Bangladesh

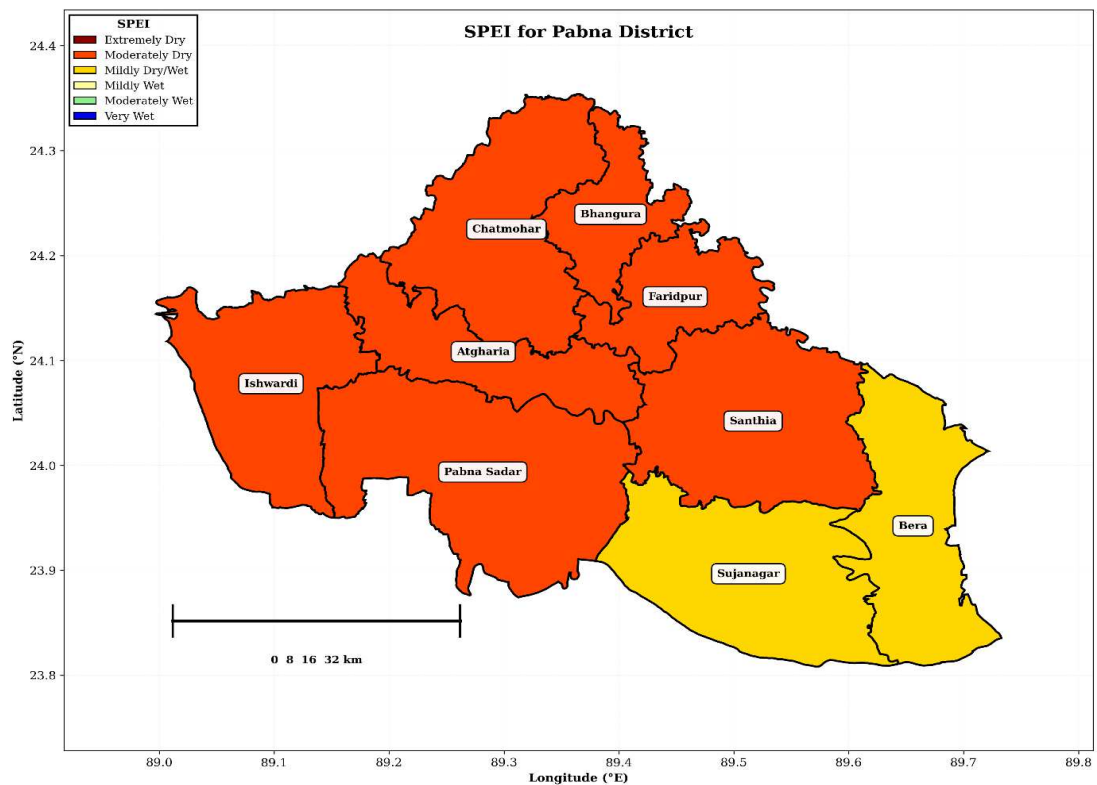


Figure 2: Drought Scenario 2022 for Pabna District, Bangladesh

As Figure 2 shows, the Pabna district is also highly vulnerable to moderate drought. The district has several rivers, including the main rivers of Padma and Jamuna and Beel (low-lying water land) in Sujanagar and Bera, which make those areas mild dry, and the other area has high drought intensity. Rising temperatures and declining precipitation worsen the drought conditions in the study area (BMD, 2022; Eyasmin et al. 2017). Warmer temperatures, erratic precipitation, and heightened evapotranspiration exacerbate climate change and drought intensity in Bangladesh. Earlier literature (Kamruzzaman et al., 2022; Khan et al., 2020) has found a rise in the frequency and severity of SPEI-based droughts in Bangladesh, which requires understanding drought in relation to both agriculture and health. Comparing two districts, Natore experiences more severe drought than Pabna. The growing intensity of drought in the study area is significantly linked to global climate change. The northwestern region of Bangladesh is projected to be one of the most vulnerable areas to meteorological droughts as a result of ongoing warming, according to Khan et al. (2020), who used a bias-corrected CMIP5 multi-model ensemble operating under a high-emission (RCP8.5) scenario. The study computes SPEI only for the observed record (1972-2022) and does not model future projections (Khan et al., 2022; Kamruzzaman et al., 2022).

4.2 Regression Analysis

The SPEI values are gridded (0.05° , ~ 5 km) from two stations, interpolated at the upazila level. Figures 1 and 2 illustrate the climatology of regional droughts and are not used as model regressors. The CLAD and MNL models incorporate household-level variables, including the logarithm of annual per capita health expenditure and the selection of health care services, with self-reported severity indicators (severe, moderate, weak) for the years 2022–23. As GPS coordinates for households were not collected, the upazila is the best common spatial unit for both data sources, and each sampled household is assigned the SPEI class of its upazila of residence. The corresponding results confirm that reported drought experience is consistent with the interpolated climatology shown in Figures 1 and 2. However, SPEI values were not used to identify any household effects.

4.2.1 Farming Household's Log Annual Per Capita Health Expenditure

Table 3 presents the CLAD regression of rural farming households' per capita health expenditure. The model expresses the influence of household head's age, education, spouse's age, education, dependency ratio, off-farm income, farm income, distance from the health care center, credit access use savings for treatment, and severe, moderate, and weak drought. Since 32 out of 300 samples reported no health expenditure, per capita health expenditure was censored at zero, requiring censored estimation. Before proceeding with the estimation, the Variance Inflation Factor (VIF) for multicollinearity and Breusch-Pagan (BPG) test were performed to check multicollinearity and heteroscedasticity. The mean VIF was 1.34, indicating that there was no multicollinearity. However, health expenditure varied highly among households, which increased variance and the Breusch–Pagan (BPG) test for heteroscedasticity confirmed that. To reduce this heteroscedasticity, per capita health expenditure was log transformed.

Household Head's Education

Household head's education shows a negative relation with health expenditure, which is significant at 5% level of significance. According to the estimation, each additional year of schooling reduces median per capita health expenditure by 2.8%. Higher educated heads take preventive measures against health hazards and pursue potential self-care through health literacy, thereby reducing the incidence and severity of illness and the need for costly health care. Educated heads of households may also have a greater propensity to comprehend and employ insurance or alternative risk-management strategies, potentially reducing out-of-pocket costs. This finding is consistent with Ehrlich et al. (2006) and Fletcher et al. (2009).

Table 3: Estimation of Farming Household's Log Annual Per Capita Health Expenditure

Explanatory Variable	Coefficient	Standard Error
Household Head's Age	-0.000016	0.00421
Household Head's Education	-0.028016**	0.01351
Spouse Age	-0.004296*	0.00254
Spouse Education	-0.009353	0.01356
Dependency Ratio	-0.216964	0.17539
Off-farm Income (Tk '000)	0.000580*	0.00034
Farm Income (Tk '000)	0.000431*	0.00026
Distance of Healthcare Centre	-0.005419	0.01369
Credit Access	0.067943***	0.00963
Use Savings	0.0152377*	0.00931
Severe Drought (1/0)	0.052984**	0.02801
Moderate Drought (1/0)	0.099061***	0.02672
Weak Drought (1/0)	0.066876***	0.03229
Pseudo R²	0.2468988	
Note: ***, **, and * represent 1%, 5%, and 10% significance levels respectively		

Source: Author's own Calculation

Spouse Age

The spouse's age is negatively correlated with health expenditure, albeit only at the 10% level of significance, indicating a reduction in out-of-pocket (OOP) health expenditure as the spouse grows older. A possible explanation is that older spouses often move away from strenuous and perilous physical work to less intensive supervisory positions, thus diminishing their risk of physical injuries and acute health problems arising from farm labor. Cumulative experience of regional disease trends and healthcare systems may provide more efficient preventative actions and prompt, cost-effective healthcare utilization, thereby reducing the frequency of expensive medical care. This trend conforms with previous studies in rural Bangladesh, indicating that wealth, health shocks, and household demographic characteristics frequently overshadow more gradual demographic influences in accounting for differences in out-of-pocket health spending (Molla et al., 2017; Rahman et al., 2024).

Farm and Off-farm Income

Both farm and non-farm activities are significantly associated with health expenses. The positive sign on the coefficients suggests that households with greater opportunities for farm or off-farm work tend to allocate more expenditure towards health expenses. Although the effects are small for both off-farm ($\beta = 0.00058$, $p < .10$) and farm income ($\beta = 0.000431$, $p < .10$). an additional ten thousand takas of off farm and farm income raises per capita health spending by 0.58 % and 0.431%. A likely reason for the results is that health costs, including diagnostics, medication, and travel, are also rising in parallel, so the gap between income and health spending remains unchanged. High inflation erodes real income, which cannot minimize the gap between income and the high cost of health in terms of diagnostics, visits, and medicine costs. Lohmann et al., (2015) also revealed that off-firm income is positively associated with health expenses.

Credit Access

The association between access to credit and substantially greater health expenditure ($\beta = 0.0679$, $p < .01$) suggests that credit alleviates liquidity constraints and allows households to support more extensive or expeditious healthcare. This corroborates theoretical and empirical studies showing that current liquidity and access to credit are decisive in determining when households seek medical care, given out-of-pocket costs and inadequate insurance opportunities. Access to credit alleviates these limitations, allowing households to pursue more extensive and prompt care—such as trips to advanced facilities and prescribed medications—resulting in increased out-of-pocket expenditures. This finding aligns with that of Islam et al., (2024).

Use of Savings

Health expenditure is positively related to the precautionary savings of households at the 10% level of significance. This means that savings increase health expenses by 1.5%. As out-of-pocket expenditure and simultaneous health risks are higher in Bangladesh, households often forgo treatment due to their low income and financial access. Household savings are a rational adaptation that makes treatment affordable and strengthens the health safety net. This result is similar to that of Srivastava et al. (2023) and Beylik et al. (2022).

Drought Shocks

Drought conditions are a prominent indicator that intensifies the demand for treatment and healthcare services and is positively associated with health expenditures. Drought poses a significant threat to health, increasing susceptibility to illness through greater exposure and reduced capacity to cope. Weak drought raises increased the health expenditure by 6.69%, moderate drought by 9.90% and severe drought by 5.29%. This finding indicates that drought severity raises OOP expenditure through heightened morbidity, weakened coping capacity, and greater dependence on costly private healthcare (Rahman et al., 2024; Dey, 2011; Ghosh et al., 2026). Salvador et al. (2022), Alam et al. (2022), and Lohmann et al. (2015) found a similar result.

4.2.2 Elasticity of Farmer's Health Expenditure

Table 4 shows how the various explanatory variables affect the elasticity of health expenditure for the CLAD model. All estimated elasticities are less than one in absolute value; therefore, health expenditure is inelastic with respect to head's education, off-farm income, credit access, savings, and drought severity.

The elasticity of the household head's education is significant at the 10% level. This indicates that a 10% increase in the household head's education may decrease health expenditure by 0.27%. Educated individuals may adopt healthier lifestyles, access cheaper, more effective, and better healthcare and preventive measures, leading to a reduction in health costs. This result is consistent with that of Shimul et al. (2023).

The elasticity of off-farm income to health spending in CLAD is statistically significant at the 10% significance level, meaning that a 10% increase in off-farm income results in an approximate 0.2% increase in health expenditure. Households with off-farm income undertake routine check-ups, purchase supplements, and seek early diagnosis during drought seasons that incur treatment costs. Ahmed et al., (2016) reported similar findings.

Table 4: CLAD Estimation of Elasticity of Farmer's Health Expenditure

Explanatory Variables	Coefficient	Standard Error
Household Head's Age	0.000338	0.00499
Household Head's Education	-0.027717*	0.01705
Spouse Age	-0.004113	0.00283
Spouse Education	-0.002437	0.01756
Dependency Ratio	-0.276088	0.21911
Farm Income	-0.039381	0.08657
Off-farm Income	0.0192732*	0.011116
Distance of Healthcare Centre	0.001757	0.02175
Credit Access	0.630871***	0.11080
Use Savings	0.196660*	0.10191
Severe Drought (1/0)	0.509638***	0.16306
Moderate Drought (1/0)	0.536715***	0.16054
Weak Drought (1/0)	0.491167***	0.105932
Pseudo R ²	0.231210	

Note: ***, **, and * represent 1%, 5%, and 10% significance levels respectively

Source: Author's own Calculation

The elasticity of credit access and savings is positively associated with health expenditure. The results suggest that households with credit access and savings are associated with per capita health expenditure of approximately 87.79% ($100 \times [\exp(0.630871) - 1]$) and 21.7% than households without credit access or savings. The size of this difference indicates that credit and savings functions primarily as a financing mechanism for treatment costs already incurred rather as a determinant of the decision to seek care. This finding is also supported by Williams et al., (2022) and Borde, et al., (2022).

The intensity of drought is a key variable associated with health spending. The coefficients of the three drought conditions of severe, moderate, and weak of 0.052984, 0.099061, and 0.066876, respectively, report group-specific conditional medians. Moderate drought surpasses severe drought by 4.61% and weak drought by 3.22% at the 1% level of significance. Households are suffering most from those diseases which have occurred from moderate drought intensity. Perhaps this is because moderate droughts tend to be more frequent and widespread, leading to a cascade of negative health effects, such as heat exhaustion, dehydration, water scarcity, and the rapid decline in nutrition and sanitation, which incur medical costs. In contrast, severe drought occurs after moderate drought, which reduces income, government fiscal strain, and puts extra pressure on medical workers and households who have already suffered from a financial crisis that has started from weak drought. Zare et al., (2013) and Getzen (2000) found similar results for drought conditions in different countries.

4.3 Determinant of Choice of Health Care Service

Table 5 reports the estimation of the marginal effects of the MNL model of healthcare services. The farmer's healthcare decision was calculated based on the choice of healthcare services. The healthcare decision was measured as the choice among six providers, such as public services, private services, pharmacies, homeo services, traditional services, and self-medication. Each household was assigned to exactly one category according to the service used for the most recent illness episode, and the six categories together cover all sample households. Self-medication was used as the base category, and all marginal effects are reported relative to it. The Wald 114.69 is significant at the 5% level of significance. of The Box Tidwell test p-values exceed 0.005 (Appendix Table A2), indicating that the continuous regressor is linear in the logit To assess the choice of independence, the Hausman-McFadden test was used to omit each alternative in turns, which is reported in Appendix Table A3. The findings provide evidence consistent with the assumptions. Furthermore, the average VIF for the independent variables is 1.94, which indicates that there is no multicollinearity among the variables, revealed in table A1 in Appendix.

According to the results, education is negatively associated with public health services at the 10% level of significance. Each additional year of schooling reduces the probability of using public services by 0.88% relative to self-medication. Due to the lack of sufficient logistic support, including technical equipment, efficient medical staff, and inadequate doctors in public services, higher educated farming households try to choose other services. However, education has a positive and significant relationship with private services and pharma stores by 0.46% and 0.87%, respectively, over self-medication. The logistic support of private services is better than that of public services, and households take services for minor treatment. This finding is similar to that of Gao et al. (2022).

Spouse age was significantly associated with public and private services and pharma stores by 0.26%, 0.26%, and 0.2%, respectively. These results suggest that older spouses seek treatment at nearby facilities. Each upazila provides low-cost public services, which may draw households away from private services and pharmacies relative to self-medication. These results are followed by Turyamureba et al., (2023).

The dependency ratio is positively associated with the use of public health services in response to self-medication. This indicates that households' probability of choosing public health services increases by 1.323% if the dependency ratio increases by 1%. The probable reason for this result is that a higher number of dependent members increases logistic costs, including doctor fees, test costs, and medicine costs, which force households to avail public services. Further, households prefer to meet food expenditure over health expenditure, which leads them to prefer public services over self-medication. This finding is in line with that of Xu et al. (2022).

Higher off-farm income reduces the use of public and traditional services while increasing the use of private services. Off-farm income increases farmers' total income, which influences their access to better treatment. A one-unit increase in off-farm income raises the probability of choosing private services and pharma stores by 5.7% and 3.9%, respectively. This finding is also supported by Liu et al. (2019). Higher off-farm income reduces the use of suggestions from pharma stores and homeo services relative to self-medication. However, rising farm income is sufficient to avail public treatment services by 7.9% and homeo services by 5.8% than self-medication. On the other hand, if households have savings, they use them for better treatment. Use of savings has positive and significant impact on household's health expenditure which has increased the preference to choose private services by 6.90% over self-medication.

Table 5: Results of the marginal effect of the MNL model of Healthcare Services

Explanatory Variables	Public Service	Private Service	Pharma Store	Homeo Service	Traditional Service	Self Medication
Age	- 0.00063 (0.0033)	0.00108 (0.0035)	0.00154 (0.00155)	- 0.0010 (0.0020)	- 0.00010 (0.00091)	-0.00086 (0.0019)
Education	- 0.0088* (0.0085)	0.0046* (0.0090)	0.0087** (0.0040)	- 0.0049 (0.0047)	- 0.0018 (0.0022)	0.00229 (0.00463)
Spouse Age	0.0026* (0.0017)	- 0.0026* (0.0018)	- 0.002*** (0.0009)	0.000406 (0.0011)	0.00045 (0.00053)	0.00132 (0.00114)
Spouse Education	- 0.0131 (0.0119)	- 0.0060 (0.0118)	0.0059 (0.0054)	0.00018 (0.00735)	0.0037 (0.0029)	0.00924* (0.00558)
Dependency Ratio	0.01323* (0.00828)	- 0.01299 (0.01302)	0.0233 (0.0423)	0.0048 (0.0537)	- 0.0363 (0.0343)	0.00512 (0.05589)
Off Farm Income	-0.0026 (0.0034)	0.0070** (0.0033)	0.0048** (0.0020)	-0.0036 (0.0032)	-0.0032 (0.0023)	-0.0024 (0.0026)
Farm Income	0.0073*** (0.0022)	0.0005 (0.0027)	-0.0036 (0.0022)	-0.0053** (0.0026)	0.0018 (0.0011)	-0.0006 (0.0018)
Distance to healthcare	0.0069 (0.00540)	0.0074 (0.0052)	- 0.0038 (0.0072)	0.0014 (0.0032)	- 0.0117*** (0.0035)	0.00089 (0.00475)
Credit Access	- 0.0145 (0.0714)	- 0.0327 (0.0707)	- 0.0094 (0.0336)	0.0801 (0.0404)	- 0.0145 (0.0186)	-0.00737 (0.03815)
Use of Savings	- 0.0683 (0.0631)	0.0690** (0.066)	- 0.0190 (0.0366)	- 0.0062 (0.0419)	- 0.0154 (0.0204)	0.04761 (0.04006)
Severe Drought	- 0.1411 (0.1266)	0.0742** (0.147)	- 0.0041 (0.047)	0.01905 (0.3108)	- 0.0203 (0.0218)	0.24561** (0.10591)
Moderate Drought	- 0.1955 (0.154)	0.0092* (0.166)	0.0344 (0.0565)	- 0.0358 (0.3137)	0.01709 (0.0255)	0.18824* (0.11358)
Weak Drought	- 0.1148 (0.13)	- 0.088 (0.15)	0.043** (0.0603)	0.055 (0.3145)	- 0.0222 (0.02946)	0.23554** (0.10718)

Note: ***, **, * are significant at 1%, 5% and 10% respectively;

No. of observation = 300, Wald $\chi^2(69) = 114.69^{**}$; Log-likelihood = -445.35; Pseudo- $R^2=0.0975$;

Base Category = self-medication

Self-reported drought severity is significantly associated with the choice of provider for self-medication. Households' tendency to go for private services has increased by 9.2% and 7.42% when the intensity of drought is moderate to severe. This is because when severe to moderate drought intensity occurs, households affected by drought-related diseases seek immediate and better treatment, which is inadequate in public services. Constraints of the rural public health system shift farming households from public to private. Under weak drought, households are 4.3% more likely to use pharmacies than self-medication.

5 Conclusion and Policy Implications

Bangladesh is a low-lying deltaic country, much of which lies close to sea level. These characteristics make the country one of the hotspots for erratic climatic events. Drought is one of the most devastating weather events in Bangladesh. Low-income people, especially rural farming households, are vulnerable to droughts. Income loss, production loss, and food and water insecurity exacerbate health costs. This study aimed to analyze how self-reported drought is associated with health expenses and the choice of health care services in the northwestern region of Bangladesh. To perform this study, 300 data were collected from the Pabna and Natore districts, Bangladesh. According to the results, household education and spouses' age were negatively associated with health expenditure. Families with higher education might be more conscious of drought-related diseases, which reduces health expenditures. However, the elasticity model shows that the higher education of household heads reduces health costs related to income. Off-farm income, credit access, and savings increase household health expenses. The elasticity estimation confirmed that health expenditure responds to off farm income at 0.19%. Drought severity is a dominant factor of health expenditure assessment. Households reporting moderate drought spend about 4.6% more than severely affected and 3.2% than weakly affected households. Finally, weak drought is positively related to health costs in both models. Public, private, medicine stores, homeo services, traditional, and self-medication are available healthcare services in the study area. Education, spouse age, dependency ratio, farm income, off-farm income, and weak to severe drought are the leading variables that influence head preferences for health care services in response to self-medication. Higher cost therefore pushes households toward cheaper options like public services and self-medication, although illness among elderly member and children may still prompt a visit to public facilities rather than self-medication. Beyond Bangladesh, other farming regions that are vulnerable to drought may also benefit from these findings in terms of climate-sensitive health financing, drought preparedness, and healthcare planning for rural areas.

The approaches outlined below are derived from the previously established pattern but were not assessed in this study, leaving their efficacy in this context an open empirical inquiry. Inadequate healthcare services and high out-of-pocket expenditure push farmers toward risky self-medication and pharmacy-recommended medication; licenced professional oversight would make this both safe and more cost-effective. Because health spending is highly inelastic to income, strengthening financial risk protection mechanisms specifically for rural farmers, such as subsidized health insurance schemes that cover outpatient care for drought-related illnesses (diarrhea, skin diseases, and respiratory infections), not just hospitalization. Additionally, people use savings and credit for health expenses and integrate health financial products with existing microfinance or agricultural credit programs in these regions. Farming households are constrained by debt cycles arising from moneylender interest. Existing microfinance can ease their interest burden and financial constraints. Even weak droughts are significantly related to health budgets; drought early warning systems should be integrated with public health messaging to promote low-cost preventive measures (e.g., water purification and mosquito net use) before disease incidence rises. Furthermore, the government should increase awareness to avoid self-medication and pharmacy treatment. Transparency and monitoring can help reduce self-medication. Additionally, the media and education can play an important role in minimizing health

costs and providing better care from professionals. The government should take steps to increase media coverage and education regarding self-and pharmacy medications. Moreover, hospital and professional availability is another key factor in reducing costs and treating themselves properly.

6. Limitations and Future Research

This study was constrained by the limited time and financial resources available for data collection. This study comprises only two districts. Two adjacent districts can not be taken as representative of the whole northwestern region. Household reports of health expenditure are fully perception-based, and some households may not respond to health expenditure, which may be subject to bias in some cases. Thus, to further mitigate the effects of bias in household health expenditure data, additional studies should include longitudinal data, larger samples, and true prescription or hospital records. Farmers would benefit from an extensive study of agricultural drought, incorporating soil moisture, temperature, and rainfall. Heat exhaustion, diarrhea, starvation, respiratory diseases, and psychological distress among farmers are some of the particular health issues that could arise from a prolonged drought and need more investigation. Lastly, to lessen the financial and health impact of drought on rural households, additional studies should evaluate the efficacy of farmer health insurance, drought early-warning systems, supporting safe drinking water, and mobile health services.

Additionally, due to the absence of household-level GPS coordinates, the 5-km gridded SPEI was consolidated at the upazila level, attributing the identical drought value to all households within an upazila. The upazila-based SPEI, therefore, serves as a regional climatological classifier and not a household-level measure of exposure, and is not considered as a regressor. Household drought exposure was self-reported across three categories, and misclassification would not necessarily attenuate the coefficients. If households facing high healthcare expenses are likely to recall the season as severe, the measurement error is non-random and the direction of bias is ambiguous. Therefore, no causal claim is made. The study does not assert any significance regarding its implications. The analysis further confirmed the drought through households' observations and computed SPEI. Integrating downscaled climate forecasts with the health expenditure response assessed here would enable subsequent research to measure the extent to which anticipated drought intensification could elevate the health burden on agricultural families. Further studies could integrate household GPS data alongside high-resolution climate grids for more accurate assessments of farm-level exposure. Furthermore, studies should integrate administrative and panel data to capture dynamic drought exposure and households' responses over time. Further studies employing agricultural drought indices could capture households' income volatility and health budget allocation, strengthening evidence for targeted health interventions.

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22 November 2023, chaired by Professor Dr. Mir Khaled Iqbal Chowdhury. The study was conducted in accordance with the ethical principles set out in the Declaration of Helsinki for Social Science and with the data protection requirements of the Government of Bangladesh.

Consent to Participate: Participants were informed of the purpose of the research, the voluntary nature of their participation, their right to withdraw at any stage without consequence, and the measures taken to protect their anonymity. Written informed consent was obtained from all individual adult participants and where written consent was not applicable due to participant literacy, verbal and informed consent was obtained in the presence of the enumerator and recorded in the survey instrument, in line with established practice for rural household survey research in Bangladesh.

Consent to publish: N/A.

Authors Contribution: F.E. conceptualized the study, secured funding, supervised the research, conducted the formal analysis, and reviewed and edited the manuscript. S.A. developed the methodology, curated the data, and wrote the original draft. Both authors read and approved the final manuscript.

Data Availability: The datasets generated during the current study are available from the corresponding author on reasonable request.

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Appendix

Table A1: Variance Inflation Factor test for multicollinearity for MNL			
Variables	VIF	Variables	VIF
Age	1.44	Distance	1.25
Education	1.37	Credit Access	1.21
Spouse Age	1.45	Use of Savings	1.21
Spouse Education	1.34	Severe Drought	7.92
Dependency Ratio	1.05	Moderate Drought	3.31
Farm Income	1.05	Weak Drought	1.69
Off farm Income	1.03	Mean VIF	1.99

Table A2: Box-Tidwell test for linearity in the logit		
Variables	Coefficient	P-value
Age	- 0.0001828	0.081
Education	- 0.0017316	0.454
Spouse Age	0.0066837	0.424
Spouse Education	0.0751061	0.294
Dependency Ratio	- 0.2197976	0.663
Farm Income	-7.64e-06	0.806
Off farm income	-7.98e-07	0.755
Distance	-0.0264713	0.990
Number of iterations: 80		

Table A3: Hausman–McFadden Test of the Independence of Irrelevant Alternatives			
Alternative omitted	χ^2	df	Decision
Public service	3.359	56	Fail to reject H ₀
Private service	5.988	56	Fail to reject H ₀
Pharmacy store	1.264	56	Fail to reject H ₀
Homeopathic treatment	57.548	56	Fail to reject H ₀
Traditional treatment	0.121	56	Fail to reject H ₀

Note: Self-medication is the reference category and is therefore not omitted. Outcome are interpreted as evidence consistent with the null hypothesis (Hausman & McFadden, 1984, p. 1226). Source: Author's own calculation.