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Assessment of Indirect Disaster Losses being challenge for the economy of a country

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ABSTRACT
In the Indian context , Natural disasters, particularly floods and cyclones, are biggest threats, and a big reason for the country's economy. Visible losses like damage to infrastructure, buildings damage, destruction of bridges etc. are calculated after disaster events, however, indirect losses which are significant portion of total losses and impact broader economy are normally overlooked. This study has been conducted with a view to compute indirect losses for the Srinagar region located in (Jammu and Kashmir), very badly affected by the 2014 Jhelum River flood, resulting in a hepatic direct economic loss to the tune of 20.4 billion dollars. Input-Output tables from 2010-2020 from A.D.B. have been considered including Leontief theory to analyze the over-all flood situation of 2014 flood of Kashmir, and Static and Dynamic approach in Input-Output models were constructed. The dynamic model is developed to estimate accumulative output loss over various recovery periods. The findings indicate flood surge in the Srinagar region severely impacted. Retail trade, except motorcars and motorbikes(max.16.46%) followed by Agricultural sector ,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, indirect economic loss, Leontief theory, Emergency preparedness, Dynamic Input-Output Model.

INTRODUCTION:

Flood is really a curse for India , which cause rivers like the Brahmaputra to recede and often flood neighbouring communities. Although Floods on one hand flourishes rice and paddy cultivation bot on other hand it is a biggest reason for 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, annual precipitation have gradually decreased, 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 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). Literature Review

Overview

During the different periods , many mathematical, statistical concepts have been used in computing the direct losses from natural disaster, however very limited studies have published to cover the aspect of indirect losses which are significant portion of total losses. 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

Limited Systematic Evidence on Economic Impact and Indirect Losses:

The available literature on natural disasters particularly floods and cyclone is described as largely inconclusive, providing limited systematic evidence on how these disasters affect economic growth and indirect losses. The works cited include Cavallo & Noy (2011), Fiala (2017), and Noy & DuPont (2016).

Sector-Specific Economic Impact Studies- Not on Indirect losses:

While there have been studies examining the economic impact of these natural disasters, a few have focused on specific sectors such as agriculture, industry, and remittances. For example, studies by Fomby, Ikeda, & Loayza (2013) and Loayza, Olaberría, Rigolini, & Christiaensen (2012) have explored sector-specific impacts on gross domestic product (GDP) growth. Moreover, they have not discussed specifically indirect losses.

Indirect Losses and Economic Resilience:

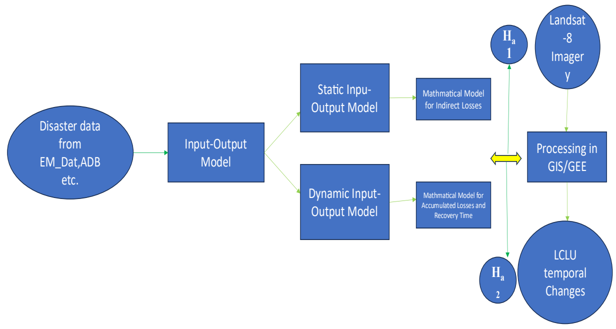
Considering the case of Haiti earthquake occurred in year 2010, observation is that indirect loss and low-income households and communities were particularly affected that increases importance of considering economic resilience . Sometimes indirect losses, often surpasses direct losses, consequently it becomes difficult to understand the over-all economic losses. As normally the wider effects are often overlooked in assessments of disaster losses.

Govt. agencies and other concerned authorities come into picture after disaster event and they assess direct economic losses but they are silent about the indirect economic losses, which may be hepatic sum . Reasonbeing the cost of reinsurance and insurance structure are under estimated by the insurance/survey agencies.

Methodology

DataandMethods

Research Design:
Indirect Loss Computation and Sectoral impact considering Remote Sensing and GIS



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).

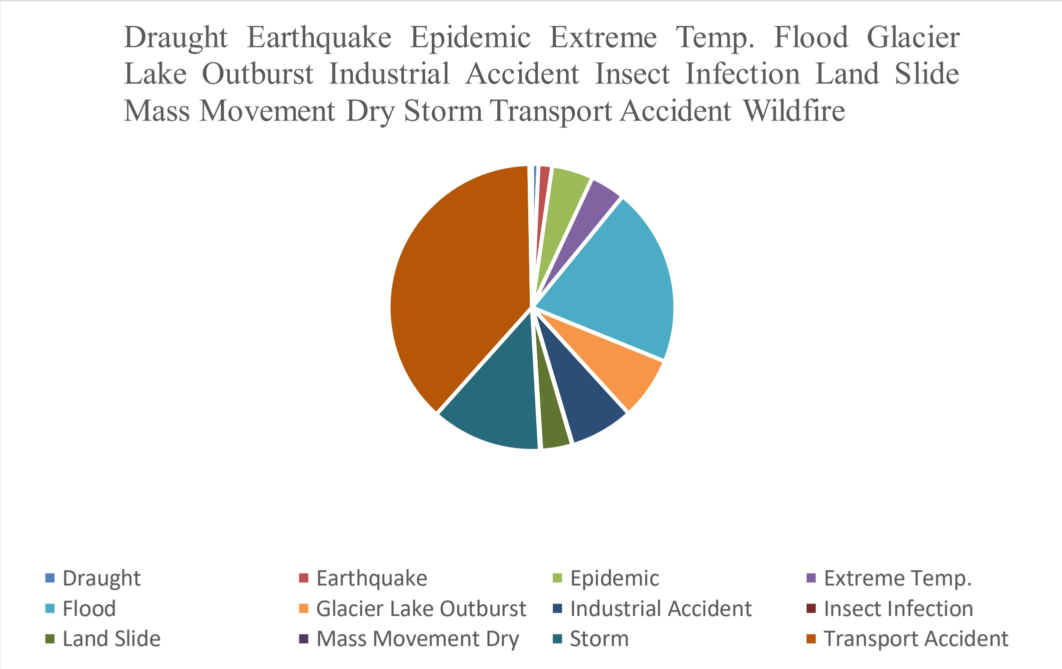
Hypothesis:

H_a1: Floods and cyclones cause significant indirect economic losses that are often greater than the direct costs associated with infrastructure damage and property loss.

H_a2: The economic impact of floods and cyclones extends beyond the immediate disaster zone, causing disruptions in supply chains, labor markets, and long-term investment decisions across various economic sectors.

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

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 $aij = (i, j = 1,2, \dots, n)$. 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

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

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

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

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.

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

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

$\Delta X = (B + I)\ \Delta Y$
(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.

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

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:

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

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 Li.i =1, 2, . . ., 6.

Overall total loss:

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

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:

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

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

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

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:

$$Lt = l(0)e - Q(I - A *)t + \int_0^1 QU * (s)\, eQ(I - A *)(s - t)ds$$

Assuming the final demand of various sectors remains constant $(U *= 0)$ $and\ t \to \infty\ l(t) \to 0$, 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:

$$Xit \int_0^T li\ (t)\ dt$$

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				
Direct Economin Loss		20354143.00	20354.143				
	Agriculture total output loss	18551764.64	18551.76464				
Agriculture	Final Product of Agriculture	212269737.54	212269.7375				
	Intermediate loss of Agriculture	1802378.36	1802.378355				
Associated Agriculture Industries			ΔXj1=bj1 ΔX1/(1+b11)	Δyi,j±i	In Million $	IN Billion $	In%
Mining and quarrying	60,203.68	60,372	84489.59	83462.8761	167.9524703750	0.16795247	1.00

Food, beverages, and tobacco	234,348.89	235,093	374466.39	369915.8704	744.3822590326	0.74438226	4.45
Textiles and textile products	139,913.42	140,236	162260.22	160288.4343	322.5486560441	0.32254866	1.93
Leather, leather products, and footwear	13,478.75	13,504	12807.94	12652.2983	25.4602387376	0.02546024	0.15
Wood and products of wood and cork	17,267.94	17,333	32826.58	32427.6710	65.2542507823	0.06525425	0.39
Pulp, paper, paper products, printing, and publishing	30,185.60	30,397	106439.08	105145.6353	211.5847191516	0.2115847 2	1.26
Coke, refined petroleum, and nuclear fuel	150,215.60	151,136	463102.49	457474.8673	920.5773593711	0.92057736	5.50
Chemicals and chemical products	165,101.76	167,008	959181.69	947525.7090	1906.7074007916	1.9067074	11.39
Rubber and plastics	52,173.93	52,333	80226.86	79251.9466	159.4788105577	0.15947881	0.95
Other nonmetallic minerals	64,501.49	64,570	34361.94	33944.3746	68.3063157097	0.06830632	0.41
Basic metals and fabricated metal	232,999.58	233,235	118415.91	116976.9148	235.3928205334	0.23539282	1.41
Machinery, nec	72,850.47	72,973	61456.77	60709.9453	122.1667137014	0.12216671	0.73
Electrical and optical equipment	82,480.87	82,640	79957.83	78986.1802	158.9440084551	0.15894401	0.95
Transport equipment	143,251.95	143,456	102780.54	101531.5539	204.3120976513	0.2043121	1.22
Manufacturing, nec; recycling	54,431.25	54,679	124852.19	123334.9878	248.1871803215	0.24818718	1.48
Electricity, gas, and water supply	157,292.35	158,541	627957.10	620326.1651	1248.2832693872	1.24828327	7.46
Construction	464,800.12	465,335	268978.26	265709.6332	534.6878920596	0.53468789	3.19
Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel	14,929.48	15,147	109242.02	107914.5117	217.1565333132	0.21715653	1.30

Wholesale trade and commission trade, except of motor vehicles and motorcycles	115,982.71	117,670	848843.84	838528.6860	1687.3725283316	1.68737253	10.08
Retail trade, except of motor vehicles and motorcycles; repair of household goods	189,391.99	192,147	1385937.49	1369095.5701	2755.0330624431	2.75503306	16.46
Hotels and restaurants	66,222.30	66,699	239778.97	236865.1733	476.6441423540	0.47664414	2.85
Inland transport	169,797.42	171,760	987087.98	975092.8825	1962.1808650746	1.96218087	11.72
Water transport	3,934.27	3,942	3840.77	3794.0989	7.6348709759	0.00763487	0.05
Air transport	13,698.93	13,701	924.67	913.4308	1.8380982004	0.00183881	0.01
Other supporting and auxiliary transport activities; activities of travel agencies	33,481.54	33,622	70514.88	69657.9855	140.1728683919	0.14017287	0.84
Post and telecommunications	80,437.20	80,632	97796.44	96608.0219	194.4044668603	0.19440447	1.16
Financial intermediation	195,598.35	197,202	806695.28	796892.3172	1603.5876012283	1.60358776	9.58
Real estate activities	191,818.54	191,827	4152.76	4102.2978	8.2550599127	0.00825506	0.05
Renting of M&Eq and other business activities	318,117.20	318,446	165300.78	163292.0403	328.5928168262	0.32859282	1.96
Public administration and defense; compulsory social security	159,003.60	159,004	0.00	0.0000	0.0000000000	0	0.00
Education	147,758.44	147,774	7587.03	7494.8324	15.0818625122	0.01508186	0.09
Health and social work	70,676.78	70,677	0.00	0.0000	0.0000000000	0	0.00
Other community, social, and personal services	71,551.05	71,551	0.00	0.0000	0.0000000000	0	0.00
Private households with employed persons	3,764.84	3,765	0.00	0.0000	0.0000000000	0	0.00
Imports	486,175.66	486,176	0.00	0.0000	0.0000000000	0	0.00
Total Indirect Loss	-		0.00	0.0000	0.0000000000	0	0.00

	-16,742.18		8422264.33	8319916.9117	16742.18123908710	16.7421812	

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:

Retail 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.

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

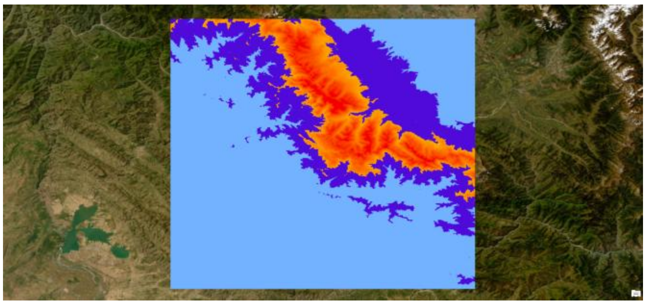
Education	0.09	15.0818625122	1,47,758.44

Table 3: Total Output of Different Sectors in 2014 and Proportion of Total Output Loss

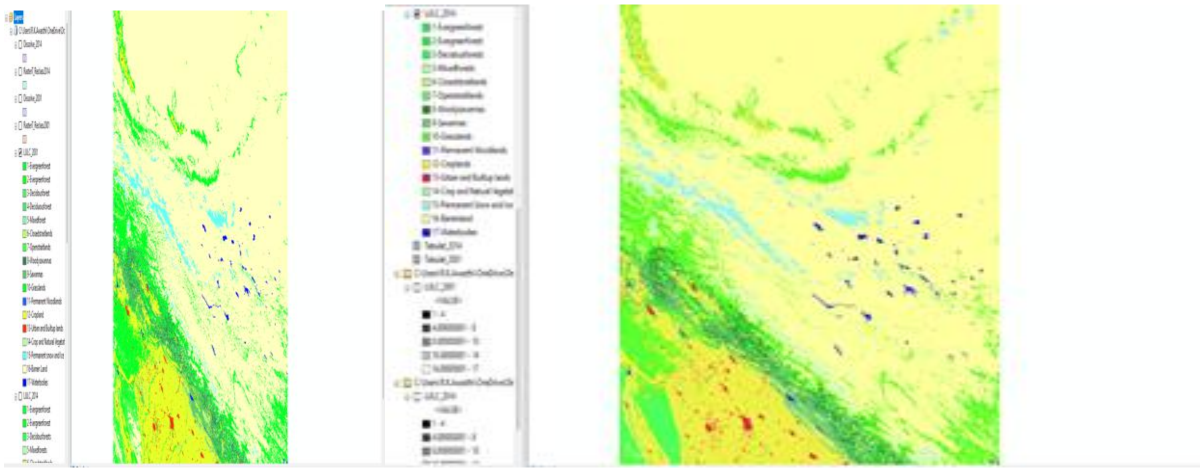
The fraction of total output loss shows the economic cause of flood concerning the entire production sector, demonstrating the overall impact on the industry (Wani, Ahmed et al. 2022). Additionally, a ratio of industrial economic recovery and accumulative output were computed. The most affected industries 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.

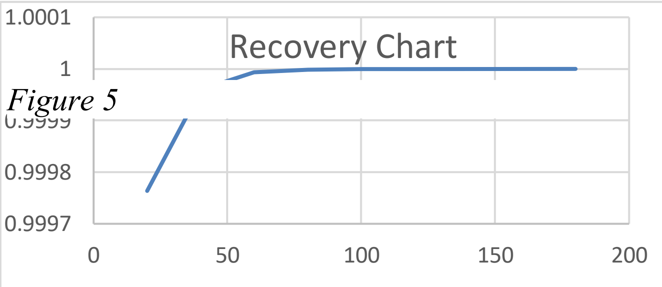


Figure 5

Figure 6

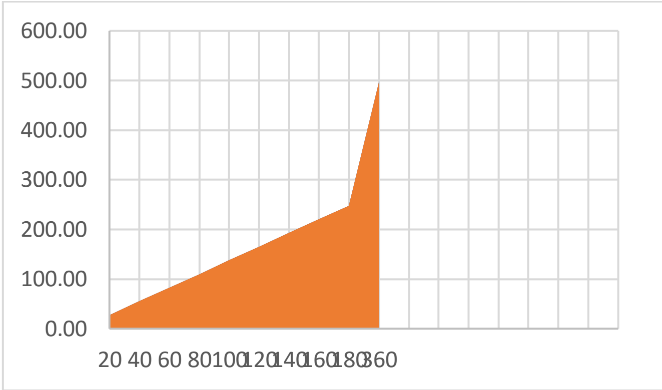


Table 4. The sector's accumulated output

Recovery period (Days)	**20**	**40**	**60**	**80**	**100**	**120**	**140**	**160**	**180**	**360**
Industrial Recovery	0.283	0.142	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	220.40	247.95	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). 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.

Comparative view of Direct and Indirect losses in different years

YEAR	Direct Loss(Billion $)	Indire4.87ct Loss(Billion $)	% of Direct Loss
2010	2.88	2.37	83
2011	2.64	1.77	67
2012	0.311	0.297	95
2013	2.98	0.0023	0.08
2014	29.00	16.74	57.7

2015	4.87	2.92	60
2016	6.84	2.48	36
2017	2.52	3.43	136
2018	5.83	4.54	78
2019	14.8	7.82	53
2020	29.88	7.03	24

H_a1: Floods and cyclones cause significant indirect economic losses that are often greater than the direct costs associated with infrastructure damage and property loss is rejected and null hypothesis $H_0$1.

H_a2: The economic impact of floods and cyclones extends beyond the immediate disaster zone, causing disruptions in supply chains, labor markets, and long-term investment decisions across various economic sectors is accepted by rejecting the null hypothesis H_o2.

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 understanding 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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