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Research Article

Unlocking India's Natural Disaster (Flood and Cyclone): Challenges in Terms of Indirect Losses and Probability of Reoccurrence

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ABSTRACT

Natural disasters, particularly floods and cyclones, are India's biggest threats, causing substantial economic losses. While tangible losses are calculated post-disaster events, indirect losses impacting the broader economy are frequently overlooked. This study aims to compute indirect losses for the Srinagar region in (Jammu and Kashmir), severely affected by the 2014 Jhelum River flood, resulting in a direct economic loss of 20 billion dollars. In this study, Input-Output tables from 2010-2020 from A.D.B. are employed under Leontief theory, and both Static and Dynamic Input-Output models were constructed. The dynamic flood surge model is developed to estimate accumulative output loss over various recovery periods. The findings indicate flood surge in the Srinagar region severely impacted the agricultural sector. Retail trade, except motorcars and motorbikes; home goods repair, inland transport, chemicals; wholesale distribution and intermediary trade, except motor vehicles and motorcycles and electricity, gas, financial intermediation, and water supply, While education, health and social work, air transport and water transport were least affected Sectors. The study reveals that retail trade commerce, except motor cars and motorbikes, experienced rapid recovery in the early stages but remained stable later. It is crucial to assess indirect loss due to disaster events as they impact various economic sectors beyond the immediate zone, including supply chain disruptions and labor market disruptions. It helps in planning for production, social and economic stability, and implementing appropriate protection measures. India faces significant financial losses due to natural catastrophes like floods and cyclones, including tangible and indirect losses that impact the country's overall economy.

Keywords: Natural disaster, Srinagar, indirect economic loss, Leontief theory, Emergency preparedness, Dynamic Input-Output Model, Asian Development Bank.

INTRODUCTION

India's most common natural disaster is floods, which cause rivers like the Brahmaputra to recede and often flood neighbouring communities. Floods, despite providing irrigation and fertilizer to rice paddy farmers, can cause significant destruction and displacement (Choudhury, Sharma et al. 2021). Over the past few decades, Central India has experienced a rise in extreme precipitation events like flash floods and heavy rains (Chaubey, Mall et al. 2022). However, yearly precipitation totals have gradually decreased due to weakened monsoon circulation and a smaller land-sea temperature differential. In recent decades, it has resulted in more intense rainfall events and prolonged dry periods across central India (Yadav 2022). The Intertropical Convergence Zone, which affects hundreds of Indian coastal districts, is predominantly driven by tropical cyclogenesis in the Indian Ocean's northern ranges, notably near the Bay of Bengal (Geen, Bordoni et al. 2020).

Cyclones in the North Indian Ocean Basin, lasting from April to December, bring heavy rains, storm surges, and strong gusts, often limiting access to relief and supplies (Sattar 2022). An average of eight storms annually, with two becoming true tropical cyclones. Cyclones with constant wind speeds over 63 km/h can develop into tropical cyclones with gusts over 117 km/h. Summer heat in the Bay of Bengal causes humid air masses, causing severe devastation along India's eastern coast and Bangladesh (RANA 2023). Cyclones cause widespread death and

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property destruction in Tamil Nadu and West Bengal, while India's western coast experiences rare cyclones, primarily striking Gujarat, Kerala, and Odisha (Benhart and Pomeroy 2021).

The 1999 Odisha cyclone, the deadliest in almost a quarter-century, devastated the state and claimed many lives in Odisha. With peak gusts of 160 miles per hour, it displaced nearly two million people and disrupted 20 million lives, killing 9,803 people and unofficial estimates of over 10,100 (Mohanty, Dubey et al. 2022). Cyclone Amphan, the worst super cyclone in India in the twenty-first century, struck West Bengal, Odisha, and Bangladesh on May 20, 2020. With 260-280 mph peak winds, it was comparable to a Category 5 hurricane (Edmonds, Mehtta et al. 2021). Almost 5 million people were made homeless, and 10 million lives were impacted. One hundred twenty-eight people expired, resulting in estimated damage and asset loss of 13.40-13.69 billion U.S. Dollars. The most costly and destructive cyclone ever to occur in the Bay of Bengal was Cyclone Tauktae, which destroyed at least 104 lives in a decade (Medha, Mondal et al. 2023). Assessing the economic impact of floods and cyclones is critical since these catastrophes inflict enormous financial damage. Tangible losses are often measured post-disaster, yet indirect losses that impact the broader economy are typically disregarded. Understanding direct, and indirect losses helps develop effective disaster management and recovery strategies (Panwar and Sen 2020).

Natural disasters cause indirect losses beyond immediate destruction, impacting the supply chain, labor market, and long-term investment decisions, necessitating comprehensive disaster impact analysis for a thorough understanding (Hallegatte and Vogt-Schilb 2019). This Study computes indirect losses in Srinagar, Jammu, and Kashmir, severely affected by the 2014 flood in the Jhelum River. It uses Input-output tables from 20210-2020 and Leontief theory to construct static and dynamic models. A dynamic flood surge model estimates cumulative output losses, aiding in planning production, social and economic stability, and protection measures.

LITERATURE REVIEW

Earlier Study on the Financial Effects of Natural Disasters

Studies have observed the economic effects of catastrophes, considering direct and indirect outcomes. Some direct effects include damage to fences, houses, and agricultural produce, which results in a lot of loss (Rosselló, Becken et al. 2020). For example, A Review of Natural Disasters in the Scenario of Building Economic Resilience (2013) analyzed how natural disasters like hurricanes and earthquakes result in significant one-off expenditures and sometimes require huge government and international involvement (Bănică, Kourtit et al. 2020). On the other hand, indirect effects, though not as observable, are as substantial because their ripple effect influences economic stability and development. Indirect impacts include disruptions to supply chains, productivity loss, and long-term economic downturns (Okuyama 2024).

Overview

Over the years, different approaches have been established to estimate different losses from natural disasters, direct and indirect. The most typical practice in implementing approach one for direct loss assessment includes damage assessment survey and satellite image analysis. For example, Satellite data to assess the apparent loss due to floods. It must be noted that indirect losses are assessed normally through economic modeling tools (Malgwi, Schlögl et al. 2021). The Input-Output (I-O) model is quite popular worldwide, which focuses on the relations between the production sectors using I-O models and C.G.E. models (Hallegatte and Vogt-Schilb 2019). Still, the I-O models used a hybrid approach to determine the various indirect economic costs of natural disasters, given changes in market and production structures. Based on Leontief's (1936) work, these models allow researchers to understand how disruptions in one sector can propagate through the economy, leading to indirect losses. (Okuyama 2024), for example, illustrated the usefulness of I-O models in capturing the cascading impacts of a disaster, when initial infrastructure damage might cause extensive disruptions across several sectors. Furthermore, I-O models assist in estimating recovery durations and the economic cost of rehabilitation programmes.

Leontief Theory

Leontief's Input-Output theory serves as the foundation for several economic impact studies. Wassily Leontief developed this theory, which requires creating a matrix depiction of an economy, illustrating the links between different industries and sectors (Sahani, Sah et al. 2023). Each item in the matrix represents the input required by one industry to produce output in another. This theory describes how economic activities are interconnected and how perturbations in one sector of the economy may affect the entire system (Carret 2022). Leontief's theory is beneficial for calculating both direct and indirect economic losses in natural disasters since it considers inter-sectoral links and disruptive ripple effects.

Gaps in Existing Research

Despite substantial research on the economic effects of natural disasters, numerous gaps remain. First, most studies focus primarily on direct losses, whereas indirect losses are overestimated (Schneiderbauer, Pisa et al. 2021). More comprehensive models for direct and indirect losses must present a complete picture of catastrophic consequences. Second, I-O models are frequently utilized but rely on obsolete data, restricting their accuracy in the present crisis (Hagen, Cutler et al. 2020). There is an urgent demand for real-time data integration and dynamic modeling techniques. Finally, regional research, such as that conducted in flood-prone places like Srinagar, is insufficient. This distinction is crucial in customising disaster management techniques to the local situation (Hussain, Hussain et al. 2024).

METHODOLOGY

Data and Methods

EM-DAT is a database that contains information on over 26,000 mass catastrophes worldwide from 1900 to the present, gathered from diverse sources. The Centre for Research on the Epidemiology of Disasters (CRED) provides the data for non-commercial usage. (Biardeau and Sahli 2024). Flooding was found to occur more often between 2015 and 2021. Secondary data from EM-DAT and A.D.B. were utilized to calculate indirect economic losses, while geospatial data was collected from the USGS's official website (Babajide 2023).

A BROADER VIEW OF VARIOUS NATURAL DISASTERS IN INDIA IS DEPICTED BELOW

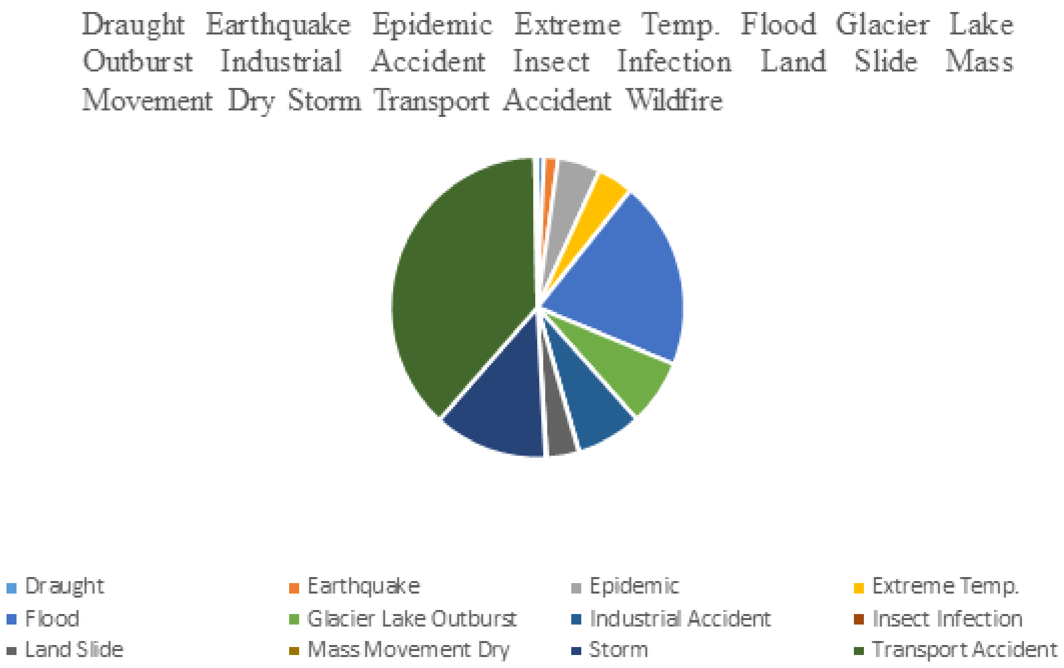


Fig.1 Overall distribution of Natural Disasters % wise

Study Area

A 2014 flood in Srinagar, Jammu and Kashmir severely affected city areas like Sonwar Bagh, Shivpora, Batwara, Soitang, Lasjan, Padshai Bagh, Natipora, Lal Chowk, Rajbagh, Jawahar Nagar, and Wazir Bagh (Malik 2022). The 2014 flood in Srinagar and its surrounding districts caused a direct economic loss of approximately $20 billion U.S. dollars (Ahmad, Pandey et al. 2019). The period 2010-2020, specifically 2014, is used to calculate indirect economic loss under dynamic and static modelling (Kumar, Maryam et al. 2020).

Methods

Input-Output Model: Static Construction

(1)Coefficient

The table calculates the physical-value relationship between social products and value-generating processes, representing the input source and the use of the result (Porcelli, Gibon et al. 2023). The value-based input-output table was utilized to define data units and link row and column directions, while the physical-value input-output table was measured in monetary units (Jin, Sumaila et al. 2020). The input-output table uses a value-based system to connect the row and column directions, representing the input source and the result's usage (Ojaleye and Narayanan 2022). The direct consumption coefficient also called the input coefficient, is represented by $aij = (i, j = 1,2, \ldots, n)$. This variable reflected the value of the products or services in the I product sector that are directly used by the total output investment of the unit output of the j product sector throughout its production and operation (Rim and An 2021). This connection is commonly organised into a table called the direct consumption coefficient matrix (A). The direct consumption coefficient matrix is calculated as follows: For the *i* product sector, the value of goods or services used directly in the production and management of Xij, represented by

$$aij = \frac{xij}{xj}(i, j = 1,2, \ldots, n) \quad (1)$$

The bij consumption coefficient measures the direct and indirect consumption of goods or services from the i product sector for each unit of the j product used for final consumption (Ojaleye and Narayanan Gopalakrishnan 2021). The coefficient matrix, commonly known as the total consumption coefficient matrix, may be created by directly consuming the coefficient matrix A using the following formula

$$B = (I - A)^{-1} - \mathrm{I} \qquad (2)$$

Where *I* is the identity matrix

Static

The static input-output model calculates final output value and total production loss in each industry by analyzing the total output value of each economic sector (Sánchez, Hoadley et al. 2019).The loss of agricultural output, denoted as ΔX1, can be determined by analyzing changes in production capacity across different sectors, provided the agricultural sector's productive capacity remains stable.

$$\Delta X = (I - A)^{-1}\Delta Y \quad (3)$$

Given that $B = (I - A)^{-1} - I$, where $Bn \times n$ is the complete consumption coefficient matrix, and $\boldsymbol{A}n\times n$ is the direct consumption coefficient matrix, we get;

$$\Delta X = (B + I)\,\Delta Y \qquad (4)$$

The change in output for the entire economic system is represented as follows:

$$\Delta X_1 = Y_1 1 Y_1 + \Delta Y_1, \text{so } \Delta Y_1 - \frac{\Delta X1}{1 + b11}$$

$$\Delta X_2 - b_{21}\ \Delta Y_1$$

$$\Delta X_n - b_{n1}\ \Delta Y_1$$

The first equation reveals a final product reduction in the agricultural sector, resulting in intermediate loss and a decrease in total output in other sectors.$\frac{\Delta X1}{1+b11}$. The intermediate loss due to the decreased agricultural production capacity is $b_{11}\Delta X_1/1+b_{11}$. The decrease in final agricultural output will lead to a reduction in intermediate consumption in other sectors, resulting in a decrease in final total output.

$$\boldsymbol{\Delta X}_{j1}=b_{j1}\Delta Y_1=bj1\Delta X_1\,/1+b_{11},\ \ j\neq 1$$

L1 expresses the total loss due to the decrease in gross agricultural output:

$$L_1 = \sum_{j=1}^{n} \quad \Delta X_{j1} + \Delta Y_1$$

For the decrease in total output, except for this sector, resulting from the reduction of the final product in other sectors:

$\Delta X_{j1} = bj1\ \Delta Y_1 = b_{j1}\ \Delta X_1/1+b_{11}, j \neq i, i=1, ..., \ 6$

The total loss resulting from decreased output in other sectors is:

$L_i = \sum_{j\neq 2} \Delta X_{j1} + \Delta Yi, j\neq i$

The total loss resulting from the decrease in the total output of fisheries and other sectors was recorded as L$i.i$ =1, 2, . . ., 6.

Overall total loss:

L = $\sum_{i=1}^{6} Li$

I-O-M: Dynamic Construction

(1) Coefficient

To fully understand the quantity, structure, and effect of fixed capital formation, a dynamic input and output model is necessary to connect the entire process of social reproduction (Han, Lou et al. 2022). The paper introduces the investment coefficient, which includes both investment and fund occupancy coefficients, and uses an investment matrix table derived from the total capital formation column vector.

Investment Matrix Table 1

Investment Elements	**Fixed Capital Formation**	**Inventory Increase**	**Total**
Investment Sector	1, 2, ...,n, subtotal		
1	K11, K12, ..., K1n, K10	K1m	K1
2	K21, K22, ..., K2n, K20	K2m	K2
...	...	...	...
N	Kn1, Kn2, Knn, Kn0	Knm	Kn
Total	K01, K02,....,K0n K0n	K00	Km

The matrix represents inventory increase and fixed capital formation in an n x n Investment Matrix, with Kij representing investment products used in sector j and total product i for fixed capital development.

$Ki0= \sum_{i=1}^{n} K_{ij}$

The total amount of fixed capital development used by sector j is:

$K_{o\,j}= \sum_{i=1}^{n} K_{ij}$

Km denotes the number of product sector i uses as inventory rises. The investment coefficient is calculated as:

$qij\ = Kij\ /\Delta Xj$ For $i, j\ = 1, 2, \ldots, n$)

Where Kij represents the number of i-type investment products required to expand production scale, ΔXj represents annual increase in production scale of sector j, known as the investment coefficient:

$$\Delta Xj\ =\ Xj(t+1) - Xj(t)$$

Thus, Qij represents the number of i products required for the unit output increase of the j sector, known as the investment coefficient:

$$Q\ =\ K.\Delta X - 1$$

Investment cost, a flow indicator indicating changes over time, represents consumption quota and demand for investment items in capital construction operations (Jin, Sumaila et al. 2020)

(2) Dynamic:

The dynamic input-output model, established by Leontief in 1965, is a mathematical model that quantifies causal links based on interdependence and interdependence (Jin, Sumaila et al. 2020)

$X(t) - AX(t) - D[X(t+1) - X(t)] = U(t)$

Where

- D is the investment coefficient matrix
- $D[X(t+1) — t)X(t)]$ is the productive investment
- $U(t)$ is the Final net demand
- D[X (t+1) –X (t)] +U (t) = Y (t).

By defining matrix $Q = -D - 1$, we get:

$X(t+1) - X(t) \ = \ Q[AX(t) \ + \ U(t) - X(t)]$

Letting $li = \Delta xi/xi$ be the total loss ratio of the sector i, represents the total loss in sector i caused by disasters, and $u * i = \Delta ui/xi$ as demand loss ratio of sector i, we obtain:

$l(t+1) - l(t) \ = \ Q[A * l(t) \ + \ U * (t) - l(t)]$

Where $A * = \ X - 1AX$

The general solution for the total loss reduction is:

1

$Lt \ = \ l(0)e - Q(I - A *)t \ + \ \ \int \ QU * \ (s) \ eQ(I - A *)(s - t)ds$

0

Assuming the final demand of various sectors remains constant ($U *= 0$) $and \ t \rightarrow \ \infty \ l(t) \rightarrow 0$, indicating that sector losses are restored over time.

Specifically for sector i:

$li \ (t) \ = \ li(0)e - qi(1 - aii)t$

The total economic loss during the recovery period of sector i is:

T

$Xit \int li \ (t) \ dt$

0

Where Xit represents the sector output value over in unit time t.

The primary objective of this paper is to compute the indirect economic losses caused by flood disasters during the period (2010-20). The Input-Output tables for this study are sourced from A.D.B., and direct economic loss is obtained from EM-DAT (Doktycz and Abkowitz 2019).

EMPIRICAL ANALYSIS

Table Structure:

This Study evaluates characteristics and effects of floods and the resultant economic losses, focusing on India. Using the Input-Output table of India for the period 2010-2014, 32 economic sectors of were considered to assess indirect losses due to floods (Liu, Wang et al. 2024).

Processing Table Data

This analysis employs direct and comprehensive consumption coefficients based on Input Output table for the period (2010-2020) across 32 economic sectors. The relevant formulas calculated these coefficients (Fan, Wu et al. 2019). The consolidated results for indirect economic losses in various sectors are presented in Table 1 below:

Table 2 Direct Loss of output in each sector.

Loss of output in each sector		**Loss in 2014 – in 000,$**	**In Million**	Δyi,j±i			
Direct Economin Loss		2155823.00	2155.823	8840.0277	**In Million $**	**IN Billion $**	**In%**
	Agriculture's total output loss	1964922.86	1964.922862	39179.8928	17.7888009601	0.0177888	1.00
Agriculture	Final Product of Agriculture	214661722.63	214661.7226	16977.0593	78.8417569246	0.07884176	4.45
	Intermediate loss of Agriculture	190900.14	190.9001382	1340.0768	34.1629618756	0.03416296	1.93
Associated Agriculture Industries			ΔXj1=bj1ΔX1/(1+b11)	3434.5990	2.6966386281	0.00269664	0.15
Mining and quarrying			8948.77	11136.5720	6.9114486758	0.00691145	0.39
Food, beverages, and tobacco			39661.86	48453.7640	22.4101404808	0.02241014	1.26
Textiles and textile products			17185.90	100357.8346	97.5035816842	0.09750358	5.50
Leather, leather products, and footwear			1356.56	8394.0242	201.9502205962	0.20195022	11.39
Wood and products of wood and cork			3476.85	3595.2417	16.8913074755	0.01689131	0.95
Pulp, paper, paper products, printing, and publishing			11273.57	12389.6901	7.2347102235	0.00723471	0.41
Coke, refined petroleum, and nuclear fuel			49049.82	6430.1354	24.9317918490	0.02493179	1.41
Chemicals and chemical products			101592.39	8365.8754	12.9393711753	0.01293937	0.73
Rubber and plastics			8497.28	10753.7841	16.8346635444	0.01683466	0.95
Other			3639.47	13063.	21.63985579	0.02163	1.22

nonmetallic minerals				1097	23	986	
Basic metals and fabricated metal			12542.10	65702.2707	26.2869152311	0.02628692	1.48
Machinery, nec			6509.24	28142.8178	132.2127776473	0.13221278	7.46
Electrical and optical equipment			8468.79	11429.8394	56.6318343899	0.05663183	3.19
Transport equipment			10886.07	88813.3402	23.0002829948	0.02300028	1.30
Manufacturing, nec; recycling			13223.81	145008.6952	178.7192173183	0.17871922	10.08
Electricity, gas, and water supply			66510.51	25087.7371	291.8012142184	0.29180121	16.46
Construction			28489.02	103277.6307	50.4840908754	0.05048409	2.85
Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel			11570.44	401.8546	207.8257305693	0.20782573	11.72
Wholesale trade and commission trade, except for motor vehicles and motorcycles			89905.88	96.7467	0.8086525899	0.00080865	0.05
Retail trade, except of motor vehicles and motorcycles; repair of household goods			146792.52	7377.8733	0.1946834301	0.00019468	0.01
Hotels and restaurants			25396.35	10232.3048	14.8465053849	0.01484651	0.84
Inland transport			104548.10	84403.3957	20.5904822895	0.02059048	1.16
Water transport			406.80	434.4977	169.8450793651	0.16984508	9.58
Air transport			97.94	17295.1883	0.8743403260	0.00087434	0.05
Other supporting and			7468.63	0.0000	34.8031333055	0.03480313	1.96

auxiliary transport activities; activities of travel agencies.							
Post and telecommunications			10358.18	793.8203	0.0000000000	0	0.00
Financial intermediation			85441.68	0.0000	1.5974058002	0.00159741	0.09
Real estate activities			439.84	0.0000	0.0000000000	0	0.00
Renting of M&Eq and other business activities			17507.94	0.0000	0.0000000000	0	0.00
Public administration and defense; compulsory social security			0.00	0.0000	0.0000000000	0	0.00
Education			803.59	0.0000	0.0000000000	0	0.00
Health and social work			0.00	881209.6995	0.0000000000	0	0.00
Other community, social, and personal services			0.00		1773.25959562103	1.7732596	
Private households with employed persons			0.00				
Imports			0.00				
Total Indirect Loss			0.00				
			892049.90				

THE DATA IN TABLE 2 HAS BEEN THOROUGHLY ANALYSED

- From 2010 to 2020, India experienced total agricultural output losses of USD 2628.79 million, with the largest loss occurring in 2014 in J&K due to floods, resulting in a final agricultural product loss of USD 15541.78 million and indirect economic loss of USD 25560.67 million. (Rasool, Hamdani et al. 2020).
- Ranked by indirect loss to various sectors caused by agricultural loss, the most affected sectors were:

- Wholesale trade, excluding automobiles and motorcycles, repair of home items.
- Inland transportation
- Chemicals and chemical products
- Financial intermediation

- Power, gas, and water supply
- Beverage, refined petroleum, and nuclear fuel
- Wholesale commerce and commission trade, excluding automobiles and motorcycles
- Construction
- Leasing of machinery and equipment, among other economic operations.
- Food, drinks, and tobacco (Medha, Mondal et al. 2023)

The study found that indirect losses accounted for 82.18% of direct economic loss in 2010 and 45.13% in 2014, with retail trade being the most affected sector, while other sectors were minimally affected (Fang and Yang 2021). Thus, indirect losses due to floods constitute a substantial proportion of the total loss, highlighting the need for effective prevention and reduction measures for indirect disasters.

1. DYNAMIC EMPIRICAL ANALYSIS

Data Processing

The dynamic model analysis used the largest flood in Kashmir in 2014, assuming constant input-output link between sectors, excluding agriculture, and the 2014 Input-output table.

Table 3. *Total output of different sectors*

Sector	Total output loss Ratio%	Total indirect loss (Million $)	Total Output (Million $)
Mining and quarrying	1.00	167.9524703750	60,203.68
Food, beverages, and tobacco	4.45	744.3822590326	2,34,348.89
Textiles and textile products	1.93	322.5486560441	1,39,913.42
Leather, Leather products, and footwear	0.15	25.4602387376	13,478.75
Wood and products of wood and cork	0.39	65.2542507823	17,267.94
Pulp, paper, paper products, printing, and publishing	1.26	211.5847191516	30,185.60
Coke, refined petroleum, and nuclear fuel	5.50	920.5773593711	1,50,215.60
Chemicals and chemical products	11.39	1906.7074007916	1,65,101.76
Rubber and plastics	0.95	159.4788105577	52,173.93
Other nonmetallic minerals	0.41	68.3063157097	64,501.49
Basic metals and fabricated metal	1.41	235.3928205334	2,32,999.58
Machinery, nec	0.73	122.1667137014	72,850.47
Electrical and optical equipment	0.95	158.9440084551	82,480.87
Transport equipment	1.22	204.3120976513	1,43,251.95
Manufacturing, nec; recycling	1.48	248.1871803215	54,431.25
Electricity, gas, and water supply	7.46	1248.2832693872	1,57,292.35
Construction	3.19	534.6878920596	4,64,800.12

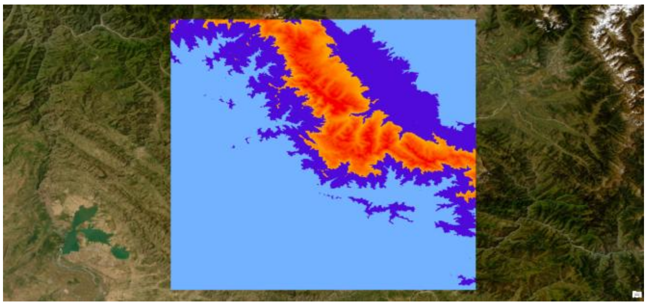
Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel	1.30	217.1565333132	14,929.48
Wholesale trade and commission trade, except for motor vehicles and motorcycles	10.08	1687.3725283316	1,15,982.71
Retail trade, except of motor vehicles and motorcycles; repair of household goods	16.46	2755.0330624431	1,89,391.99
Hotels and restaurants	2.85	476.6441423540	66,222.30
Inland transport	11.72	1962.1808650746	1,69,797.42
Water transport	0.05	7.6348709759	3,934.27
Air transport	0.01	1.8380982004	13,698.93
Other supporting and auxiliary transport activities; activities of travel agencies	0.84	140.1728683919	33,481.54
Post and telecommunications	1.16	194.4044668603	80,437.20
Financial intermediation	9.58	1603.5876012283	1,95,598.35
Real estate activities	0.05	8.2550599127	1,91,818.54
Renting of M&EQ and other business activities	1.96	328.5928168262	3,18,117.20
Public administration and defense; compulsory social security	0.00	0.0000000000	1,59,003.60
Education	0.09	15.0818625122	1,47,758.44

TABLE 3: TOTAL OUTPUT OF DIFFERENT SECTORS IN 2014 AND PROPORTION OF TOTAL OUTPUT LOSS

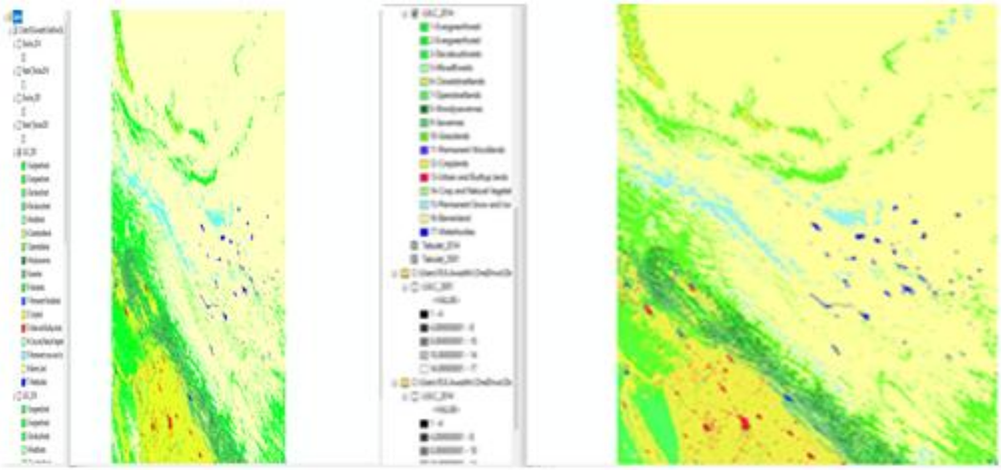
The fraction of total output loss shows the economic cause of flood concerning the entire production sector, demonstrating the overall impact on the industry (Wani, Ahmed et al. 2022). Additionally, a ratio of industrial economic recovery and accumulative output were computed. The most affected industries were wholesale and commission commerce, excluding motorcars and motorbikes, the trade, maintenance, and repair of motorcars and motorcycles, and retail gasoline sales.

The G.I.S. study was also conducted for the 2014 flood in Srinagar using Remote sensing ArcGIS and ArcScene with data downloaded from USGS (Ahmad, Pandey et al. 2019). The GIS-generated map (Fig.2) clearly shows that Srinagar and its adjacent districts were fully submerged during flood in September 2014, with only high-altitude areas unaffected.

Inundation and Land Use Land Cover (2001-2014)



G.I.S./Arc scene simulation



LULC-2014 ***LULC-2001***

The G.I.S. study reveals a significant decrease in Barren land, permanent snow and ice increase, and an upward change in crop and natural vegetation.

Dynamic I-O-M Result

The results show that wholesale and commission commerce was the most impacted industry in 2014, excluding automobiles and motorcycles. The results show that wholesale and commission commerce was the most impacted industry in 2014, excluding autos and motorcycles. (Dash, Agrawal et al. 2021). The loss ratio of this sector was 0.1433985%, $l(0) = 0.0014$. Assuming the sector would recover to 99.95% of its original output after 180 days, the equation becomes:

1

$$Lt = l(0)e - Q(I - A*)t + \int QU*(s)\, eQ(I - A*)(s - t)ds$$

0

Where q for wholesale trade and commission trade is calculated as 0.00611.

The recovery situation is as follows:

$$1 - l(t)1 = 1 - 0.014e\text{^}(1 - 0..05848)t$$

Using the formula :

$$Xit \int_0^T l\, i(t)dt$$

We find that a 60-day recovery period results in an accumulated output value of USD2755 million for the sector Figure 5. The cumulative production loss for the whole economic system is the total accumulated output loss in all sectors (Dash, Agrawal et al. 2021). Varying the recovery period changes the cumulative output loss values, as shown in Table 4.

Analysing the retrieval period of the retail trade sector (excluding automobiles and motorbikes, and repair of home goods) as shown in Figure.6, we observe that the industry recovers relatively quickly initially, but the recovery rate stabilizes over time. Overall, the proportion of loss in this sector remains within an acceptable range, shortening the recovery period and reducing the economic losses.

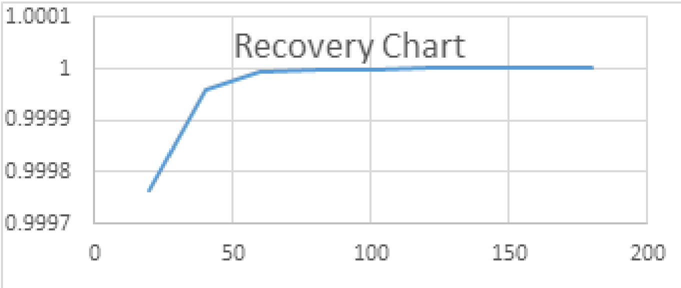


Figure 5

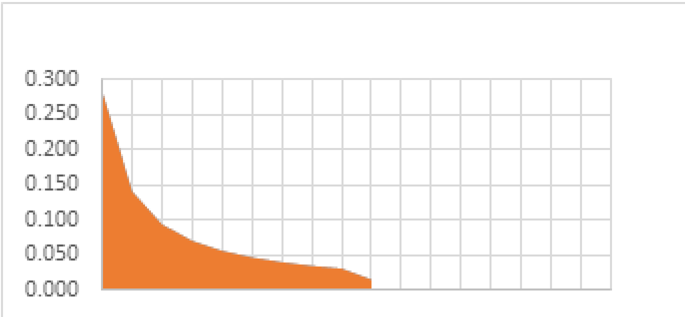


Figure 6

Table 4. *The sector's accumulated output*

Recovery period (Days)	20	40	60	80	100	120	140	160	180	360
Industrial Recovery	0.283	0.14 2	0.094	0.071	0.057	0.047	0.040	0.035	0.031	0.016
Accumulated Output Loss (million USD)	27.55	55.10	82.65	110.20	137.75	165.30	193.85	220.4 0	247.9 5	495.90

The cumulative production loss value rises with the delay of the retrieval period due to extended recovery duration and slower production rates. Therefore, sectors affected by floods should implement timely and adequate measures to restore normalcy quickly and minimize economic losses.

DISCUSSION

Wassily W. Leontief argues that the input-output model offers a significant advantage in statistically analyzing and investigating the connections between various sectors within a complex economy (Ahmad, Pandey et al. 2019). Input-output analysis is a crucial tool in structural analysis, economic calculation, and profit analysis, calculating indirect economic losses using empirical coefficient methods. This model ensures consistent data and high application precision, allowing for sectoral comparison and reversing effect relationships among various sectors (Ahmad, Pandey et al. 2019). The I-O static model is concerned the economic quantifiable relationship in a specific times, without considering time factors (Jin, Sumaila et al. 2020). However, the dynamic model focuses on economic structural change, which includes time-varying variables. The effect of resilience is considered when calculating economic losses due to natural disasters through dynamic model. In this paper, the indirect loss in the Retail trade, exclude automobiles and motorcycles; repair of household items, is influenced by both the sector's recovery and the recovery of economic system. Taking appropriate measures will decide the speed and process of the retail trade sector, while external variables such flood intensity, location, and socioeconomic changes determine indirect economic loss size. Given the impact of resilience, each region can mitigate potential loss by alternative assets when there is a shortage of demand or supplies (Gao, Geddes et al. 2020).

This study utilized G.I.S. and remote sensing concepts to ascertain the I-O model's authenticity. It was established that crop, natural vegetation, and permanent woodland areas increased during 2001-2014. According to the Economic Survey Report 2013-14 of the J&K Government, several sectors were impacted indirectly by the 2014 floods (Dinda, Das et al. 2019). The Industry sector's growth at constant price (2004- 05) decreased from 5.86% in 2012-13 to 3.79% in 2013-14. Land utilization increased from 350000 hectares (2011-12) to 352000 hectares (2013-14). However, fruit production reduced from 21.62 Lacs MT in 2011-12 to 17.42 Lacs MT in 2012-13, and foreign exchange earnings fell from Rs.232.86 Crores in 2011 and 2012 to Rs.204.75 Crores in 2012-13. Import of fruits and vegetables also declined by 1.93 &2.43 Lacs MT in 2012-13 reduced to 1.65 & 1.35 Lacs MT in 2013-14. Revenue from forest produce dropped from 4137.83 Lacs in 2012-13 reduced to 2906.72 Lacs in 2013-14, and timber import decreased from 47.03 Lacs, in 2012-13 reduced to 29.37 Lacs in 2013-14. Investment in small scale industries reduced from 257.11 Crores in 2012-13 to 173.46 Crores in 2013-14 (Kiguchi, Takata et al. 2021). This survey data indicates indirect loss in Retail trade, excluding automobiles and motorcycles and repair of household items, as per table 2.

The sector that was most affected was the Retail trade, sub-sector namely, Retail trade exclude automobiles and motorcycles and the repair of home appliances. The measures and external factors influenced this sector's recovery and the recovery of the entire system. The recovery was fast initially, but it slowed down in the later periods (Orlale 2023). The speed and process influenced by flood intensity, intensity, geographical factors, and socioeconomic occurrences also greatly impacted it.

The I-O model only considers economic quantitative relationships during specific periods but does not consider time factors. While dynamic model is based on the evolution of the sectors and their characteristics, such as resilience factors (Wu, Guo et al. 2021). By highlighting equal losses and recovery processes, the dynamic model provides a more comprehensive analysis of the effects of natural calamity on the economy of the sectors involved (Kumar, Poonia et al. 2021). The dynamic model outcomes presented the accumulating loss of output and different sectors' recovery periods, which presented nuanced insights into the long-term effects.

The economic effect of the 2014 floods in Srinagar yields prolongs economic impacts. The decline in industrial growth, fruit production, foreign exchange earnings, and investment in the growth of small-scale industries highlights the social cost of such events (Wani, Ahmed et al. 2022; Semara et al., 2024). The fall in imports of fruits and vegetables and forest produce highlights long-term economic challenges and in need for comprehensive recovery and resilience strategies (Patel, Nanda et al. 2020). The following variables affected the restoration and revival of the most affected sectors among Srinagar: The severity of flood, the geographic settings, and socio-political transformations assumed important roles regarding the indirect losses (Amin, Dar et al. 2023). While analyzing these variables, it was found that the availability of the other resources relative to the sector's main operational resources helped determine the level of resilience after the disaster and the success of the recovery measures in restoring the used-up resources (Verma, Kumar et al. 2022). The methodological approach, the G.I.S., and the remote sensing enabled the analysis of crop, and natural vegetation changes and P.W. as a factor in the region's resilience and recovery process.

CONCLUSION

Floods in India significantly impact economic growth, resulting in substantial losses. Estimating indirect and direct losses is challenging, and this paper uses Input-Output tables from 2010-2020 from A.D.B. to calculate these losses. A dynamic model was designed for 2014 due to Kashmir's large direct economic loss. The flood economy has the most impact on agriculture, while sectors like public management, defences, social security, education, and health experience minimal impact. The dynamic model of flood disaster assessment was constructed, analyzing general trade and charge trade, excluding automobiles and motorbikes, to determine the cumulative loss value over various recovery durations. The dynamic model's output loss value is higher during longer recovery periods, but the overall output loss value is lower than the static model. The production loss rises proportionately with recovery intervals, becoming more significant as the recovery period lengthens. The static model's overall production loss exceeds the dynamic models.

LIMITATIONS

The study's limitations include its dependence on data from A.D.B. and EM-DAT, which may not capture all local economic activity, and its emphasis on the 2014 Kashmir flood, which limits its generalizability to other geographies and disaster circumstances(Kimuli, Di et al. 2021). Furthermore, it lacks advanced probabilistic models like Occurrence Exceedance Probability and Aggregate Exceedance Probability, which might provide a more nuanced view of flood risks and costs.

FUTURE RESEARCH DIRECTION

Future studies should combine localized data sources, probabilistic models such as Occurrence Exceedance Probability and Aggregate Exceedance Probability, and GIS-based risk and hazard analysis to improve flood risk understand

ing and reinsurance structure. Extending the scope of the study to include new natural disasters and locales might improve generalizability and lead to more effective disaster management approaches (da Silva, Humberto et al. 2020).

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