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Original Article

Impacts of Flood in India from 1953 to 2020

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Abstract

In this paper, authors endeavour to evaluate the impacts of flood in India during 1953-2020 in fatalities of human lives lost, area damaged, population affected, cattle lost, damaged houses, public utilities lost, etc. by applying econometric models like linear and nonlinear trend lines and the decomposition analysis through Hamilton model. The paper also showed structural breaks utilizing Bai-Perron model and found that all the damages have linear and nonlinear shapes with cycles and cyclical trend and seasonal variations. In addition to that the policy framework of Niti Aayog have been described.

Keywords: *Floods; Human Life Lost; Population Affected; House Damaged; Public Utilities Damaged; Cattle Lost; Management of Flood*

JEL Classification codes-*C32, Q25, Q54, Q58*

Introduction

Floods happen when a big volume of water covers normally dry ground. Flooding is the sudden submersion or flooding of land with water. The occurrence of floods can be done to both natural and human causes. Natural causes include, [i] excessive rainfall, [ii]storm surges, [iii] melting snow, [iv] global atmospheric processes, [v]earthquakes. Anthropogenic causes of floods include[i] clearing forest, [ii]urban development, [iii]improper farming and other land use practices, [iv]enhanced greenhouse gas effects respectively.

The frequency and intensity of floods are predicted to rise as a result of climate change, urbanization, and changes in land use, particularly in developing nations. The rising flood hazards are concerning, particularly how they affect the population that is most at risk and has the least ability to adapt. But there is some evidence, according to recent systematic reviews of the literature, that exposure to flooding increases the risk of non-communicable illnesses, poor mental health, malnutrition, and poor birth outcomes.

India being a peninsular country, and surrounded by the Bay of Bengal, Arabian sea and Indian Ocean is quite prone to flood which increases water borne diseases such as Typhoid, Cholera, Leptospirosis and Hepatitis through pollution of drinking water sources and increase vector borne diseases such as malaria, dengue and encephalitis other than human life lost and different types of damages.

Floods have an indirect influence on SDG-5 and SDG-15 as well as a direct natural impact on SDG-1 and SDG-2. Additionally, SDG-8 and SDG-9 are probably connected to the effect of flood since it ruins workers' homes and places of employment, causing job losses and disrupting industry, infrastructure, and innovation, particularly in metropolitan areas. SDG-13 is also strongly tied to the causes of flood. Therefore, measures for managing flood disasters may encourage the elimination of hunger and poverty as well as the development of land, infrastructure, and employment, respectively. Since the SDGs are linked to issues like water management, climate change, resilient infrastructure, sustainable cities and

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communities, and sustainable use of terrestrial ecosystems, more proactive ways to dealing with floods and other severe weather disasters are urgently required (Owen, 2022).

The effects of Nature Based Solutions for Fluvial Flood Risk Mitigation (FFRM), which can be implemented through 4 steps in accordance with UN 2030 Agenda within the dimensions of economy, environment, society, policy, and technical, were described using a preliminary list of 32 fluvial flooding indicators spread across the five dimensions (Environment 8, Society 5, Economy 5, Technical 6, Policy—Procedural 8).

In this paper, the authors expressed the detailed impacts of flood in India in the long run from 1953 to 2020 and included some important government policies relating to flood disaster management.

Review of Literature

The important researches are available on Indian floods and its impacts, some of which are described here. Hollis (1975) showed that there is a correlation between the increase of urbanization, the percentage of the basin paved and the recurrence interval of the flood.

Singh and Kumar (2013) conducted long-term research of floods in India between 1978 and 2006 and discovered that 2443 flood occurrences claimed 44991 lives, or an average of 1551 per year, with severe floods accounting for 56% of flood deaths and heavy rains accounting for 65%. The most deaths happened in Uttar Pradesh, where there were 17% of all fatalities, followed by Maharashtra (13%), Bihar (9%), and Gujarat (1%), where 30% of fatalities occurred in August, followed by 29% in July and 20% in September. 16 billion and 1.6 billion dollars in economic loss were calculated for the year 2000 alone.

De, Singh and Rase(2013) described the urban floods in metropolitan cities in India during 1988-2007 and stated that total deaths occurred 35,111,1876 and 136 in Delhi, Kolkata, Mumbai and Chennai respectively and total injured people were accounted as 15,88,535 and 12.The authors suggested preventive and active measures for controlling urban flood as better forecasting, identification of measurable zone, improvement of old drainage system, improvement of health and sanitation measures, preparation of long run plan, greater awareness, and good pollution control measures.

Flooding puts human lives at risk, according to a 2014 study by Blaikie, Cannon, Davis, and Wisner. Floods can disrupt business operations, increase health concerns in the neighborhood, harm agricultural crops and result in a food shortage. They can also damage infrastructure and make it difficult to access services.

From 1915 to 2015, India saw 649 calamities, according to Tripathy (2015). Out of these 649 incidents, 302 disasters (or 3 floods on average per year) were caused by flooding. This accounted for almost 47% of all disasters that occurred in India over the previous 100 years. The average number of lives lost due to these floods increased from 1000 per year in the decade from 1965 to 1975 to 1700 per year in the decade from 2005 to 2015. The total economic loss from 2005 to 2015, or the last ten years, was close to 2% of India's current GDP. The last decade indicates a sharp increase in the economic burden brought on by floods when compared to earlier decadal loss. From USD 11.6 billion in 1995–2005 to USD 34.5 billion in 2005–2015, the decadal economic burden skyrocketed. Over time, the frequency and severity increased, severely harming both lives and the economy. Although the Indian government has implemented numerous efforts to mitigate the harm caused by floods and other calamities, more work remains. Utilizing science, technology, telecommunication, and the media for warning and preventative steps before to a disaster can decrease the destruction.

Out of 104.1 million people, 76% of Bihar's population has been living under the constant danger of flooding, according to research by Kumar, Cheng, and Singh (2016) on the Bihar floods.Over 20 rural villages, including Saharsa, Khagaria, Gopalganj, Katihar, Darbhanga, Madhubani, Supaul, East and West Champaran, and Begusarai, were impacted, affecting 2.3 million people in 2013 and 5.9 million people in 3768 villages. Property, infrastructure, and social and health services were all affected by floods. It led to the ongoing marginalization and isolation of flood victims.

According to Mukherjee's (2016) research, urbanization typically increases the size and frequency of floods and may put communities at greater risk of flooding. Information on current streamflows provides a scientific basis for urban flood planning and management.

Kansal, Kishore and Kumar (2017) prescribed some flood management measures for Bihar such as [i] structural measures which include, [a] construction of flood embarkment, [b] channel improvement, [c] embarkment protection works, and [ii] nonstructural such as, [a] land use planning, [b] zoning of flood prone lands, [c] redevelopment of flood prone areas, [d] compensation and incentives, [e] flood insurance, [f] silt management and [g] flood forecasting and warning.

In their 2019 study, Muttarak and Dimitrova highlighted the urgency of taking into account the long-term health effects of floods on young children and discovered that abnormally wet conditions increased the likelihood of undernutrition for children under the age of five as indicated by stunting and wasting. The authors hypothesized that nutritional, water, and sanitation interventions during the crucial time of exposure to floods might stop the progression of undernutrition, which could lower the long-term costs of poor human development.

In order to protect people's lives and priceless assets, Glago (2020) covered disaster management topics such flood and early warning systems, flood migration and adaption techniques, monitoring, assessment, and planning. She also encouraged innovative technologies and discussed how to analyze real-time flood data with all stakeholders.

Prasad (2020) examined the effect of flood for two time periods, i.e. before 1978 and after 1979, by considering the maximum area (million hectares) and population (million) in a particular year from 1953 to 2018. Ordinal least squares were used to compare the before and after rates of change in impacted area (million hectares), population (million), crop area damage (million hectares), damage to dwellings (million hectares), human lives lost (Rs. Cr.), and total damage (Rs. A number of variables, including population (million), crop damage (million hectares), home damage (Rs. Cr.), and total damage (Rs. Cr.), were found to be statistically significant at the 1% level, while others, including area affected (million hectares) and human lives lost (at the 5% level). The population (million), total damage (Rs. Cr.), and area damaged (million hectares) were significant at the 1% and 5% levels, respectively, according to data from the succeeding era, whereas the other study variables were not. The government's reaction to floods via disaster management legislation and regulations has reduced further flood losses.

Saharia, Jain, Baishya, Haobam, Pai, and Rafieeinasab (2021) studied that flood is one of the natural hazards and cause worst fatalities and economic damages. Research needed to find the complex hydrometeorological and geomorphic factors and should design solution to minimise the impacts of floods. Due to factors like a sole focus on large floods, a constrained temporal scope, non-standard data formats, etc., the global inventory lacks the spatio-temporal fidelity required to be useful for computational research. This called for a new database from global and previously underutilized local datasets using an extensible and common schema where authors described India Flood Inventory (IFI).

Gupta, Barwal, Madan, Sood and Kishore(2021) suggested to improve monitoring, increase transparency and regulatory oversight to better estimate the effects of flood and drought, to ensure investment in resilient WASH systems in areas identifying as being highest risk contribute to building community resilience to the impacts of climate change, to address knowledge and policy gaps, strengthen institutional coordination and participation and implementation of new activities to prevent water related disasters, to define clear roles and responsibilities of department ,agencies, ministers and government in confronting the disasters.

Using Poisson and Tobit estimation methods, Parida, Roy Chowdhury, Saini, and Dash(2022) looked at empirical studies on Indian flood deaths and found that disaster deaths and damages decrease monotonically with increasing per capita income. However, they also found a nonmonotonic (inverted U-shaped) relationship between per capita income and food impact in terms of deaths, people affected, and damages due to foods in 19 major Indian states between 1980 and 2011. Researchers found that despite government efforts to reduce food-related deaths, the trend still follows a non-linear, inverted U shape using the fixed-effects methodology. Poisson estimating approach looks at the government's involvement in protecting residents from disaster risk, with an emphasis on regional differences in India;

nonetheless, the influence of government responsiveness on food deaths and food damage is statistically insignificant. The authors found that there were fewer deaths due to flooding in states with higher per capita earnings. When it comes to natural disasters and the prevention of deaths caused by them, high-income (rich) states can afford to spend more money than low-income (poor) governments. The poorest nations have significant budgetary restrictions and limited resources to reduce the incidence of food-related mortality. To mitigate the negative impacts of food insecurity, public policy should focus on increasing incomes, strengthening governance, and improving disaster management strategies, especially in the poorest nations.

Methodology

Source of data source of data

The econometric models used in this paper have been expressed below.
The semi-log linear regression model can be written as
$\text{Log}(x)=a+bt+u_i$
Where x= variable, t is the time, u= random error, i=1,2,3…..n, a and b are constants.

The semi-log non-linear regression model is used to clarify the non-linear trend line. The estimated equation can be written as: $\log(x_i)=a+bt+ct^2+dt^3+et^4+u_i$ where x_i=variable to be estimated, a, b, c, d and e are constants, t=time(year), u_i=random error, for all values of i=1,2,3,………n.

Bai-Perron (2003) model was used to find out the structural breaks where HAC standard errors and covariance (Bartlett kernel, Newey-West fixed bandwidth=4) was assumed selecting trimming=0.15 and 5% significant level under the conditions of L+1vs L sequentially determined breaks (maximum five breaks).

Bai-Perron model (2003) for structural breaks is as follows.

Let multiple linear regression model with m breaks(m+1regimes)

$y_t=x'_t\beta+A'_t\alpha+u_t$

Where j=1,2,…….m+1,y_t=dependent variable, x_t (px1)and A_t(qx1) are vectors of covariates,β and α_j (j=1,2,…..m+1) are corresponding vector of coefficients, u_t =disturbance term. T_1………T_m are break points (pure structural change model is obtained when p=0, and under convention,T_0=0 and T_{m+1}=T were used).

In the matrix, $Y=X\beta+\bar{A}\alpha+U$

Where $Y=(y_1,y_2,\ldots\ldots y_T)'$

$X=(x_1,x_2,\ldots\ldots\ldots x_T)'$

$U=(u_1,u_2,\ldots\ldots u_T)'$

$A\alpha=(\alpha'_1, \alpha'_2,\ldots\ldots\alpha'_{m+1})'$

Ā is the matrix which diagonally partitioned at $(T_1,T_2\ldots\ldots T_m)$, i.e., $\bar{A}=\text{diag}(A_1,A_2,\ldots\ldots A_{m+1})$ with $A_t=(A_{Tj-1}+1\ldots\ldots\ldots\ldots AT_j)'$

To estimate the unknown regression coefficient BP, let F type test of number of structural break(m=0) Vs m=k breaks, let R=conventional matrix such that $(R\alpha)'=(\alpha'_1-\alpha'_2,\ldots\ldots\alpha'_k-\alpha'_{k+1})$.

Define, $F_T(\lambda_1\ldots\ldots\lambda_k;q)=\frac{1}{T}\left(\frac{T-(k+1)q-p}{kq}\right)\ \widehat{\alpha}'R'(R\tilde{v}(\widehat{\alpha})R')^{-1}R\ \widehat{\alpha}$ where $\tilde{v}(\widehat{\alpha})$ is an estimate of covariance matrix of α_i i.e., a consistent estimate of

$V(\widehat{\alpha})=p\lim_{T\to\infty}T(\bar{A}'M_x\bar{A})^{-1}\bar{A}'M_x\Omega M_x\bar{A}(\bar{A}'M_x\bar{A})^{-1}$

where $M_x=I-X(X'X)^{-1}X'$ and $V(\widehat{\alpha})$=p limit T tends to infinity for $T(\bar{A}'M_x\bar{A})^{-1}$

By OLS, to estimate under T observations on (y_t, x_t, z_t) and it obtained β and α_j by minimising sum of squared residuals;

$$(Y-X\beta-\bar{A}\alpha)'(Y-X\beta-\bar{A}\alpha)=\sum_{i=1}^{m+1}\sum_{t=Ti-1+1}^{Ti}[y_t-x'_t\beta-A'_t\alpha_i]^2$$

To get asymptotically distinct breaks, let $\lambda_i=T_i/T$ (i=1,2,…….m) defining number of trimming parameter $\epsilon=h/T$ where h=minimum length.

$Z\epsilon=\{(\lambda_1,\ldots\ldots\lambda_m);|\lambda_{i+1}-i_n|\geq\epsilon,\lambda_1\geq\epsilon,\lambda_m\leq 1-\epsilon\}$

Let $\widehat{\beta}$ =estimate of β, the estimate of break points of ($T_1,T_2,\ldots\ldots\ldots T_m$) are ($\dot{T}_1$, $\dot{T}_2$….. $\dot{T}_m$)

let $\widehat{\beta}$ ({Tj}) and $\widehat{\alpha}$ ({Tj}) denote the estimates based on given m partitions ($T_1,T_2,\ldots\ldots\ldots\ldots T_m$) denoted by {Tj}.Substituting these in objective function and denoting the resulting sum of squared residuals as S_T ($T_1,T_2,\ldots\ldots\ldots\ldots T_m$),the estimated break points ($\dot{T}_1$, $\dot{T}_2$….. $\dot{T}_m$) are

($\dot{T}_1$, $\dot{T}_2$….. $\dot{T}_m$)= argmin $(\lambda_1,\ldots\ldots\lambda_m)\epsilon A_\epsilon S_T$ ($T_1,T_2,\ldots\ldots\ldots\ldots T_m$)

i.e., with the minimisation taken over all partitions ($T_1,T_2,\ldots\ldots\ldots\ldots T_m$) such that

$T_i-T_{i-1}\geq h=T_\epsilon$

The regression parameters estimates are the estimates associated with the m partition { $\dot{T}_j$} which was presented by Bai and Perron(2003). Thus, the test becomes,

$supF_T(k;q)=F_T(\lambda^*_1,\lambda^*_2,\ldots\ldots\lambda^*_k;q)$ where ($\lambda_1^*\ldots\ldots\lambda^*_k$) is estimates of ($\lambda_1\ldots\ldots\lambda_m$).

Bai-Perron proposed l vs l+1 breaks levelling $supF_T(l+1vs\ l)$ at H0= no breaks by alternative hypothesis of a single change containing observations using the above mentioned conventions. Reject the Ho if over all maximum value of $F_T(1;q)$.

For decomposition of trends and cycles, the Hamilton (2018) regression filter model was used which can be expressed in the following manner.

$y_{t+8}=\alpha_0+\alpha_1y_t+\alpha_2y_{t-1}+\alpha_3y_{t-2}+\alpha_4y_{t-3}+v_{t+8}$ where y=variable to be regressed.

Or, $v_{t+8}=y_{t+8}-(\acute{\alpha}_0+\acute{\alpha}_1y_t+\acute{\alpha}_2y_{t-1}+\acute{\alpha}_3y_{t-2}+\acute{\alpha}_4y_{t-3})$

So, $y_t=\alpha_0+\alpha_1y_{t-8}+\alpha_2y_{t-9}+\alpha_3y_{t-10}+\alpha_4y_{t-11}+v_t$

Therefore, $v_t=y_t-(\acute{\alpha}_0+\acute{\alpha}_1y_{t-8}+\acute{\alpha}_2y_{t-9}+\acute{\alpha}_3y_{t-10}+\acute{\alpha}_4y_{t-11})$ where $\acute{\alpha}_i$ are estimated.

$v_{t+h}=y_{t+h}-y_t$ is the difference i.e., how the series changes over h periods. For h=8, the filter $1-L^h$ wipes out any cycle with frequencies exactly one year and thus taking out both long run trend as well as any strictly seasonal components.

It also applies to random walk: $y_t=y_{t-1}-\varepsilon_t$ where d=1 and $\omega_t^h=\varepsilon_{t+h}+\varepsilon_{t+h-1}+\ldots\ldots\ldots\ldots+\varepsilon_{t+1}$

Regression filter reduces to a difference filter when applied to a random walk. Hamilton suggested h=8 for business cycles and h=20 for studies in financial cycles. Regression v_t converges in large samples to α_1=1 and all other α_j =0. Thus, the forecast error is $v_{t+h}=y_{t+h}-y_t$.

The residual equation v_t can be decomposed into trend, cycle and seasonally adjusted through SEATS/TRAMO or STL or census X-13 packages. The STL method is developed by Cleveland, Cleveland, McRae and Terpenning (1990).

Q stat, ACF and PACF were developed by using Ljung and Box (1978) model. Q-statistic is calculated as:

$Q=T(T+2)\ \Sigma r^2_k/(T-k)$ where k=1 to s

Autocorrelation Function (ACF) can be derived from the formula

$ACF=\rho_s=a_1\rho_{s-1}+a_2\rho_{s-2}$ where s=1,2,3……………n

And Partial Autocorrelation Function (PACF) can be derived from the formula

$\Phi_{ss}=(\rho_s-\Sigma\phi_{s-1,j}\rho_{s-j})/(1-\Sigma\phi_{s-1,j}\rho_j)$ where s=3,4,5,………..,$\phi_{sj}=\phi_{s-1,j}-\phi_{ss}\phi_{s-1,s-j}$,j=1,2,3….s-1

The data on damages to flood viz human life lost(x_1), area affected(x_2), population affected(x_3), crop damaged(x_4), houses damaged(x_5), cattle lost(x_6), and public utilities lost(x_7) from 1953 to 2020 were collected from Water Resource Commission of India.

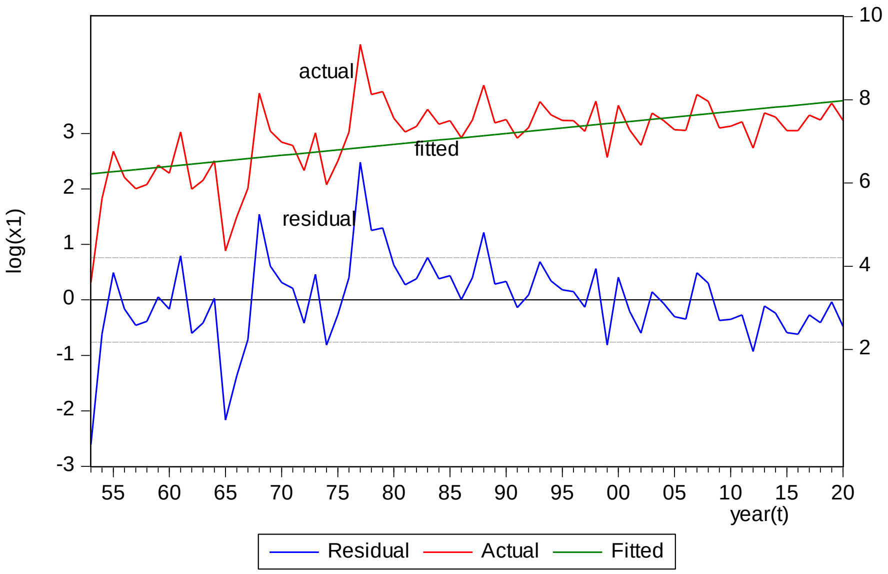
Results

Total fatalities of death of human life as a result of flood in India from 1953 to 2020 has been catapulting at the rate of 2.62% per year significantly under semi-log linear trend regression model which is given below.

$$\text{Log}(x_1)=6.1924+0.02629t+u_i$$
$$(33.13)^*\ (5.58)^*$$

R^2=0.32,F=31.17*,DW=1.09,n=68,x_1= death of human life ,t= year,*=significant at 5% level and u_i=random error.

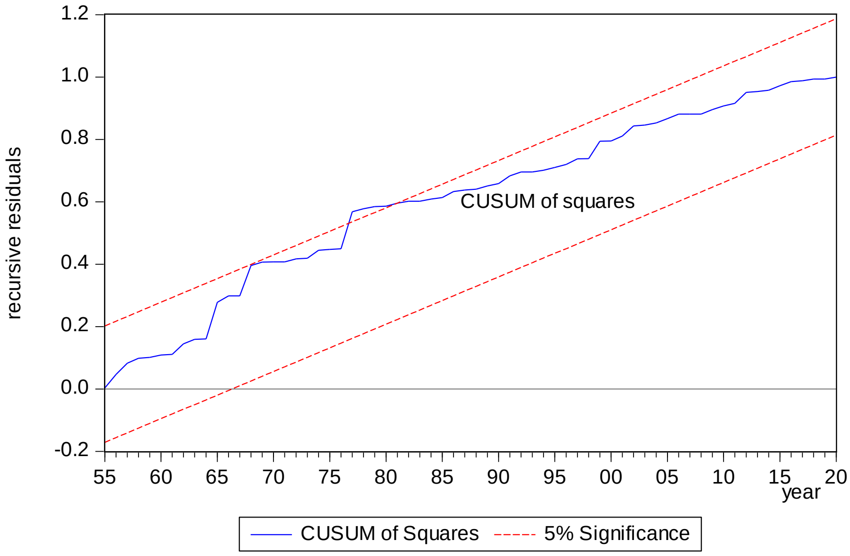
In Figure 1, the fitted linear trend line with the actual line of human life lost from 1953 to 2020 has been depicted where the fitted linear trend line is upward rising. The average human life lost was 1676 during 1953-2020 and the maximum life lost was 11316 in 1977.



Source: Primary

Figure 1: Linear trend line of human life lost

This linear trend line estimate is obtained as stable since its line of CUSUM of squares pass through ±5% significant level which is seen in Figure 2 below.



Source: Primary
Figure 2: Stability of trend line

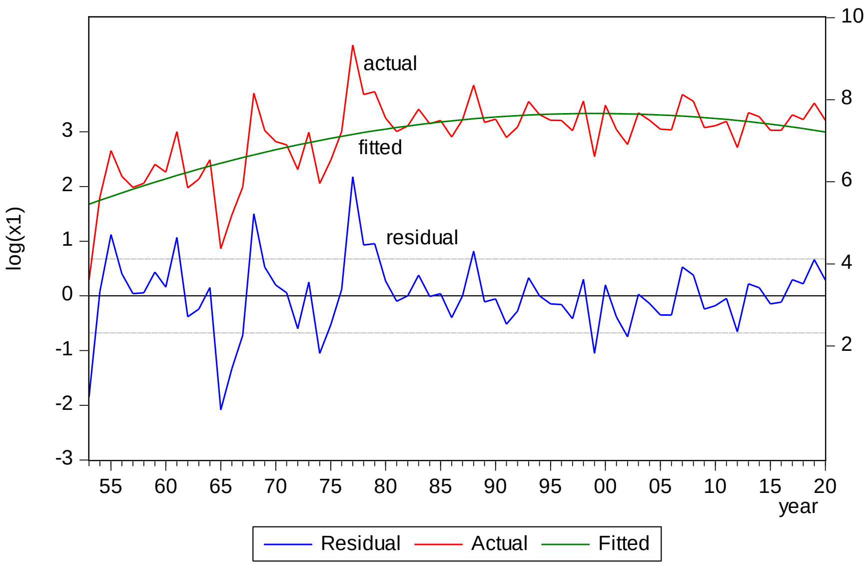
The nonlinear trend line of human life lost for flood in India from 1953 to 2020 is estimated where both the phases are significant.

$\text{Log}(x_1)=5.3567+0.0979t-0.001038t^2+u_i$

(21.16)* (5.78)* (-4.36)*

$R^2=0.47, F=29.38^*, DW=1.408, n=68$, *=significant at 5% level, u_i=random error.

In Figure 3, it is shown that the estimated nonlinear trend is seen as inverse U shaped.



Source: Primary
Figure 3: Nonlinear trend

For decomposition analysis, Hamilton regression filter equation is estimated below.

$\text{Log}(x_1)_t=3.537+0.1319\log(x_1)_{t-8}+0.2990\log(x_1)_{t-9}+0.0895\log(x_1)_{t-10}+0.0099\log(x_1)_{t-11}+v_t$

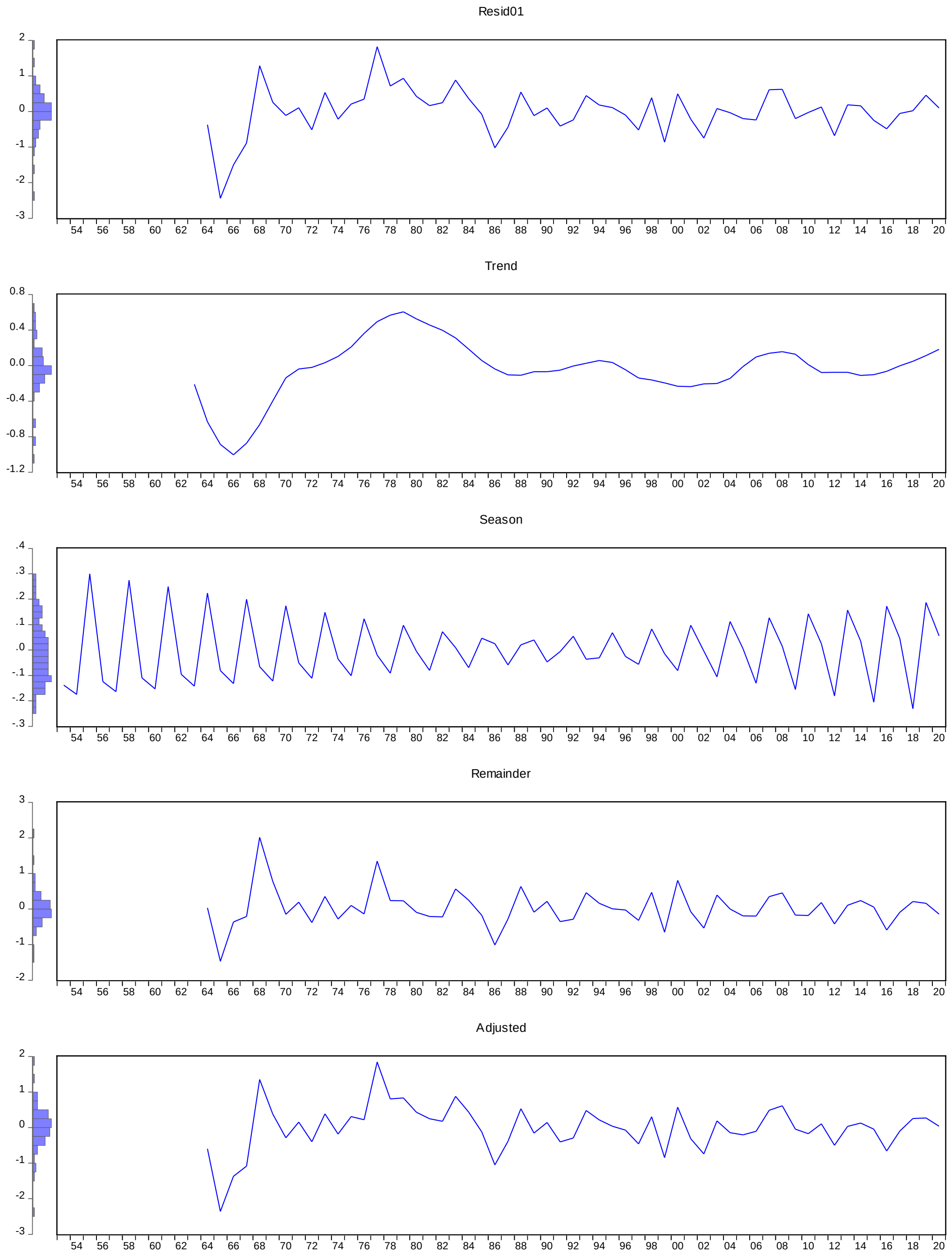
(3.77)* (1.01) (2.11)* (0.62) (0.08)

$R^2=0.25, F=4.55^*, DW=1.33, n=57$, *=significant at 5% , v_t=residual

Thus,

$V_t= \text{Log}(x_1)_t-[3.537+0.1319\log(x_1)_{t-8}+0.2990\log(x_1)_{t-9}+0.0895\log(x_1)_{t-10}+0.0099\log(x_1)_{t-11}]$

This v_t can be transformed into Hamilton cyclical trend, cycles, seasonal variation by applying STL method which is shown in the Figure 4 below.



Source: Primary
Figure 4: Cyclical trend, cycles and seasonal variation

In the cycle of human life lost consists of 16 peaks and 16 troughs during 1953-2020 in panel 1 but in the cyclical trend there are only three peaks and four troughs after estimation whose direction is upward with minimum amplitudes which was observed in panel 2.The seasonal variation is found as inverse v shaped whose volatility decreased then increased gradually which is shown in panel 3.The remainder and adjusted cycles have no abnormal movement which are plotted in panel 4 and 5 respectively.
The seasonal fluctuations of Hamilton residual can be verified by using correlogram of residuals where the autocorrelation functions and partial autocorrelation functions continuously varied from positive to negative values and its Q stats are not significant at 5% level. All these have been seen in Figure 5.

	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1			0.329	0.329	6.5131	0.011
2			0.106	-0.002	7.2060	0.027
3			-0.099	-0.150	7.8215	0.050
4			-0.006	0.082	7.8238	0.098
5			0.117	0.133	8.7085	0.121
6			0.061	-0.050	8.9572	0.176
7			0.013	-0.015	8.9680	0.255
8			-0.096	-0.067	9.5989	0.294
9			-0.062	-0.007	9.8656	0.361
10			-0.003	0.020	9.8663	0.452
11			-0.102	-0.154	10.633	0.475
12			-0.266	-0.241	15.903	0.196
13			-0.133	0.093	17.251	0.188
14			-0.160	-0.137	19.256	0.155
15			0.029	0.048	19.323	0.199
16			-0.043	-0.045	19.476	0.245
17			-0.103	-0.091	20.368	0.256
18			-0.218	-0.154	24.484	0.140
19			-0.041	0.141	24.636	0.173
20			0.075	-0.011	25.153	0.196
21			0.077	-0.022	25.713	0.218
22			-0.100	-0.164	26.677	0.224
23			-0.079	0.019	27.288	0.244
24			-0.024	-0.028	27.344	0.289

Source: Primary
Figure 5: ACF and PACF of Vt

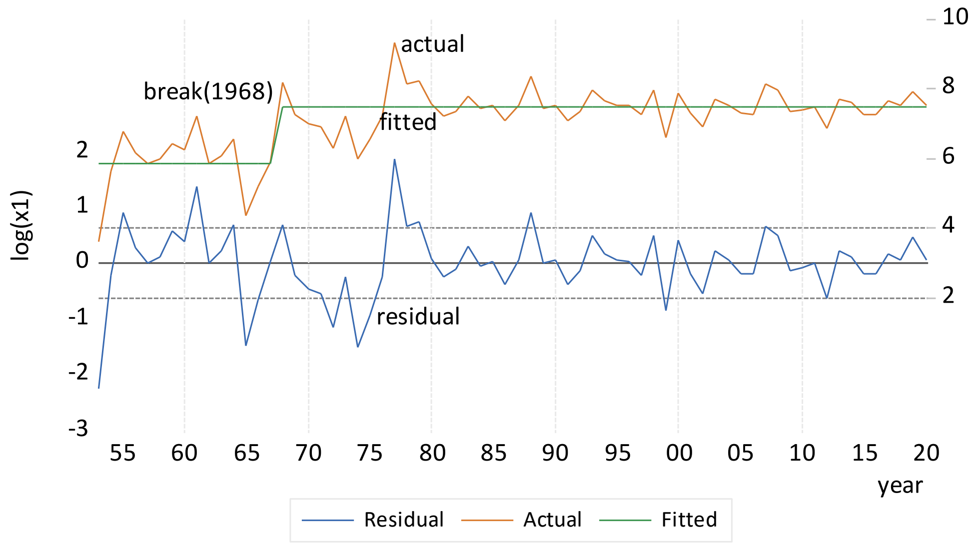
Human lives lost due to flood in India during 1953-2020 revealed one upward structural break in 1968 which is depicted in Figure 6 and was obtained by applying Bai-Perron test (2003) of L+1 vs L sequentially determined breaks assuming HAC standard errors and covariance having trimming =0.15 with 5 maximum breaks at 5% significant level. The estimated regression is given in Table 1 below.

Table 1: Structural Breaks

Variable	Coefficient	Standard error	t-statistic	Probability
		1953-1967—15 observations		
C	5.849	0.2376	24.615	0.000
		1968-2020---53 observations		
C	7.453	0.0877	84.963	0.000

R^2=0.532, F=75.16*,DW=1.419,AIC=1.95,SC=2.015,*=significant at 5% level, n=68

Source: Primary



Source: Primary
Figure 6: Structural breaks of human lives lost

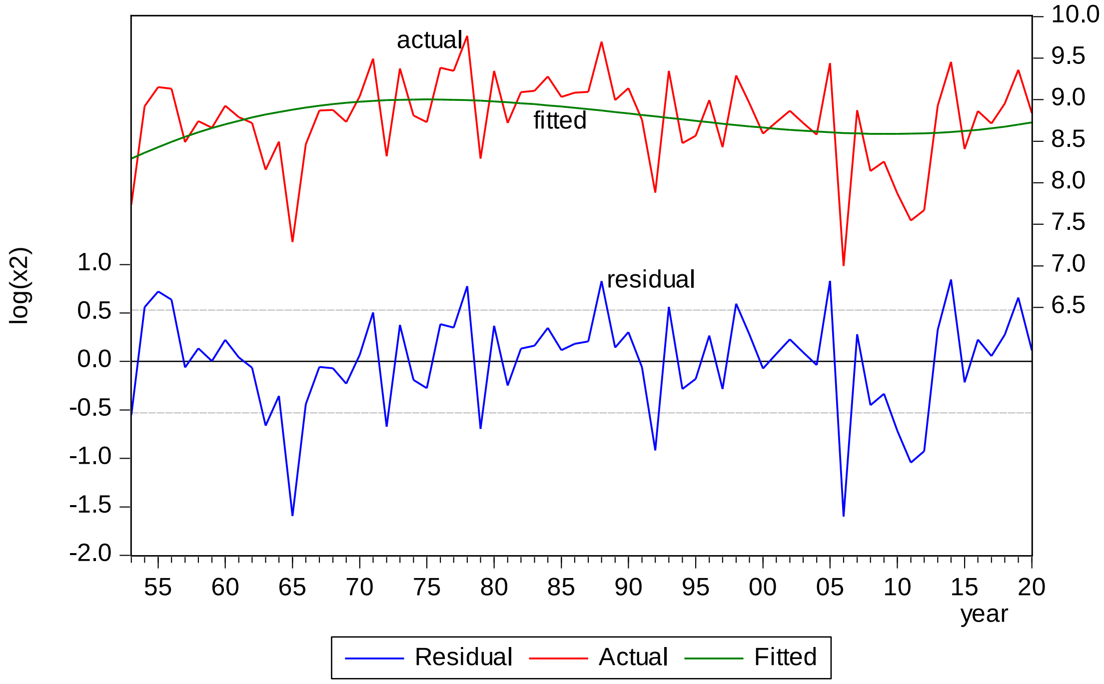
The affected areas in million hectares showed three phased shapes of nonlinear trend in which first phase is increasing followed by declining and upswing significantly during 1953-2020.

$Log(x_2)=8.212+0.0794t – 0.002425t^2+2.01e^{-05}t^3 +u_i$

(30.14) (2.34)* (-2.12)* (1.85)*

R^2=0.1015,F=2.41*,DW=1.884,n=68,x_2= area damages in million hectares,*=significant at 6% level, u_i=random error..

This nonlinear trend line is seen in Figure 7 below.



Source: Primary

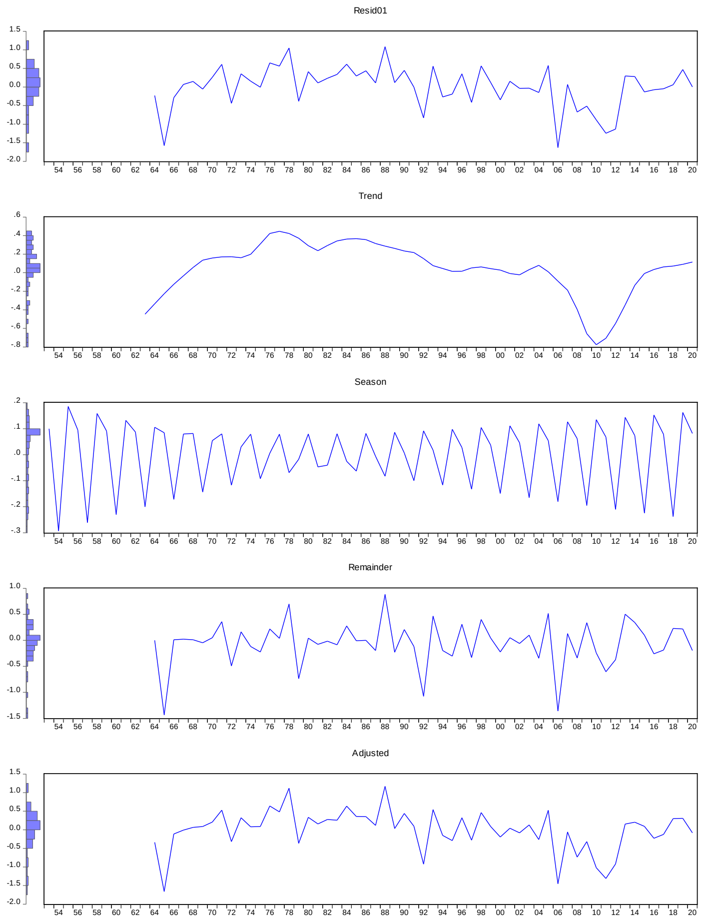
Figure 7: Nonlinear trend of area damaged

It was observed that the average area affected was 7.243 million hectares during 1953-2020 and the highest area affected was 17.500 million hectares in 1978.

Hamilton regression residual filter is given below,

$V_t=9.323-[\log(x_2)_t -0.183\log(x_2)_{t-8}+0.113\log(x_2)_{t-9} -0.0127\log(x_2)_{t-10}+0.0205\log(x_2)_{t-11}]$

This v_t is decomposed by using STL method to have cycle, cyclical trend and seasonal variations of area damages due to flood in India during 1953-2020 which is seen in Figure 8 in which panel 1 showed cycle of area damaged which consists of 19 peaks and 19 troughs, panel 2 showed cyclical trend which consists of 5 peaks and 5 troughs and it is more or less inverse U shaped. Panel 3 describes the seasonal variation which is v shaped where intensity decreases and then increases. The remainder and adjusted cycles showed in panel 4 and 5 are similar to cycles.



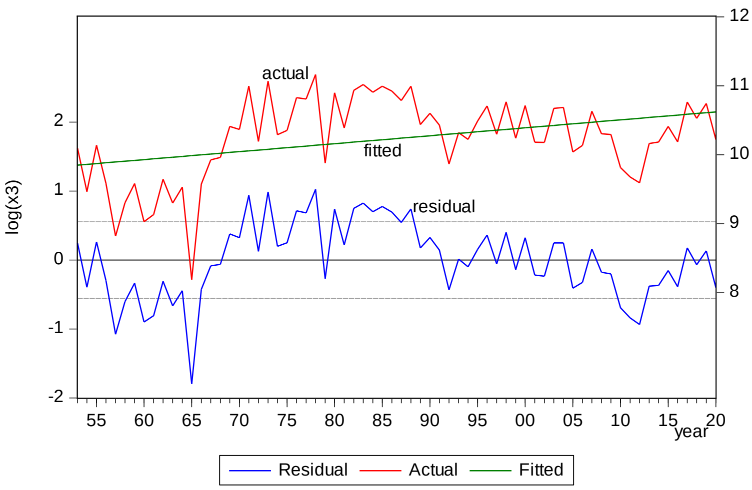
Source: Plotted by author
Figure 8: Cycles of area damaged

The population affected in million had been increasing at the rate of 1.15% per year significantly during 1953-2020 which is estimated below.

$\text{Log}(x_3)=9.887+0.011529t+u_i$
(72.28)* (3.36)*

R^2=0.146, F=11.30*, DW=0.86, n=68, x_3= crop damages in value in Rs crores, *=significant at 5% level, and u_i=random error.

In Figure 9, the linear trendline is plotted below.



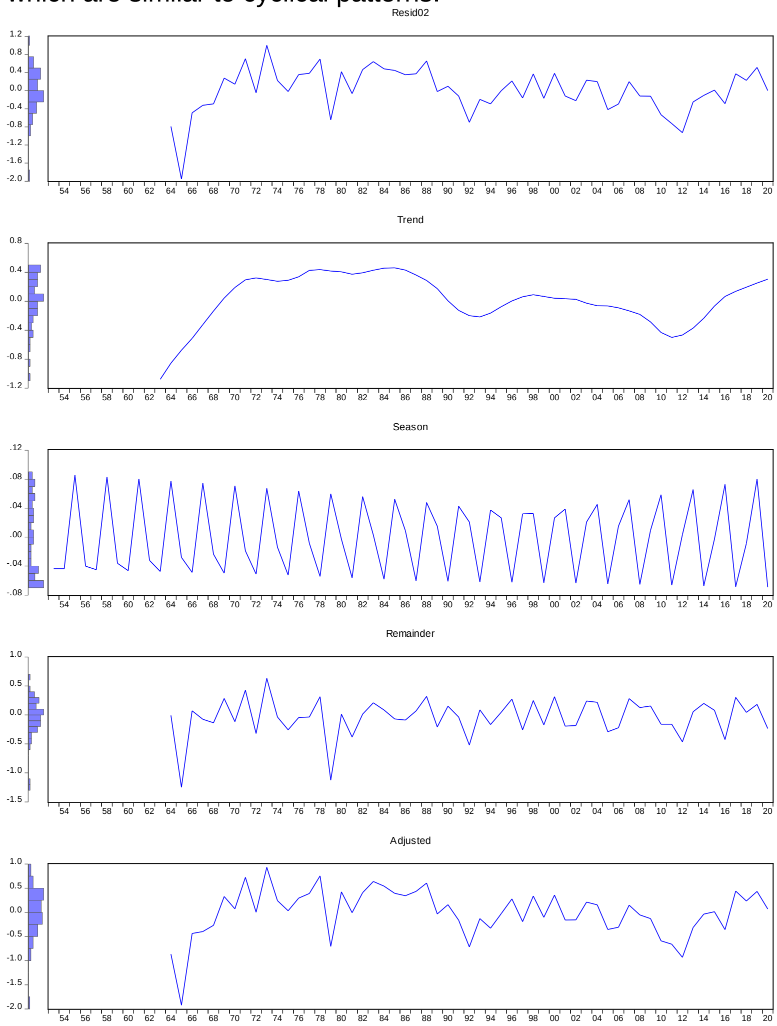
Source: Plotted by author
Figure 9: Population affected in million

The average population affected was 32.335 million during 1953-2020 and the maximum population affected was 70.450 million in 1978.

The residual of Hamilton regression filter model of population affected in million is estimated below.

$V_t=8.4955-[\log(x_3)_t -0.1405\log(x_3)_{t-8}+0.158\log(x_3)_{t-9}-0.0415\log(x_3)_{t-10}-0.0726\log(x_3)_{t-11}]$

This v_t is decomposed into cycles, cyclical trend and seasonal variation by applying STL method which is seen in Figure 9 below where in panel 1, cycle consists of 18 peaks and 18 troughs, in panel 2, cyclical trend consists of only 4 peaks and 4 troughs and as a whole it is inverse u shaped, in panel 3, the seasonal variation showed inverse v shaped. Panel 4 and 5 verify remainder and adjusted cycle which are similar to cyclical patterns.



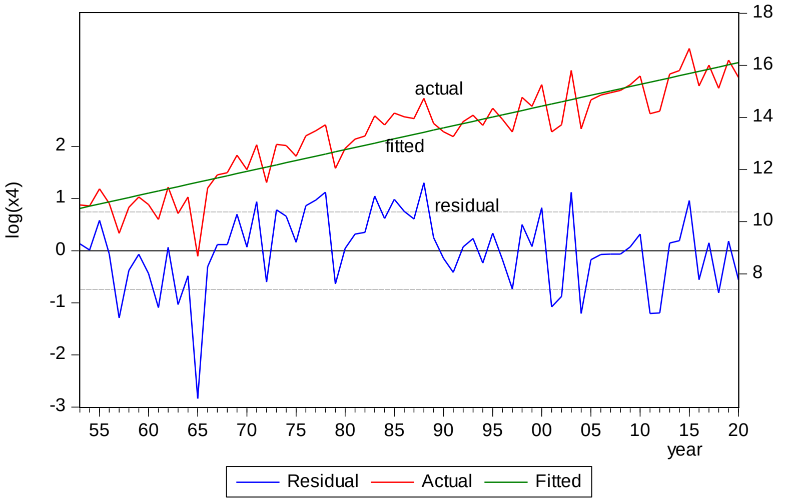
Source: Plotted by author
Figure 10: Cycle of population affected

The damaged crop value in Rs crores has been increasing at the rate of 8.34% per year significantly during 1953-2020 which is estimated below.

$$\text{Log}(x_4)=10.429+0.083454t+u_i$$
$$(57.16)^* \quad (18.15)^*$$

$R^2=0.83$, F=329.63*, DW=1.629, x_4=value of damaged crop in Rs crores, n=6,*=significant at 5% level and u_i=random error.

In Figure 11, the estimated linear trendline is shown which is upward rising from left to right.

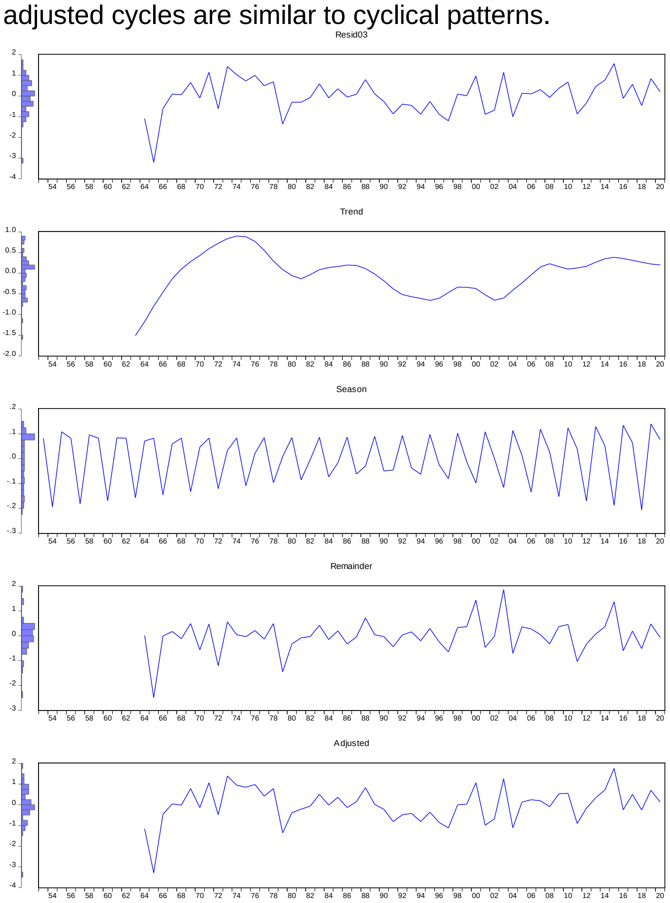


Source: Plotted by author
Figure 11: Linear trend of crop damaged

The average damage to crops was recorded as Rs1933.257 Crores during 1953-2020 and the maximum damages was Rs17043.946 crore in 2015.

The regression filter of Hamilton model whose residual v_t of crop damaged in value is given below:
V_t=3.523-[log$(x_4)_t$+0.232log$(x_4)_{t-8}$+0.125log$(x_4)_{t-9}$+0.291log$(x_4)_{t-10}$+0.143log$(x_4)_{t-11}$]

This v_t is decomposed into cycles, cyclical trend and seasonal variation by using STL method which is seen in Figure 12 below. In panel 1, cycle consists of 21 peaks and 20 troughs, in panel 2 cyclical trend consists of 5 peaks and 4 troughs, in panel 3, seasonal variation is v shaped and remainder and adjusted cycles are similar to cyclical patterns.



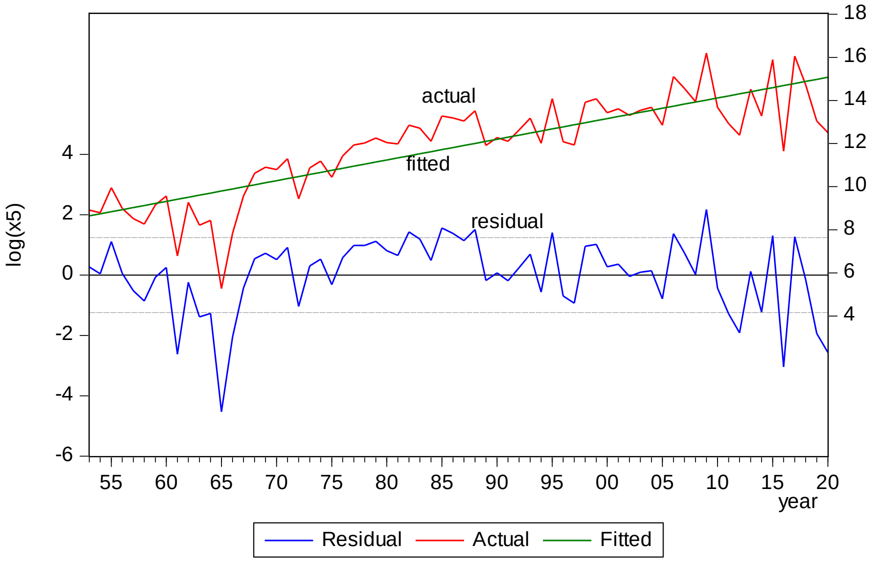
Source: Plotted by author
Figure 12: Decomposition of crop damaged in value

The value of damaged house as a result of flood has been rising at the rate of 9.59% per year significantly during 1953-2020 which is estimated below.

$Log(x_5)=8.551+0.09594t+u_i$
(28.11)* (12.51)*

$R^2=0.70, F=156.72^*, DW=1.39, n=68, x_5$=value of damaged house in Rs crore,*=significant at 5% level and u_i=random error.

In Figure 13, the linear estimated trendline of damaged houses has been depicted which is upward rising from left to right.



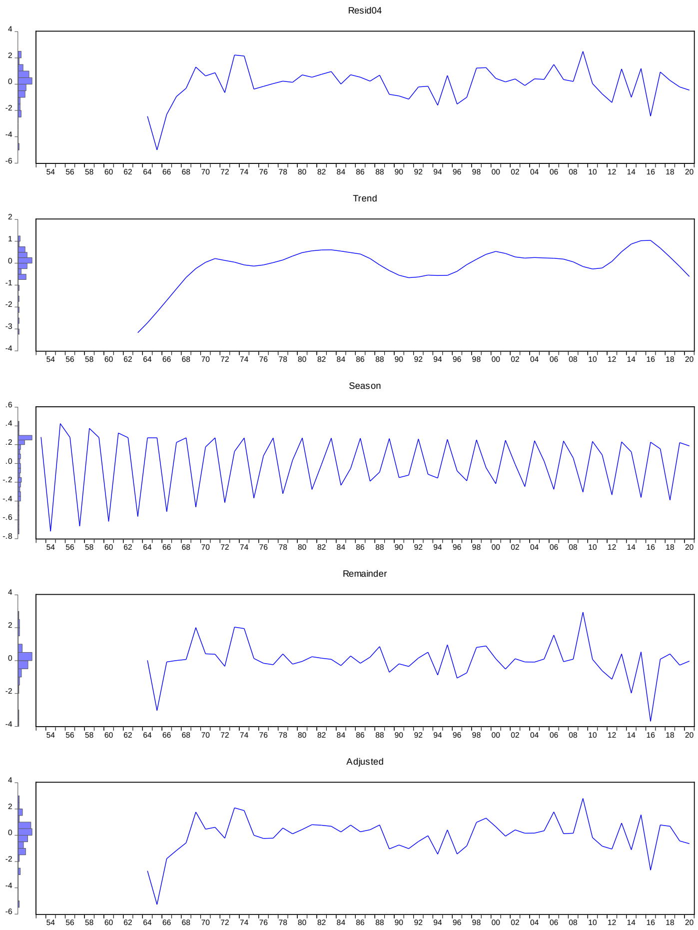
Source: Plotted by author
Figure 13: Trendline of damaged houses

The average damage to houses was Rs 838.499 crore during 1953-2020 and the maximum damages to houses was Rs10809.795 crores in 2009.

The Hamilton regression filter residual v_t is estimated below.

$V_t=4.1187-[\log(x_5)_t+0.5017\log(x_5)_{t-8}+0.255\log(x_5)_{t-9}-0.0765\log(x_5)_{t-10}+0.0345\log(x_5)_{t-11}]$

This v_t can be decomposed into cycles, cyclical trend and seasonal variation by applying STL method which is depicted in Figure 14 below in which panel 1 showed the cycles of house damaged during 1953-2020 which consists of 17 peaks and 18 troughs, panel 2 showed cyclical trend which consists of 4 peaks and 3 troughs, panel 3 showed seasonal variation of v shaped and panel 4 and 5 showed remainder and adjusted cycle which look like cycle of panel 1.

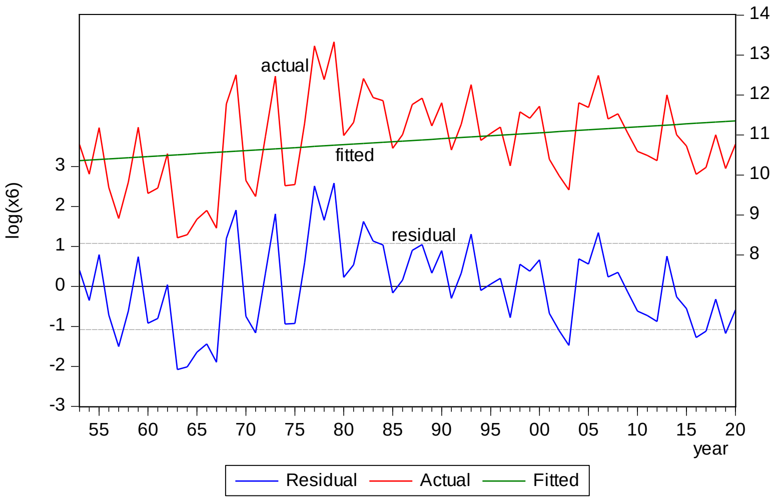


Source: Plotted by author
Figure 14: Cycles of house damaged

Total cattle lost due to flood during 1953-2020 has been increasing at the rate of 1.48% per year significantly which is estimated below.

$$\text{Log}(x_6)=10.3425+0.01486t+u_i$$
$$(39.08)^* \quad (2.22)^*$$

R^2=0.070, F=4.96*, DW=1.116, n=68, x_6=total cattle lost,*=significant at 5% level of significant, and u_i=random error.



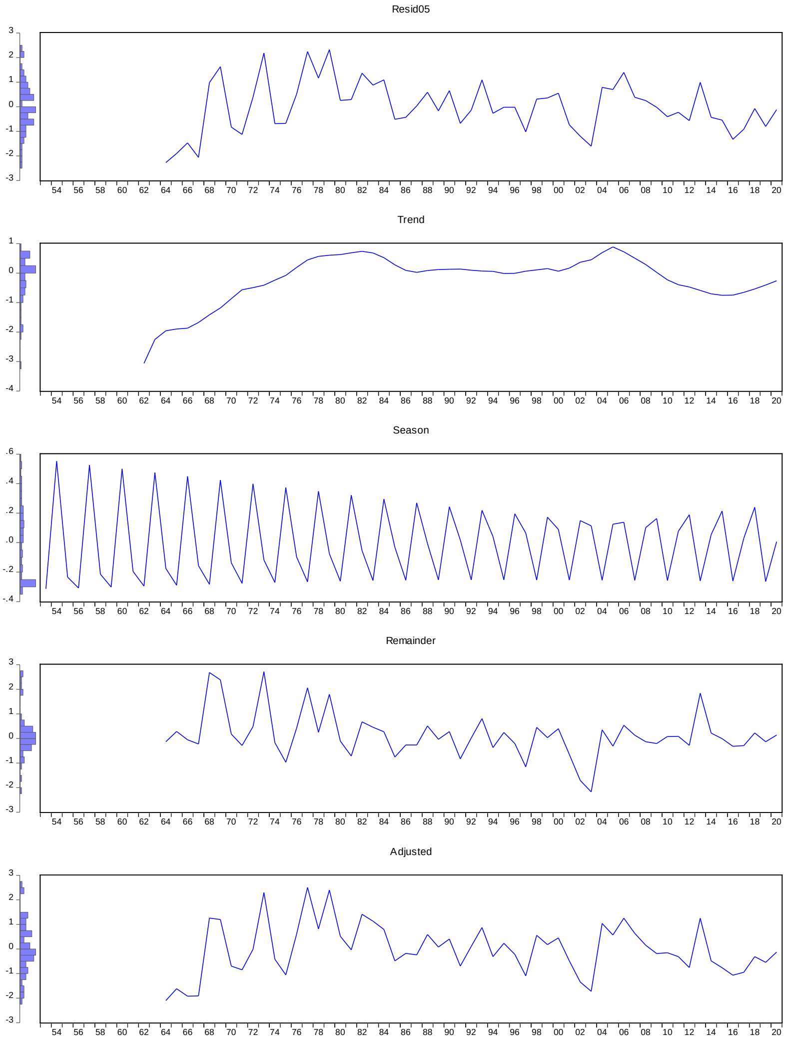
Source: Plotted by author
Figure 15: Cattle lost

In Figure 15, the fitted and actual line of cattle lost has been plotted where fitted trendline showed upward rising.

The average cattle lost was recorded as 90926 during 1953-2020 and the maximum cattle lost was found as 618248 in 1979.
The residual of Hamilton regression filter of cattle lost during 1953-2020 is estimated below.

$$V_t=7.8307-[\log(x_6)_t-0.1124\log(x_6)_{t-8}+0.064\log(x_6)_{t-9}+0.1507\log(x_6)_{t-10}-0.0338\log(x_6)_{t-11}]$$

This v_t has been decomposed into cycles, cyclical trend and seasonal variation by using STL method which is plotted in Figure 16 where in panel 1 the cycle consists of 17 peaks and 17 troughs, in panel 2 the cyclical trend consists of 2 peaks and 2 troughs, in panel 3,the seasonal variation is inverse v shaped, in panel 4 and 5,the remainder and adjusted cycles look like the cycles of panel 1.



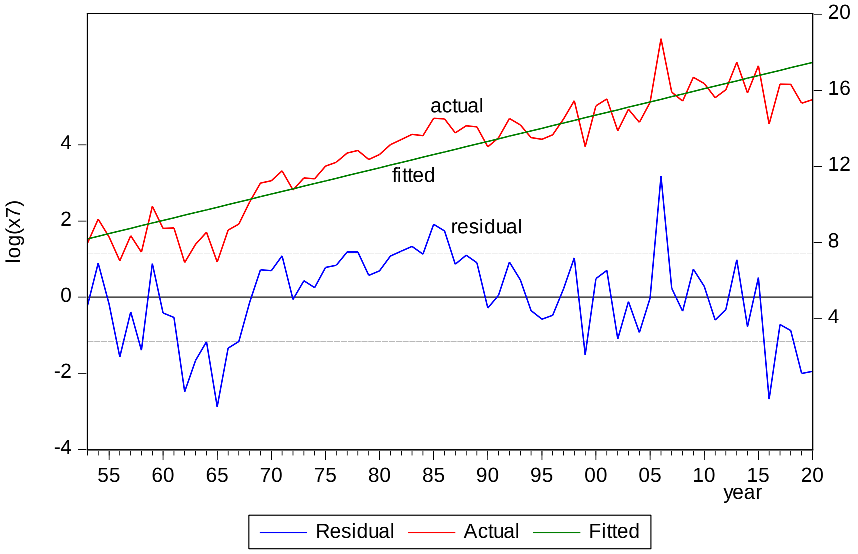
Source: Plotted by author
Figure 16: Cycles of cattle lost

The damage to public utilities in Rs crore has been catapulting at the rate of 13.83% per year significantly during 1953-2020 which is estimated below.

$$\text{Log}(x_7)=8.056+0.13834t+u_i$$
$$(28.36)^* \ (19.33)^*$$

R^2=0.849, F=373.71*, DW=1.059, n=68, x_7= total values of public utilities in Rs crore,*=significant at 5% level and u_i=random error.

In Figure 17, the linear trendline of damage of public utilities has been depicted where the trendline is upward rising from left to right.



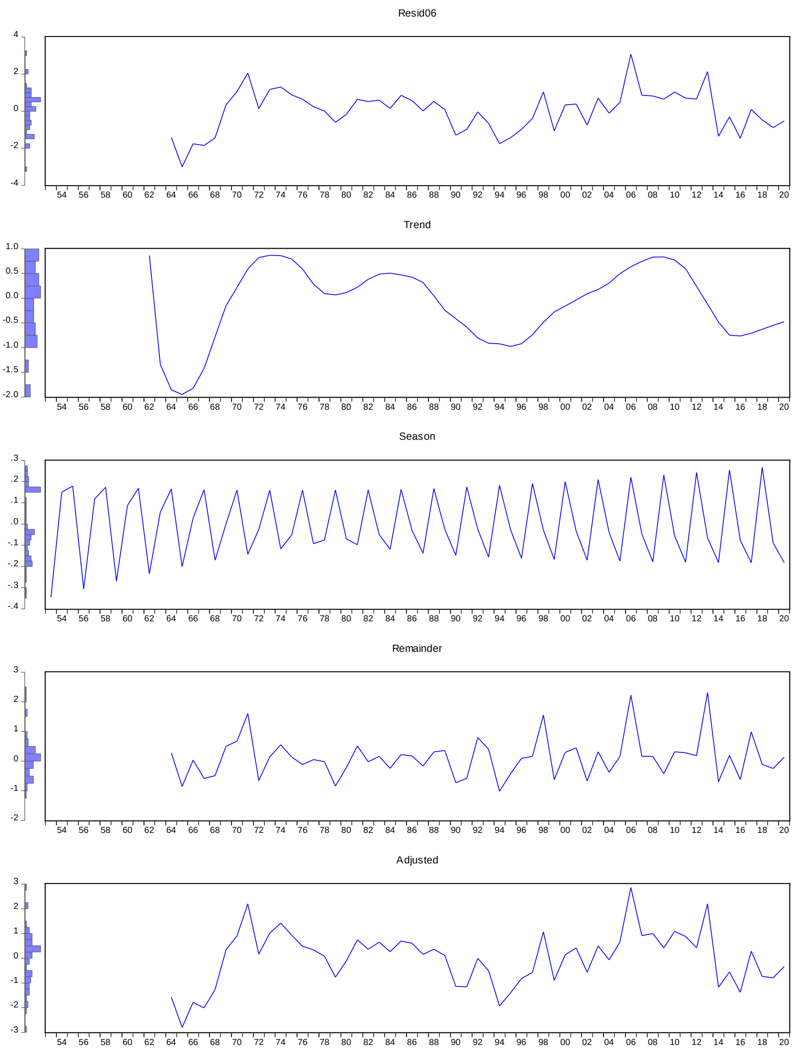
Source: Plotted by author
Figure 17: Damage of public utilities

The average damage of public utilities was seen as Rs 3443.372 Crores during 1953-2020 and the maximum damage of public utilities was recorded as Rs 38937.843 crores in 2013.

Residual of Hamilton regression filter of damages of public utilities is estimated below.

V_t=4.4269-[log$(x_7)_t$+0.3916log$(x_7)_{t-8}$+0.473log$(x_7)_{t-9}$-0.1138log$(x_7)_{t-10}$-0.0116log$(x_7)_{t-11}$]

This v_t has been decomposed into cycles, cyclical trend and seasonal variation of damages of public utilities during 1953-2020 by using STL method in which the panel 1 showed cycles which consist of 15 peaks and 16 troughs, the panel 2 showed cyclical trend which consists of 3 peaks and 4 troughs where two peaks and one trough have long amplitudes, panel 3 showed inverse v shaped seasonal variation and panel 4 and 5 explained as remainder and adjusted cycles respectively in Figure 18.



Source: Plotted by author
Figure 18: Cycles of damaged public utilities

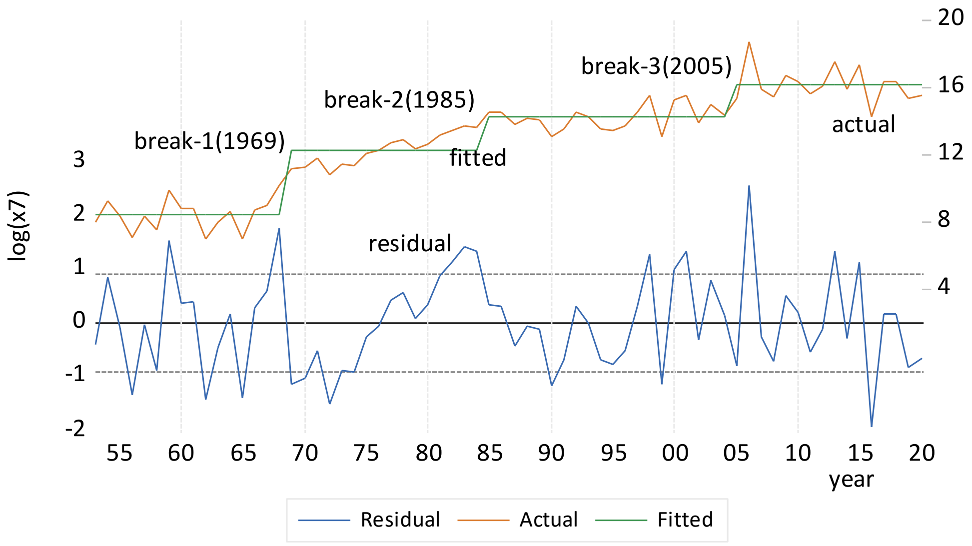
Damages to public utilities in Rs Crores in India due to flood during 1953-2020 revealed three upward structural breaks in 1969,1985 and 2005 respectively which was estimated below in Table 2. It was found by applying Bai-Perron test (2003) of L+1 vs L sequentially determined breaks assuming HAC standard errors and covariance having trimming =0.15 with 5 maximum breaks at 5% significant level.

Table 2: Structural break of public utilities lost

Variable	Coefficient	Standard error	t-statistic	Probability
		1953-1968---16 observations		
C	8.372	0.211	39.498	0.000
		1969-1984---16 observations		
C	12.266	0.398	30.765	0.000
		1985-2004—20 observations		
C	14.188	0.171	82.962	0.000
		2005-2020—16 observations		
C	16.150	0.173	92.897	0.000

R^2=0.909, F=213.67*, DW=1.904, SC=2.84, AIC=2.716, n=68, *=significant at 5% level.

These structural breaks of public utilities lost have been depicted in Figure 19 below.



Source: Plotted by author
Figure 19: Structural breaks of public utilities lost

Policy framework

According to NITI Aayog (2021), the flood management and anti-erosion schemes have been planned, investigated and implemented by the State Governments with own resources as per priority within the State. The Union Government only renders assistance to States which is technical, advisory, catalytic and promotional in nature which is carried out through Entry 56 of List I (Union List) which is “Regulation and development of inter-State rivers and river valleys to the extent to which such regulation and development under the control of the Union is declared by Parliament by law to be expedient in the public interest.”
The structural measures for flood control are:

A]. A reservoir created behind a dam across a river

B]. A natural depression suitably improved and regulated, if necessary

C]. By diversion of a part of the peak flow to another river or basin, where such diversion would not cause appreciable damage.

D]. By constructing a parallel channel by-passing a particular town/reach of the river prone to flooding. The structural methods of flood protection/anti erosion are given below.

a) Embankments which artificially raise the effective river bank and thereby prevent spilling.

b) Channel and drainage improvement work, which artificially reduce the flood water level so as to keep the same, confined within the river banks and thus prevent spilling.

c) Anti-erosion measures which prevent further loss of valuable land.

d) River channelization works to train the braided rivers to flow in a desired course to prevent further loss of land and to induce siltation.

Through their investments in flood management projects, anti-erosion, anti-sea erosion, drainage construction, and maintenance work through the State WR/Irrigation/Flood Control/Public Health Departments, the State/UT Governments have mostly focused on the structural measures. Under the Flood Management Programme (FMP), the Government of India has been offering States promotional financial support for such projects in priority areas subject to budgetary allocations.

Integrated flood approach is described as:

Flood Plain Zoning, Flood Forecasting (Modernisation of Data Collection and Transmission System, Advancements in Flood Forecast Formulation, Modernisation of Forecast Dissemination,), Reservoir

Operation, Integrated Reservoir Operation, Dam Safety and Emergency Action Plan, Application of Space Technology, Adherence to Coastal Zone Regulations.

Other government initiative is the two-tier system for flood management in India which is done through:

[i] Central Government (Central Water Commission, Ganga Flood Control Commission (GFCC), Brahmaputra Board (BB), National Disaster Management Authority (NDMA))

[ii] State Government (Water Resources Departments, State Technical Advisory Committees (STAC), Flood Control Boards, Irrigation Departments, Public Works Departments)

Discussion

Planners argued that flood risk management should be incorporated directly into the urban planning process (Van Herk et al., 2011). Although, it is critical for governing and regulation bodies to address the intensifying risk of flooding resulting from the increase in flood vulnerable areas due to climate change and urbanization (Pérez-Morales et al., 2018). The importance of floodplain discounting research is necessary because flood risk is priced into market without shock event. Increased risk capitalization is desirable under government sponsored insurance programs amidst uneven impacts in the society (Miler & Pinter,2022). Although, flood insurance provides incentives for flood mitigation, marketable permits and transferable development rights.

Flood zone mapping, land-use planning, flood zone building restrictions, business and crop insurance, disaster assistance payments, preventative instruments (including environmental farm planning), e.g., soil and water management, farm infrastructure projects, and recovery from crippling flood losses were all recommended by the Hurlbert *et al*. (2019).

Vörösmarty et al. (2018) emphasized that investment in water security and flood management directly supports adoption of and public commitment to the SDGs. Therefore, Aly *et al*. (2022) found that the 10 SDGs out of 17 have positive impact with the implementation of the holistic sustainable approach to flood management.

Flood Insurance Policy, River Corridor Redevelopment Plan, Riverfront Crossing Master Plan, integrated flood risk management by combining structural and non-structural mitigation policies are better flood mitigation strategy to reach the target of SDG-11 to reduce flood vulnerability (Tetteh, 2021).

Overall, there are significant and rare opportunities to integrate social, economic, ecological, and hydrological aspects of flood risk management to produce long-term solutions that increase resilience and decrease vulnerability to flooding both now and in the future (Binns, 2022). Finally, by putting the required infrastructure in place as a control mechanism, the government and concerned stakeholders should play a crucial role in acting to prevent flooding (Satterthwaite, 2013).

Conclusion

The paper discussed about the impacts of flood in India and concludes that the human life lost has increased at the rate of 2.62% per year significantly during 1953-2020 in the stable model where it is also a nonlinear stable model. It is decomposed into 3peaks and 4 troughs in cyclical trend and 16 peaks and troughs in the cycles and its seasonal variation is v shaped. It showed upward structural breaks in 1968**.**Total area affected by flood has nonlinear trend of three phases in which it is decomposed into 5 peaks and troughs in cyclical trend under the cycles of 19 peaks and troughs. Total population affected had risen by 1.15% per year during the study period where it showed 18 peaks and troughs in cycles and 4 peaks and 4 troughs in the cyclical trend showing v shaped seasonal variation. Cropped damaged increased at the rate 8.34% per year significantly during 1953-2020.It consists of 21peaks and 20 troughs in cycles and 5peaks and 4 troughs in cyclical trend and v shaped seasonal variation. The value of damaged houses increased at the rate of 9.59% per year during 1953-2020 where it consists of 17peaks and 18 troughs in cycles and 4 peaks and 3 troughs in the cyclical trend and v shaped seasonal variation. Total cattle lost stepped up at the rate of 1.48% per year during the study period significantly. Its cycle showed 17 peaks and troughs and 2 peaks and troughs in the cyclical trend and v shaped seasonal variation. The damaged public utilities increased at the rate of 13.83% per year during 1953-2020 significantly and it has three upward structural breaks in 1969,1985 and 2005.The cycles consists of 15 peaks and 16 troughs, and its cyclical trend showed 3 peaks and 4 troughs and its seasonal variation is inverse v shaped. The paper also discussed the policy prescription. Emphasis on sustainable flood management practices through government inclusive target planning is utmost important.

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Conflict of Interest:

The authors declare that they do not have any conflict of interests that influence the work reported in this paper.

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