Climatic Impacts on Basic Human Needs in the United States of America: A Panel Data Analysis

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Abstract: This study empirically investigates the impact (overall, regional, and seasonal) of weather and climate extremes on basic human needs by employing a new poverty index, i.e., the Human Needs Index (HNI), in the United States of America. Detecting the contemporaneous correlations between errors, we apply second-generation unit root tests on monthly statewide panel data ranging from January 2004 to December 2018. The results obtained through cross-sectional time-series feasible generalized least square (i.e., FGLS) regression suggest that human necessities statistically and significantly correlate with a positive response to the weather extremes (cold, low precipitation) and with extreme events (drought, flood). However, the response is the opposite of that in the case of high precipitation. The seasonal variations in necessities indicate that there is a significant escalation of the needs between July and December (January is taken as the reference month), but, in February, they substantially shrink. Furthermore, the regional implications imply that, with the West of the US taken as the reference region, needs are significantly augmented in the Midwest; conversely, in the east and the south, they are significantly decreased. We also observe that some interaction effects, such as high precipitation and personal income as an interaction term, significantly, but negatively, correlate with HNI, indicating a 0.025% shared effect. Contrary to these findings, high precipitation, coupled with supplements to wages and salaries, shows a positive joint association of 0.274% with HNI. Besides, low precipitation, coupled with the unemployment rate, personal income, and flooding, shows an additional positive and significant mutual effect, while low precipitation has a negative effect on basic human needs when coupled with supplements to wages and salaries. The corresponding estimated interacting coefficients are 3.77, scoring 0.053%, 0.592%, and −0.67%, respectively.

Keywords: Extreme climatic impacts; basic human needs; panel data; FGLS; the US; interaction effect

1. Introduction

The word “extreme” corresponds to a condition or a situation that is not normal or usual in a specific context. Accordingly, extreme weather or events are referred to as the exceptional dispersions of key weather-related variables (i.e., temperature, precipitation) from the mean value. In this research, we use the following categories of weather extremes (events): hot and cold, low and high precipitation, whereas heatwaves, cold-waves, droughts, and floods are categorized as climate extremes (phenomena). Collectively, these are termed as extreme climatic events or climatic extremes. By definition, the previous ones are classified as an excess of the value of the temperature or precipitation (or both) beyond a certain level, once in a specified period, and the latter ones are classified as the continuous spell(s) of weather extremes for a specific period.
The climate is a crucial determinant of the quality and other essential aspects of human lives [1,2]. In response to the climate-affected activities of individuals [3–10], significant changes in climate conditions may become the cause of deep human concerns [11]. Due to the heterogeneous implications of extremes, a few resource-owning communities in extreme-event-prone regions may require mechanisms to protect their living standards and privileges.

Consistently with the Emergency Events Database (EM-DAT), precipitation-related extreme events (floods and droughts) and temperature-related extremes (hot and cold) mutually affected about 3.5 billion individuals globally in terms of emergency needs for homes and health over the past two decades (1995–2015). One of the highest numbers of severe weather-related catastrophes is accounted for by the US, which can be attributed to its vast and diverse landmass and its population concentration. Freezing weather harshly hit more than 5 million Americans, mainly in the Midwest and South of the US, in the period 2003–2015 [12]. Nearly 30,000 homeless poor Americans face the extreme cold in winter, extreme heat in summer, hunger, and scarcity of drinking water need emergency assistance at night [13] (Also see Figure 1,2).

Historically, the United States has experienced increasingly high climatic (i.e., hydrological, meteorological, and climatological) risks (Also refer to see Figure 3). Accurately, droughts have presented the US with profound challenges [8]. For example, the Dust Bowl, one of the worst climate conditions in US history, took place in 1930. Associated droughts in the Midwest and the Great Plains had an adverse impact throughout the countryside. Moreover, the drought in 1988–1989 was the most economically distressing natural disaster in US history [14]. The worst one-year drought coupled with heat waves in the summer of 2012 [15] influenced over half of the US; specifically, the South and the Central regions faced higher crop losses in the form of reduced corn and soybean yields. Overall, in economic terms, damages were calculated at levels above $30 billion, and there were 123 fatalities [16]. Predominantly, heat waves and cold waves have been leading causes of significant health deterioration, causing hundreds of deaths in Chicago in 1995 [17].

Generally, poor and marginalized segments of society are more vulnerable to extreme weather and climate conditions than their affluent counterparts [10]. During the last five decades, the socioeconomic status gap (and in particular the income gap) between higher- and lower-income groups has grown significantly.

The projections of growing temperature-related extreme conditions at a high degree of certainty, as well as of future increasing precipitation-related extremes at low levels of assurance, droughts (particularly in the South, West, and Central regions), and floods (mainly in the East and Midwest) can have multifaceted and severe socioeconomic and environmental impacts on the United States [8].

Consequently, a better understanding of the implications of extreme events on human needs is required because various decision-making processes in society are closely linked to weather events. Therefore, the recently developed poverty-measuring metric called “Human Needs Index (HNI)” is employed in this study to empirically investigate the impact of weather and climate extremes on poverty-related human needs in the US (see Section 3 for a detailed description). Additionally, it may be consistent with the decision of the experts’ meeting in Dublin (2015), which aimed at developing a new and better measure of basic human needs (e.g., food security) [18].

This study has the following aims:

i. To examine the impact of weather extremes (hot, cold, low precipitation, as well as high precipitation) and climatic extremes (heat waves, cold waves, droughts, and floods) on basic human needs in the United States;

ii. To explore the regional impact of extreme climate conditions on human needs;

iii. To probe the effects of seasonal variations of weather and climate extremes to necessities.

As the regional impact of weather and climate extremes is not homogenous [19], and seasonality is considered a critical factor affecting basic needs [20,21], the bulk of prior climatic-impact-related research has been limited to either a specific state (California), a region (South) or the country as a whole [7,22]. Thus, our research intends to explore the overall climatic, regional, and seasonal variations of Americans’ basic needs.
The official poverty measure not only understates the population in poverty by ignoring the impoverished and deprived segments in the community [23]; it also does not take into account the regional variation regarding the requirements [24]. The present study utilizes quality data collected by a nonprofit organization based on the consumption of necessities and utilities. It also focuses on geographical and regional differences.

Because the main aim is to get better results due to the potential enhancement of weather extremes in the future [18,25,26] this paper pioneers a contribution to the mostly sector-specific existing literature by applying second-generation panel unit root tests, detecting a contemporaneous correlation between errors, and, finally, by employing generalized least squares (GLS) regression through the efficient estimator Feasible Generalized Least Square (FGLS) under certain conditions [27].

This paper is structured in the following manner: Section 2 describes regional and seasonal vulnerability. Section 3 elucidates data, model, and methodological descriptions. Section 4 gives a descriptive data analysis. Section 5 is about the results and interpretations of this study. Section 6 and Section 7 are about the discussion, conclusion, and limitations of this study, respectively.

2. Regional and Seasonal Vulnerability

Poverty and vulnerability to extreme climatic events and excessive heat, in particular, are interrelated [16]. The Southern (mainly corn-belt), Western, and the Midwestern regions are not only poverty-concentrated and vulnerable to climatic extremes. The Southwest, the driest, and the hottest area hosting more than 22% of the US population may be at higher risk of experiencing changing climatic conditions rapidly [28]. As is the case with other regions, the Southeastern one is home of about 30% of the total US population and is highly vulnerable to droughts and coastal floods. However, hurricanes, extreme heat events, cyclones, and blizzards are also frequent in this region [29]. Several communities in Louisiana, Florida, and South Carolina are at a significant disadvantage concerning vulnerability to floods [23,30]. Projected hotter summer and mounting flooding events due to heavy precipitation may have detrimental impacts, particularly on local communities living in coastal areas [29]. Forty percent of the hydroelectricity of the US is produced in the Northwest. The rising population reduced precipitation, and projection of low rain, particularly in summer, is likely to result in increased energy demands (e.g., due to more extensive use of air conditioners) and supply concerns as the demand/supply gap is projected to widen in the future [31].

For decades, economic inequality between top income and lower classes has increased giving rise to a rising number of “poverty pockets” in the U.S. Persistent poverty-stricken regions are generally those inhabited by higher concentrations of Hispanics, African Americans, and single-parent families (mother) with more than one child, which usually belong to classes with smaller access to resources [32]. Hispanics live mostly in California (which has a dry and drought-prone climate), in Texas (drought-prone), and Florida (characterized by higher sea level and floods), and are often employed in the farming sector may suffer from additional negative impact in cases of frequent intense extreme situations. Indigenous Americans live in remote areas and primarily rely on environment-dependent natural resources for their sustenance, as well as the elderly and the disabled, are expected to find themselves at higher health-related risks (e.g., undernourishment) and thus are more vulnerable to extreme weather conditions.
Figure 1 overall human need (i.e., at the national level) in the United States, Source: the author drew himself (origin 8) using data retrieved from the source [33].

Figure 1 depicts the fluctuations in basic needs in the US in the period 2004–2018. The oscillations range from 0.7 to 2.4. The highest HNI score, 2.35 on average, indicates the maximum requirements in the years 2011, possibly linked to the one-year worst drought in the US, the lowest HNI score (0.7) in 2004, indicating minimum needs. However, the HNI score might be notably smaller at the national level [25].

Figure 2. Regional human necessities in the US, Source: The author has drawn himself (origin 8) using data from [13].
Figure 2 elucidates the regional human needs in the US through the human necessities index score. Higher HNI scores in the south and the west reveal an elevated level of requirements compared to the central and eastern areas. As historically, the southern, western, and central US has been prone to climatic extremes, mostly droughts and floods. Furthermore, poverty has been the highest in the South and rising in the West [10].

![Figure 3](image)

**Figure 3** The month-wise number of extreme events in the US. Source: [34,35].

Figure 3 illustrates the monthly numbers of extreme events in the US. It can be observed that every year, the number of extreme events gradually increases from spring to half of the winter (summer, fall inclusive). Furthermore, a higher number of events have occurred during 2011, 2016, and 2017.

3. Data, Model, and Methodological Description

In the present study, the index of the human need (HNI) is taken as a responsive indicator to explanatory climatic situations representing indicators and is representative of seven (e.g., food, energy, medicine, grocery, shelter, clothing, and furniture) wellbeing requisites based on reliable, enduring real-time data of basic needs assistance provided by the nonprofit organization to the needy individuals. It has been created by the aggregated efforts of the Lily family school of philanthropy of Indiana University and the US Salvation Army since 2004. HNI instigates from 0, which indicative of the least level of requirements as (0.78) during 2004 and the maximum (1.33) of the decade in 2012. Any change in one of these seven components causes changes in the overall HNI. The meal needs have the highest impact, producing a sharp increase in HNI score due to the Super Tuesday Tornado in 2008. Moreover, after 2015, the national HNI score continuously slid downward from (1.25) in 2015 to (0.95) in 2019. Still, a rise of approximately 27 percent in energy and about 23 percent in clothing needs to be observed in 2019 as compared to 2018. In contrast to the conventional poverty-measures, it personifies human needs manifested on consumption rather than income [13].

There is no universally accepted definition of extreme climate events. A part of the research up to date has classified an event that is not very common (or is quite rare) at a particular location and time as an “extreme climatic event,” and some might describe it as the leading cause of extraordinary socio-economic damage and disruption [36]. According to the usual practice in economic analysis, three ways have been used to define climate extremes as absolute amounts of weather indicators beyond a specified level, fixed thresholds, and percentile methods [37]. We chose the percentile and fixed threshold indicators. Following the percentile limits selected by the authors of reference [38], the 99th percentile for
hot and high precipitation and the first percentile for cold and low rainfall are taken as the number of months per year above the 99th percentile of both average temperature and precipitation—the time-span of the data selected covers the period from January 2004 to December 2018. It is essential to point to two distinctive aspects cases of our data: first, the frequency of the data used (daily data of temperature and precipitation), but we used monthly data (due to availability limitations); and second, the different data periods. We consider the following functional form and our linear econometric model.

\[
HNI_{it} = \beta_1 + D_{1it}Y + D_{2it}\delta + D_{3it}\alpha + \beta_2X_{2it} + \beta_3X_{3it} + \beta_4X_{4it} + \beta Y_{it} + \epsilon_{it}
\]  

(1)

Here, HNI is human needs index, \(D_{1it}\) is a set of the key (explanatory) dummy variables. \(D_{2it}, D_{3it}\) are collections of seasonal (months) and dummies for regions, respectively. The parameters \(Y, \delta, \alpha\) are sets of estimated coefficients of climate, seasonal, and regional dummy variables. The controlled variables as \(X_{2it}, X_{3it}, X_{4it}\) are the unemployment rate, personal income, and supplements to wages and salaries. We have taken a natural logarithm of personal income (million dollars) and supplements to wages and salaries (million dollars) for scaling down their values. The parameters \(\beta_1\), the intercept and \(\beta_2, \beta_3, \beta_4\) are estimated regression coefficients and \(\beta Y_{it}\) is a group of interaction terms and \(\epsilon_{it}\) is a stochastic disturbance term.

The unemployment rate is included as a controlled variable to manage the effects of the Great-recession across the US in 2008. For the sake of robustness, personal income, one of the most critical components of the household security [18], and supplements to wages and salaries as providing cash as well as non-cash transfers, are added as controlled indicators in our panel data regression analysis.

3.1. Percentile Thresholds for Climatic Variables

3.1.1. Average Temperature Thresholds (99th percentile)

- Hot \(\geq 28^\circ C\): If the temperature in a month in a state on average is equal or higher than 28°C (99th percentile threshold), then \(D = 1\) (0 otherwise)
- Heatwave: spells of at least two consecutive hot months, \(D = 1\) (0 otherwise)
- Cold \(\leq -10^\circ C\): If average temperature in a month in a state is equal or less than \(-10^\circ C\) (1st percentile threshold) then \(D = 1\) (0 otherwise)
- Cold wave: spells of at least two consecutive cold months, \(D = 1\) (0 otherwise)

3.1.2. Precipitation thresholds (99th percentile)

- Low precipitation \(\leq 5\text{mm}\): If on the average amount of precipitation fall in a month in a state is equal or less than 5mm (1st percentile threshold) then, \(D = 1\) (0 otherwise)
- Drought: Continuity of low rainfall for at least two consecutive months, \(D = 1\) (0 otherwise)
- High Precipitation \(\geq 230\text{mm}\): If on average the amount of precipitation fall in a state is or more than 230mm per month (99th percentile threshold) then \(D = 1\) (0 otherwise)
- Flood: Continuity of high rainfall for at least two consecutive months, \(D = 1\) (0 otherwise)

3.2. Data Type and Methodology

This study uses balanced monthly panel data available for different states. This method has certain benefits over selecting time series, and cross-sectional data, including a higher number of observations in our research, is expected to provide us with precise and accurate estimates. Furthermore, it helps researchers to take serious consideration of the problem of cross-sectional dependence, potential endogeneity, varying variance of error terms, and the interaction effect.

According to Baltagi, unlike micro panels, cross-section dependence is a hitch in macro groups with large time-series [39]. For instance, it reduces the efficiency of the results as well as the overestimates. To
fix this problem, we decided to use Pesaran cross-section dependence (CD) [40] and Breusch–Pagan Lagrange multiplier (LM) tests [39].

Furthermore, because of their low power, first-generation tests may provide misleading stationary results in the case of cross-sectionally dependent panel data series [41]. Therefore, we preferred to use second-generation unit root tests [42,43] to avoid producing a spurious analysis. We have not applied the unit root test on climate indicators because of being dummy variables, as their mean and variance remains constant over time.

Because of our critical explanatory variables as dummies and due to the existence of all these problems in our data, we have the choice of feasible generalized least squares estimator (i.e., FGLS) through generalized least square regression (i.e., GLS): specifically, in the case of heteroskedastic and correlated errors formation across the panels. In the case of time-period (T) < no. of cross-sections (n), panel corrected standard errors (i.e., PCSE) is a better available option, whereas in the case of time-period (T) > no. of cross-sections (n), (180 > 48, as in our case), GLS is the better option available [27]. To prevent our study from falling into the trap of endogeneity, we have included lagged low precipitation, lagged unemployment rate, and supplements to wages and salaries. Interaction terms have also been added for their likely mutual effect.

3.3. Data Sources

HNI retrieved from the Human Needs Index official website [33].
Precipitation and average temperature retrieved from the National Climatic Data Center [44].
Personal income and supplements to wages and salaries retrieved from the Bureau of Economic Analysis official [45].
Data on the unemployment rate retrieved from the U.S. Bureau of Labor Statistics [46].

4. Descriptive Data Analysis

4.1. Overall Data Analysis

We used percentile thresholds and exceeding definite limits [6] for climatic extremes (the 99th percentiles for both temperature and precipitation extremes) when examining our dataset, which ranged from January 2004 to December 2018. As a result, for this period, we observed 198 temperature-related extreme events in the US: 80 cold events, 75 hot events, 20 cold waves, and 22 heat waves. We also noted a total of 218 precipitation-related events: 117 low precipitation events, 64 high precipitation events, 35 droughts, and five flooding events. The numbers of extreme temperature-related events in terms of hot or cold and heat waves or cold waves are almost equal. Still, in the case of precipitation-related extreme events, low precipitation and droughts occurred more often than high precipitation and floods.

In conclusion, in the period covered by our data, precipitation-related happenings were higher in number than temperature-related severe occurrences.

4.2. State-Wide Data Analysis

4.2.1. Precipitation-Related Events

From January 2004 to December 2018, the following precipitation-related extreme events were observed:

Arizona: 28 low precipitation events and 11 droughts;
California: 25 low precipitation events and 15 droughts;
Alabama: three high precipitation events;
Connecticut: six top precipitation events;
Delaware: three high precipitation events;
Florida and Louisiana: seven high precipitation events and one flood for each state;
Georgia: four top precipitation events;
Indiana, Maine, Maryland, and Kentucky: one high precipitation event for each state;
Iowa: three high precipitation and one low precipitation event;
Kansas: four low precipitation events;
Massachusetts: five top precipitation events;
Mississippi: three top precipitation events and one little precipitation;
Missouri: one high precipitation event;
Montana: one little precipitation event;
Nebraska: four low precipitation events;
Nevada: 10 small precipitation events and one drought;
New Hampshire: four high precipitation events and one flood event;
New Jersey: three top precipitation events;
New Mexico: 16 little precipitation events and five droughts;
North Dakota: 10 low precipitation events;
Oklahoma: one high precipitation event;
Oregon: six low precipitation events and one drought;
Pennsylvania and South Carolina: 1 high precipitation event for each state
South Dakota: three low precipitation and one high precipitation event
Utah: two low precipitation events
Vermont: three high precipitation events, and
Washington: four low precipitation, one drought, and two top precipitation events

4.2.2. Temperature-Related Events

From January 2004 to December 2018, the following temperature-related extreme events were observed:
   Alabama: three hot and one heatwave;
   Alaska: 36 cold and 13 cold waves events;
   Arizona: two hot events;
   Arkansas: five hot and one heatwave events
   Florida: 12 hot and five heatwaves
   Iowa: 12 hot and five heatwaves
   Minnesota: 12 cold and one cold-wave;
   Mississippi: 6sx hot and two heatwaves
   New York: one cold event
   North Dakota: 17 cold and three cold waves
   Oklahoma: eight warm and three heat waves
   South Carolina: three hot events
   Tennessee: one hot event
   Texas: 16 hot events and six heat waves
   Vermont: two cold events, and
   Wisconsin: four cold events.

Like climate extremes, on average, throughout the years, higher human needs (from Human needs index score) were also observed predominantly in the western and Midwestern regions and some of the southern states. Overall, the leading states which show both towering necessities as well as experiencing high numbers of climatic extremes (deficient precipitation, droughts, cold, and cold waves events) are Alaska, Arizona, California, Kansas, Minnesota, North Dakota, Nevada, New Mexico, Oregon, and Washington. Seasonally, it has been observed that from summer to winter, including the fall season (July–December), the basic life requirements of Americans tend to grow significantly, and they typically peak in December.
5. Results and Interpretation

Table 1 delineates the robust outcomes of the Pesaran Cross-sectional Dependence (CD) test [40] significantly (at 1% significance level), rejecting the null hypothesis of no cross-sectional dependence, which ultimately confirms the cross-sectional relationship. Furthermore, Breusch–Pagan Lagrange Multiplier (LM) test [39] in Table 2 also confirms the same results about cross-sectional dependence as the Pesaran-CD test in Table 1. For robustness, we use both the tests of cross-sectional dependence.

Table 1. Results of Pesaran Cross-sectional Dependence (CD) test

| Indicators                      | Pesaran Cross-Sectional Dependence (CD) Test | p-value |
|---------------------------------|---------------------------------------------|---------|
| Human Needs Index (HNI)         | 66.66                                       | 0.00    |
| Hot                             | 10.95                                       | 0.00    |
| Cold                            | 4.52                                        | 0.00    |
| Low Precipitation               | 13.14                                       | 0.00    |
| High Precipitation              | 25.81                                       | 0.00    |
| Heatwave                        | 3.40                                        | 0.00    |
| Cold-wave                       | 0.26                                        | 0.79    |
| Drought                         | 4.60                                        | 0.00    |
| Flood                           | 13.89                                       | 0.00    |
| Unemployment Rate               | 397.73                                      | 0.00    |
| Personal Income                 | 440.77                                      | 0.00    |
| Supplements to wages and salaries | 428.24                                    | 0.00    |

Source: Calculation of the Author.

Table 2. Results of the Breusch—pagan Lagrange Multiplier (LM) test

| Ho: No Cross-Sectional Dependence                                                                 |
|-------------------------------------------------------------------------------------------------|
| ch²(1128) = 5563.656                                                                                   | P-value = 0.00 |
| Pesaran Test = 10.290                                                                              | P-value = 0.00 |
| Avg. the absolute value of the off-diagonal elements = 0.126                                            |

Source: Estimate of the Author.

While rejecting the null hypothesis of non-stationarity at the level and the first difference, the panel unit root tests confirm the stationarity of HNI, average temperature, and precipitation at a 1% significance level Table 3. By applying the CIPS test, the unemployment rate is stable at the 1st difference, and using the Breitung test, it is stationary at both levels and the 1st difference (at 1% level of significance).

Personal income is stationary only at first difference following both of the unit root tests. Whereas according to the CIPS results, supplements to wages and salaries are stable at both levels, and at the 1st difference, following the Breitung test results, the null hypothesis of non-stationarity is rejected (at 1% significance level). Overall, both of the second-generation test results validate the stationarity of all the variables at the level and first difference, ruling out the spurious regression results. None of the variables is stationary beyond the 1st difference. The results of the second-generation unit root test confirming the stability of most of the indicators at level guide us to use regression analysis as the most suitable method for our study.

No Multicollinearity was detected except between personal income and supplements to wages & salaries. No serial correlation, but group-wise Heteroskedasticity was noticed. (See Appendix, Table A1–A7 for preliminary test estimates).
Table 3. Results of the unit root tests

| Indicators                        | CIPS Test Statistic (Ho: Homogeneous non-stationary, bi = 0 for all i) | Breitung Test (Ho: Panels contain unit roots) |
|-----------------------------------|------------------------------------------------------------------------|------------------------------------------------|
|                                   | Level                         | 1st Difference                        | Level                         | 1st Difference                        |
| Human Needs Index (HNI)           | −6.13 ***                     | −6.19 ***                             | −30.59 ***                    | −75.90 ***                             |
| Average Temperature (°C)          | −6.03 ***                     | −6.19 ***                             | −6.834 ***                    | −37.312 ***                            |
| Precipitation (millimeter)        | −6.19 ***                     | −6.19 ***                             | −21.408 ***                   | −64.044 ***                            |

Controlled Variables

|                                   | Level                         | 1st Difference                        |
|-----------------------------------|-------------------------------|---------------------------------------|
| Unemployment Rate (%)             | −1.99                         | −6.17 ***                             |
| Ln (Personal Income)              | −1.65                         | −6.19 ***                             |
| Ln (Supplements to Wages and salaries) | −2.21 **                     | −6.19 ***                             |

Source: Computation by the Author. * shows the corresponding variable is significant at 10% significance level; ** indicates significance at 5% level; *** means significance of the corresponding variables at 1% level of significance.

Table 4 illustrates the regression results of our model (except for the regional dimension). We find a positive as well as a significantly negative response of basic human needs to climate extremes. Observing the results from Table 4, impoverished, unemployed Americans are more vulnerable to cold, low precipitation, droughts, and flooding events. For instance, in the case of one drought event in a month on average, there is a resulting increase in human needs by a score of 0.121 at a 1% significance level, while the effect on social necessities is shown by a score of 0.054 on average to one flood event in a month at 5% significance level. One low precipitation event in a month also causes a decrease in the share of human needs by a score of 0.741 at a 5% level of significance. The occurrence of one cold event in a month raises human necessities by a score of 0.185 at a 5 percent significance level.

Surprisingly, any change (1% increase or decrease) in monthly personal income impacts basic human needs, i.e., it causes an increase or reduction of human necessities by a score of 0.244, respectively, on the HNI scale. Additionally, more supplements to lower wages and low salary workers reduce the workers’ basic needs: a 1% increase/decrease in supplement amount reduces/increases human necessities by a score of 0.219. There are a few possible reasons for the personal income negatively impacting human needs: firstly, it may be due to the Multicollinearity problem [2] between personal income and supplements to wages and salaries; secondly, one of the possible reasons behind this result may be economic inequality, as the high-income communities already consume nearly 27% more than that of low-income individuals [32].

We also witness some interaction effects: high precipitation and personal income, as an interaction term, had a significant but negative relationship with HNI, indicating a 0.025% of the shared effect. Contrary to this finding, high precipitation with supplements to wages & salaries were found to have a positive joint association of 0.274% with HNI. On the other hand, low precipitation was found to have a positive and significant combined effect with the flood, unemployment rate, and personal income, but a negative effect with supplements to wages and salaries. The corresponding interaction term coefficients are 3.77 score, 0.053%, 0.592% and −0.67% respectively.

Moving forward to results on seasonality, which is vital for determining basic human needs, the findings indicate that three seasons, i.e., summer (June exclusive), autumn, and winter (February exclusive), positively and significantly impact needs compared to January, which is the category used as a reference. The demands increase by a score of 0.796 in December as compared to January, which is the highest increase and remains the highest throughout the years, from July to November the coefficients representing marginal effects are 0.126, 0.185, 0.230, 0.074 and 0.126 respectively.
Table 5, as shown below, displays the regression results, including regional variations in needs as a response to weather and climate extremes. In the case of regional differences, inclusive of cold, droughts and floods, there are significant and positive effects on basic needs (any of the events once in a month cause increases in human necessities by scores of 0.187 at 5% level, 0.099 at 1% level and by a score of 0.061 at 5% level, respectively). On the contrary, low precipitation and high precipitation events show significant but negative impacts on basic needs (one high precipitation event in a month diminishes human necessities by 0.61 at a 10% level of significance and 0.049 scores at a 1% significance level, respectively).

Low precipitation shows a positive and significant correlation with flooding occurrences, unemployment rate, and personal income, but it also indicates adverse interacting effects on supplements to wages & salaries on necessities (see Table 5 for subsequent coefficients).

Seasonal variations remain almost the same in all the US case regression results (in Table 4), except October. Regional variations demonstrate that the Midwestern Americans faced positive and direct impacts whereas, in the South and the East, human necessities were negatively influenced by climate extremes, in comparison to the West (as a reference category). For instance, in the Midwestern region, human needs significantly increase by a score of 0.122 at a 1% level of significance; however, in the East and the South, they drop by scores 0.272 and 0.252, respectively.

Table 4. Estimation of generalized least squares (GLS) coefficients using cross-sectional time-series feasible generalized least square (FGLS) regression.

| Indicators                  | Coefficients | Stand. Error | z-statistic | p-value |
|-----------------------------|--------------|--------------|-------------|---------|
| **Dep. Variable: Human Needs Index (HNI)** |              |              |             |         |
| **Weather Extremes**        |              |              |             |         |
| Hot                         | −0.048       | 0.052        | −0.94       | 0.350   |
| Cold                        | 0.185 **     | 0.083        | 2.24        | 0.025   |
| L1.Low Precipitation        | −0.741 **    | 0.354        | −2.1        | 0.036   |
| High Precipitation          | −0.094       | 0.281        | −0.34       | 0.736   |
| **Climate Extremes**        |              |              |             |         |
| Heatwave                    | −0.018       | 0.096        | −0.19       | 0.847   |
| Cold wave                   | 0.161        | 0.145        | 1.11        | 0.268   |
| Drought                     | 0.121 ***    | 0.027        | 4.41        | 0.000   |
| Flood                       | 0.054 **     | 0.028        | 1.86        | 0.042   |
| **Controlled Variables**    |              |              |             |         |
| L1.Unemployment Rate        | 0.027 ***    | 0.003        | 8.70        | 0.000   |
| L1.In (personal income)     | 0.248 ***    | 0.045        | 5.46        | 0.000   |
| L1.In (supplements to Wages & Salaries) | −0.213 *** | 0.046 | −4.67 | 0.000 |
| **Interaction Terms**       |              |              |             |         |
| High Ppt.*L1.InPI           | −0.225       | 0.132        | −1.71       | 0.088   |
| High Ppt.*L1.InSWS          | 0.274 **     | 0.136        | 2.02        | 0.044   |
| L1.Low Ppt.*L1.Flood        | 3.777 ***    | 0.678        | 5.57        | 0.000   |
| L1.Low Ppt.*L1.U.R          | 0.053 ***    | 0.007        | 7.42        | 0.000   |
| L1.Low Ppt.*L1.InPI         | 0.592 ***    | 0.148        | 4.01        | 0.000   |
| L1.Low Ppt.*L1.InSWS        | −0.671 ***   | 0.148        | −4.55       | 0.000   |
| **Results of Seasonality**  |              |              |             |         |
| January                     |              |              |             |         |
| February                    | −0.117 ***   | 0.038        | −3.11       | 0.002   |
| March                       | 0.048        | 0.038        | 1.28        | 0.202   |
| April                       | 0.028        | 0.039        | 0.75        | 0.451   |
| May                         | 0.037        | 0.038        | 0.99        | 0.322   |
| June                        | 0.049        | 0.038        | 1.29        | 0.196   |
| July                        | 0.126 ***    | 0.038        | 3.31        | 0.000   |
Table 5. Estimation of generalized least squares (GLS) regression coefficients using cross-sectional time-series feasible generalized least square (FGLS) regression.

| Indicators                      | Coefficients | Stand. Error | z-statistic | p-value |
|--------------------------------|--------------|--------------|-------------|---------|
| **Weather Extremes**           |              |              |             |         |
| Hot                            | -0.044       | 0.052        | -0.84       | 0.400   |
| Cold                           | 0.187        | 0.081        | 2.33        | 0.020   |
| L1.Low Precipitation           | -0.611*      | 0.346        | -1.76       | 0.078   |
| High Precipitation             | -0.049***    | 0.015        | -3.29       | 0.001   |
| **Climate Extremes**           |              |              |             |         |
| Heatwave                       | -0.004       | 0.095        | -0.05       | 0.960   |
| Cold wave                      | 0.185        | 0.145        | 1.28        | 0.202   |
| Drought                        | 0.099***     | 0.027        | 3.68        | 0.000   |
| Flood                          | 0.061**      | 0.029        | 2.10        | 0.035   |
| **Controlled Variables**       |              |              |             |         |
| L1.Unemployment Rate           | 0.033***     | 0.003        | 10.64       | 0.000   |
| L1.ln (personal income)        | 0.783***     | 0.044        | 18.00       | 0.000   |
| L1.ln (supplements to Wages & Salaries) | -0.731*** | 0.044        | -16.64      | 0.000   |
| **Interaction Terms**          |              |              |             |         |
| L1.Low Ppt.*Flood              | 3.745***     | 0.671        | 5.58        | 0.000   |
| L1.Low Ppt.*L1.U.R             | 0.055***     | 0.007        | 7.83        | 0.000   |
| L1.Low Ppt.*L1.lnPI            | 0.415***     | 0.149        | 2.79        | 0.005   |
| L1.Low Ppt.*L1.lnSWS           | -0.500***    | 0.149        | -3.36       | 0.001   |
| **Regional Results**           |              |              |             |         |
| East                           | -0.262***    | 0.014        | -20.96      | 0.000   |
| Midwest                        | 0.125***     | 0.012        | 9.65        | 0.000   |
| South                          | -0.242***    | 0.015        | -17.92      | 0.000   |
| West                           | Reference Category |        |         |         |
| **Seasonal Output**            |              |              |             |         |
| January                        | Reference Category |        |         |         |
| February                       | -0.126***    | 0.037        | -3.40       | 0.001   |
| March                          | 0.032        | 0.037        | 1.86        | 0.389   |
| April                          | 0.000        | 0.037        | 0.01        | 0.993   |
| May                            | 0.011        | 0.037        | 0.29        | 0.773   |
| June                           | 0.026        | 0.038        | 0.69        | 0.492   |
| July                           | 0.106***     | 0.038        | 2.83        | 0.005   |
| August                         | 0.167***     | 0.038        | 4.43        | 0.000   |
| September                      | 0.213***     | 0.038        | 5.69        | 0.000   |

Source: Estimation of the Author. * shows the corresponding variable is significant at 10% significance level; ** indicates significance at 5% level; *** means significance of the corresponding variables at 1% level of significance.
|          | October       | November     | December     | Constant     |
|----------|---------------|--------------|--------------|--------------|
|          | 0.048 *       | 0.123 ***    | 0.776 ***    | −1.512 ***   |
|          | 0.038         | 0.037        | 0.037        | 0.114        |
|          | 1.30          | 3.32         | 20.90        | −13.29       |
|          | 0.050         | 0.001        | 0.000        | 0.000        |

Wald Chi²(21) 3640 ***

Source: Estimation of the author. * shows the corresponding variable is significant at 10% significance level; ** indicates significance at 5% level; *** means significance of the corresponding variables at 1% level of significance.

6. Discussion

As the precipitation extremes distinctively, the droughts are less predictable [47] as compared to temperature extremes [48] with the project changing precipitation-related extremes in the future in combination with persistent swift enhance in population in the US, explicitly, communities have lower socioeconomic status probably visage detrimental impacts. The simultaneous occurrences of drought events in hot summer and flood events in cold winter noticeably contribute to exacerbating their life challenges (food needs, health needs, energy needs for heating/cooling, housing needs, summer, and winter clothing). The western region which is the home of millions of marginalized Native Americans and rapidly growing scarce resource groups whose livelihoods mainly depend on irrigation agriculture, tourism, and recreational activities is at higher risks, the states Arizona, California, Nevada, New Mexico, Oregon, and Washington in particular in this region.

Low precipitation interacting with flooding events, in case of the high unemployment rate and increasing personal income significantly and positively causes to affect the necessities. Furthermore, the employment of thousands of locals is highly attached to the tourism activities as tourists in terms of recreation activities (skiing, fishing, and other water-related sports). Water shortage causes to significantly and negatively impact these activities, leading to an increase, unemployment in the region resulting in indirect impacts on needs. The anticipation of amplifying drought events, particularly from summer to winter (coupled with hotter and colder situations) in combination with rapidly increasing population, increasing coastal habilitation (vulnerable to floods) in the region calls for serious concern.

Alaska is significantly susceptible to precipitation extremes tied with summer and extreme cold season having more coastline range in comparison to other areas. Dietary needs of indigenous Alaskans are at higher threats down to reduced availability of fish, their traditional food. In the Midwestern US, in particular cardiovascular, waterborne diseases combine with climatic extremes from summer to winter will present an increasing risk to health needs because various pathogens thrive in such conditions. Kansas, Minnesota, and North Dakota show higher susceptibility levels to climate extremes in terms of altering the needs of the groups having limited resources.

Lastly, drought, which has been historically the more significant challenge for the US, directly or indirectly, can also be the likely vulnerability cause. It cannot just have multifaceted adverse effects on food, water, and health security [49] but also can spoil water-providing infrastructure, decreasing the quality and quantity of protected water together demands rise to keep homes and themselves warm. Moreover, extreme weather in winter can also exacerbate existing challenges of poor society segments in the form of making choices between energy needs for heating, food needs, and health needs.

7. Conclusion

Since the humanitarian concerns are consistent with the living needs and vulnerabilities to climatic extremes [10], purposefully, this study is aimed at investigating the climatic impacts on basic human needs in the US. It is the first study to use a new poverty measure based on the consumption of social security assistance provided for poverty-related human needs by one of the largest non-profit
organizations. Exploring the climatic effects on basic human needs in the United States is likely to have global poverty-related effects (positive or negative) in the interconnected world through different aspects.

We created dummies for climatic extremes as our critical explanatory variables against the 99th percentile thresholds using data of climate variables (temperature and precipitation). On the regressor side projecting some combined effects, the likely significant interaction terms have also been included along with vital socio-economic indicators. The findings at a national level reveal that the impoverished Americans are at higher risks of precipitation-related extremes (droughts, and floods in particular) than temperature-related heights for their well-being. Seasonally from summer to winter (July–December), basic needs are considerably elevated as compared to January. Also, lagged low precipitation with floods, unemployment, and personal income, and high rainfall with supplements to wages and salaries have a significant extra positive shared impact on necessities whereas lagged low precipitation with supplements and high rainfall coupled with personal income clarifies the contrasting effect (refer to Table 4 for corresponding estimated coefficients).

Region-wise, in the West and Midwest, more social security assistance will be required in comparison to the east and south. Likewise, the findings at a national level indicate that lagged low precipitation, together with flooding lagged unemployment and lagged personal income jointly, cause the increase of the basic daily-life needs of poor Americans. Finally, we conclude that climatic extremes (cold, drought, and floods), seasonal, and socio-economic factors are crucial determining agents for well-being and poverty-related needs. Their simultaneous occurrence can exacerbate the existing challenges of vulnerable individuals and communities. Furthermore, our findings are in harmony with the analysis that the changing climate has heterogeneous, positive as well as negative impacts in the United States [19].

Earlier the increasing frequency and intensification of climatic extremes have been projected [37]. It is a severe matter of concern for policymakers to think about to avoid unpredictable and unexpected global implications in the future in which the climate increasingly changes, particularly in the situation of widely extended summer droughts and flooding events. Therefore, this research might not just be beneficial to target the needy ones at national and regional levels following different seasons but also for policymaking in advance for the higher seasonal risks and specific climatic extremes.

7.1. Limitations to Our Study

First, we could not find statewide disposable personal income and supplements to wages and salaries against the month’s frequency. Second, we also could not include demographic-related indicators like population, family size, and the population size of different ethnicities (due to unavailability). It might be beneficial for making better and targeted extreme climate-relevant policy as Hispanics and African Americans share a more substantial proportion to lower socioeconomic status groups.

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Appendix A

| Table A1 Results of Descriptive Statistics |
|-------------------------------------------|
| Indicators | Observations | Mean | Std. Dev. | Minimum | Maximum |
| HNI | 8640 | 1.067 | 1.046 | 0 | 28.7 |
| Avg. Temperature | 8640 | 11.47 | 9.943 | −24.9 | 31.8 |
| Precipitation | 8640 | 80.47 | 52.12 | 0.25 | 404.37 |
| Weather Extremes | | | | |
| Hot | 8640 | 0.012 | 0.108 | 0 | 1 |
|                          |     |     |     |    |    |
|--------------------------|-----|-----|-----|----|----|
| **Cold**                 | 8640| 0.011| 0.103| 0  | 1  |
| **Low Precipitation**    | 8640| 0.019| 0.136| 0  | 1  |
| **High Precipitation**   | 8640| 0.012| 0.107| 0  | 1  |
| **Climatic Extremes**    |     |     |     |    |    |
| **Heatwave**             | 8640| 0.012| 0.108| 0  | 1  |
| **Cold wave**            | 8640| 0.005| 0.067| 0  | 1  |
| **Drought**              | 8640| 0.006| 0.072| 0  | 1  |
| **Flood**                | 8640| 0.001| 0.019| 0  | 1  |
| **Controlled Variables** |     |     |     |    |    |
| **Unemployment Rate**    | 8640| 5.842| 2.146| 2.3| 14.92|
| **Ln (Personal Income)** | 8640| 12.02 | 1.038| 9.76 | 14.73 |
| **Ln (Supplements to W & S)** | 8640| 9.903| 1.030| 7.619| 12.54 |
### Table A2. Results of Correlation Coefficients

|         | HNI   | Low Ppt. | High Ppt. | Hot  | Cold | Drought | Flood | Heatwave | Cold wave | Unem. rate | Inpi   | Supplements |
|---------|-------|----------|-----------|------|------|---------|-------|----------|-----------|------------|--------|-------------|
| HNI     | 1     |          |           |      |      |         |       |          |           |            |        |             |
| Low Ppt.| 0.07  | 1        |           |      |      |         |       |          |           |            |        |             |
| High Ppt.| −0.03 | −0.12    | 1         |      |      |         |       |          |           |            |        |             |
| Hot     | 0.003 | −0.03    | 0.04      | 1    |      |         |       |          |           |            |        |             |
| Cold    | 0.06  | 0.04     | −0.04     | −0.01| 1    |         |       |          |           |            |        |             |
| Drought | 0.18  | 0.67     | −0.08     | −0.02| 0.04 | 1       |       |          |           |            |        |             |
| Flood   | 0.012 | −0.05    | 0.48      | 0.07 | −0.02| −0.04   | 1     |          |           |            |        |             |
| Heatwave| −0.003| −0.01    | 0.03      | 0.53 | −0.01| 0.00    | 0.05  | 1        |           |            |        |             |
| Cold wave| 0.048 | 0.03     | −0.02     | −0.01| 0.65 | 0.02    | −0.01 | −0.00    | 1         |            |        |             |
| Unem. rate| 0.07  | −0.04    | 0.06      | 0.01 | −0.00| −0.01   | 0.03  | 0.02     | 0.01      | 1         |        |             |
| Inpi    | 0.03  | −0.07    | 0.06      | 0.07 | −0.11| −0.03   | 0.04  | 0.05     | −0.09     | 0.19      | 1      |             |
| Supplements| 0.03  | −0.07    | 0.06      | 0.06 | −0.10| −0.03   | 0.03  | 0.04     | −0.08     | 0.21      | 0.99  | 1           |
Table A3. Results of group-wise Heteroskedasticity by Modified Wald test

| Ho: sigma(i)**2 = sigma**2 for all i (i.e., Variance of the error term is constant, homoskedasticity) |
|---|
| chi²(48) = 4430.15 |
| Prob. > chi² = 0.000 |

Here rejecting the null hypothesis as (Prob. > chi²< 0.000) concludes that variance of error terms not constant over time,
i.e., error terms have GroupWise Heteroskedasticity.

Table A4. Results of serial correlation (autocorrelation) through Wooldridge test

| Ho: There is no first-order Autocorrelation |
|---|
| F(1, 47) = 0.003 |
| Prob. > F =0.957 |

Here not rejecting the null hypothesis as (Prob. > 0.05) concludes that there is no first-order autocorrelation in our model.
Table A5. Results of Multicollinearity test

| Indicators               | VIF  | 1/VIF |
|--------------------------|------|-------|
| Hot                      | 1.45 | 0.689 |
| Cold                     | 1.76 | 0.567 |
| Low Precipitation        | 1.38 | 0.723 |
| High Precipitation       | 1.03 | 0.966 |
| Heatwave                 | 1.41 | 0.708 |
| Cold wave                | 1.73 | 0.567 |
| Drought                  | 1.39 | 0.729 |
| Flood                    | 1.03 | 0.969 |
| Unemployment Rate        | 1.04 | 0.958 |
| Personal Income          | 128.04 | 0.008 |
| Supplements to wages & salaries | 128.09 | 0.008 |
| Mean VIF                 | 24.39 |       |

None of the factors has a Variance Inflation Factor (i.e., VIF-value) greater than 5, concluding no Multicollinearity problem except personal income and supplements to wages & salaries (Table A5).

Table A6. Results of a fixed effect regression model

| Indicators                          | Coefficients | Stand. Error | t-statistic | p-value |
|-------------------------------------|--------------|--------------|-------------|---------|
| **Weather Extremes**                |              |              |             |         |
| Hot                                 | 0.062        | 0.110        | 0.56        | 0.573   |
| Cold                                | 0.195        | 0.130        | 1.50        | 0.134   |
| L1.Low Precipitation                | -0.028       | 0.045        | -0.62       | 0.535   |
| High Precipitation                  | -0.100 ***   | 0.037        | -2.74       | 0.006   |
| **Climate Extremes**                |              |              |             |         |
| Heatwave                            | -0.156       | 0.096        | -0.78       | 0.434   |
| Cold wave                           | 0.293        | 0.191        | 1.53        | 0.125   |
| Drought                             | 0.004        | 0.061        | 0.06        | 0.951   |
| Flood                               | 0.162 **     | 0.068        | 2.40        | 0.017   |
| **Controlled Variables**            |              |              |             |         |
| L1.Unemployment Rate                | 0.028 ***    | 0.005        | 5.33        | 0.000   |
| L1.In (personal income)             | 1.070 ***    | 0.060        | 17.96       | 0.000   |
| L1.In (supplements to Wages & Salaries) | -0.120       | 0.284        | -0.42       | 0.672   |
| **Results of Seasonality**          |              |              |             |         |
| January                             |              |              |             |         |
| February                            | -0.089 *     | 0.047        | -1.88       | 0.060   |
| March                               | 0.020        | 0.048        | 0.42        | 0.674   |
| April                               | -0.002       | 0.048        | -0.04       | 0.969   |
| May                                 | 0.019        | 0.048        | 0.39        | 0.698   |
| June                                | -0.001       | 0.048        | -0.02       | 0.986   |
| July                                | 0.112 **     | 0.048        | 2.32        | 0.020   |
| August                              | 0.177 ***    | 0.048        | 3.68        | 0.000   |
| September                           | 0.184 ***    | 0.048        | 3.86        | 0.000   |
| October                             | 0.103 **     | 0.049        | 2.16        | 0.031   |
| November                            | 0.134 ***    | 0.049        | 2.81        | 0.005   |
| December                            | 0.845 ***    | 0.048        | 17.75       | 0.000   |
| Constant                            | -12.08 ***   | 0.723        | -16.72      | 0.000   |
| F-Statistic                         | 45.2 ***     |              | 0.000       |         |
| R-Squared                           | 0.099        |              |             |         |

* shows the corresponding variable is significant at 10% significance level; ** indicates significance at 5% level; *** means significance of the corresponding variables at 1% level of significance.
Table A7. Results of the Hausman test.

| Ho: Difference in coefficients not systematic, i.e., Random effect is more appropriate than the fixed effect |
|--------------------------------------------------------------------------------------------------------|
| $\chi^2(2) = (b-B)^\prime[(V_b-V_B)^{-1}] (b-B) = 156.30$ Prob. > $\chi^2 = 0.000$ |
| ($V_b-V_B$ is not positive definite) |
| Here rejecting the null hypothesis as ($\text{Prob.} < 0.05$) concludes that the Fixed Effect is suitable in this case |

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